Bilkent Üniversitesi
Mühendislik Fakültesi
Endüstri Mühendisliği Bölümü

Üniversite-Sanayi İşbirliği Öğrenci Projeleri 2025

Derleyenler

Prof. Dr. Savaş Dayanık, Prof. Dr. Nesim K. Erkip,
Dr. Emre Uzun
Endüstri Mühendisliği Bölümü
Sistem Tasarımı Ders Koordinatörleri

Yeşim Gülseren
Üniversite-Sanayi İşbirliği Öğrenci Projeleri
Koordinatörü

ISBN: 978-605-9788-66-3
BASKI: Meteksan Matbaacılık, Mayıs 2025
YAYINCI SERTİFİKA NO: 51344
MATBAA SERTİFİKA NO: 46519

Bilkent University
Faculty of Engineering
Department of Industrial Engineering

University-Industry Collaboration Student Projects 2025

Editors

Prof. Dr. Savaş Dayanık, Prof. Dr. Nesim K. Erkip,
Dr. Emre Uzun
Department of Industrial Engineering
Systems Design Course Coordinators

Yeşim Gülseren
University-Industry Collaboration Student Projects
Coordinator

Düzenleme Kurulu

Organizing Committee

Sena Aslı Bozkurt
Kaan Çakıroğlu
Prof. Dr. Savaş Dayanık
Prof. Dr. Nesim K. Erkip
Yeşim Gülseren
Defne Tan
Dr. Emre Uzun

Değerlendirme Kurulu

Review Committee

Bilkent Üniversitesi Endüstri Mühendisliği Öğretim Üyeleri

Bilkent University Industrial Engineering Faculty Members

Prof. Dr. M. Selim Aktürk
Doç. Dr. Çağın Ararat
Prof. Dr. Savaş Dayanık
Prof. Dr. Nesim K. Erkip
Doç. Dr. Özlem Çavuş İyigün
Prof. Dr. Oya Ekin Karaşan
Doç. Dr. Özlem Karsu
Doç. Dr. Ayşe Selin Kocaman
Doç. Dr. Emre Nadar
Dr. Öğr. Üyesi Gizem Özbaygın
Prof. Dr. Mustafa Çelebi Pınar
Misafir Dr. Öğr. Üyesi Andrea Pizzuti
Prof. Dr. Alper Şen
Doç. Dr. Firdevs Ulus
Dr. Emre Uzun
Prof. Dr. Bahar Yetiş Kara

Doç. Dr., *Assoc. Prof.*; Dr. Öğr. Üyesi, *Asst. Prof.*

Önsöz

Bu kitap, 2024-2025 öğretim yılında Bilkent Üniversitesi Endüstri Mühendisliği Bölümü tarafından gerçekleştirilen *Üniversite-Sanayi İşbirliği Bitirme Projeleri* özetlerini kapsamaktadır. Programımız 31 yıl önce sistem tasarımı derslerinin sanayi projelerine dönüştürülmesi ile başlamıştır. Bu süre içerisinde farklı sektör ve büyüklükte 137 iş, sanayi, ve kâr amacı gütmeyen kuruluşlarla toplam 578 proje gerçekleştirilmiştir.

Endüstri Mühendisliği Bölümü dördüncü sınıf öğrencilerinden oluşan proje ekipleri, akademik ve iş dünyasından danışmanların gözetiminde firmanın gündemine girmiş olan ve çözüm bekleyen gerçek problemlerini çözmektedirler. Yapılan projeler sonucunda ortaya çıkan ürün, yöntem veya hizmet, ilgili firmaya önemli yarar ve katma değer sağlamaktadır.

Endüstri Mühendisliği Proje Fuarı ve Yarışması, 2003 yılında yapılan projelerin ilgili tüm firma, kuruluş ve üniversitelerle paylaşılması, iş dünyasının seçkin kuruluşlarının birbirleriyle ve üniversite ile olan etkileşiminin artırılması ve öğrencilerimizin iş hayatına daha donanımlı hazırlanmasını sağlamak amacıyla başlatılmıştır. Her yıl sistematik ve etkin bir şekilde yapılan bu çalışmaların daha kalıcı ve yaygın olarak paylaşılması amacıyla da "Endüstri Projeleri" kitabı serisi hazırlanmış ve bu dönemde gerçekleştirilen projeler gizlilik ilkesine bağlı kalınarak özet halinde sizlere sunulmuştur.

Kitapta yer alan proje özetlerinin doğru ve okunaklı olması için desteklerini esirgemeyen *Değerlendirme Kurulu*'muza, fuar ve yarışma jürimizde görev alan Utku Bayböru (Horse Technologies), Dilek Şen Güven (Prosis Danışmanlık), Ceren Acer Kezik (Garanti BBVA), Özgür Sarhan (Dünya Bankası) ve Dr. Öğr. Üyesi Gizem Özbaygın'a (Bilkent Üniversitesi) teşekkür ederiz.

Prof. Dr. Savaş Dayanık
Prof. Dr. Nesim K. Erkip
Dr. Emre Uzun

Bilkent Üniversitesi Endüstri Mühendisliği Bölümü
Sistem Tasarımı Dersi Koordinatörleri

Preface

This booklet contains 2024-2025 academic year *University-Industry Collaboration Student Project* summaries done by the senior students of the Industrial Engineering Department at Bilkent University in collaboration with industrial companies, businesses, and non-profit organizations. This program started when senior design courses were reorganized as industrial projects 31 years ago. Since then, 578 projects have been completed, with 137 companies operating in various sectors.

Senior student groups of the Industrial Engineering Department solve companies' real problems under the guidance of academic and industrial advisors. The project outcomes provide companies with many operational benefits and add value to their services and products.

Since 2003 *Industrial Engineering Project Fair and Competition* has been held to disseminate the project outcomes to firms and universities, boost the synergy, encourage collaboration between industry and university, and help senior students get better equipped before they take full industrial positions. Every year the project summaries are edited in a project booklet with care given not to disclose firm-specific sensitive information and shared with the community to spread the word and impact of projects.

We thank the *Review Committee* for their efforts that improved the correctness and readability of project summaries in the book. We also thank Utku Baybörü (Horse Technologies), Dilek Şen Güven (Prosis Consultancy), Ceren Acer Kezik (Garanti BBVA), Özgür Sarhan (World Bank) and Asst. Prof. Gizem Özbaygın (Bilkent University) for serving on the project competition jury this year.

Prof. Dr. Savaş Dayanık
Prof. Dr. Nesim K. Erkip
Dr. Emre Uzun

Bilkent University Industrial Engineering Department
Systems Design Course Coordinators

İçindekiler
Table of Contents

Bugüne kadar öğrenci projelerimize destek veren kuruluşlar

Companies participated in the student projects so far

Düzenleme kurulu, 2024-2025 programına değerli katkıları için aşağıda adı geçen Bilkent Üniversitesi mensuplarına teşekkür eder.

The organizing committee thanks Bilkent University members named below for their invaluable help to run 2024-2025 program.

Bilkent Üniversitesi Endüstri Mühendisliği Öğretim Üyeleri

Bilkent University Industrial Engineering Faculty Members

Prof. Dr. M. Selim Aktürk
Doç. Dr. Çağın Ararat
Prof. Dr. Savaş Dayanık
Prof. Dr. Nesim K. Erkip
Doç. Dr. Özlem Çavuş İyigün
Prof. Dr. Oya Ekin Karaşan
Doç. Dr. Özlem Karsu
Doç. Dr. Ayşe Selin Kocaman
Doç. Dr. Emre Nadar
Dr. Öğr. Üyesi Gizem Özbaygın
Prof. Dr. Mustafa Çelebi Pınar
Mis. Dr. Öğr. Üyesi Andrea Pizzuti
Prof. Dr. Alper Şen
Doç. Dr. Firdevs Ulus
Dr. Emre Uzun
Prof. Dr. Bahar Yetiş Kara

Üniversite Sanayi İşbirliği Öğrenci Projeleri Koordinatörü

University & Industry Cooperation Student Projects Coordinator

Yeşim Gülseren

Bilkent Üniversitesi Endüstri Mühendisliği Bölümü İdari Asistanı

Bilkent University Industrial Engineering Dept. Administrative Assistant

Vegün Ekmekçi

Bilkent Üniversitesi Hukuk Müşavirliği Ofisi

Bilkent University Legal Advising Office

Gül Gökçe Çağatay
Melike Temiz

Bilkent Üniversitesi Mali İşler Müdürlüğü

Bilkent University Financial Affairs Office

Ramazan Atmaca
Dilek Bilgili
Arda Kaya
Serdar Ser

Düzenleme kurulu, 2024-2025 programına sağladıkları işbirliği için aşağıda yer alan iş dünyasının değerli mensuplarına teşekkür eder.

The organizing committee thanks the esteemed company representatives listed below for their cooperation to run 2024-2025 program.

Ata Teknoloji Platformları
Ahmet Tuğrul Bayrak
Bekir Berker Türker

Bakioğlu Holding
Beste Yıldız
Sabahattin Bilgen

Beko Elektronik İşletmesi
Elvan Parlak
Ömer Faruk Ünal

Beko Global Ar-Ge ve Üniversite-Sanayi İlişkileri
Evrim Özgül
Merve Özhavutçu

Beko Küçük Ev Aletleri Direktörlüğü
Serdar Değirmenci

Beko Pişirici Cihazlar İşletmesi
Ufuk Çetek
Mustafa Kaçan

Bilkent Holding
Prof. Dr. Abdullah Atalar
Ceyda Kitapçıgil

Emeklilik Gözetim Merkezi
Mustafa Akmaz
Hicran Aktaş Coşar
Samet Özben

Enerjisa
Aslı Abes
Buğçe Demirkol
Sibel Kesgin
Volkan Umar

Hayat Finans
Özer Baran
Aylin Gücüyener
Suzan Öztürk
Açelya Tanışman

İstanbul Gübre Sanayi
Betül Merve Çetin
Yavuz Çetin

Memorial Sağlık Grubu
Berna Dursun
Banu Kurtaran
Bora Uludüz

Meteksan Savunma
Okan Akay
Eda Şenol

Nesco Gıda
Nazlı Esen Ummansu

Nevzat Ecza Deposu
Osman Bozkurt
Bora Dilik
Harika Karpuzcu Dilik

Nestlé Türkiye
Yunus Arslan
Haydar Ateşok
Nazlı Çetin Berber
Selami Çakmak
Elçin Kocaman
Görkem Sayalı

Ortadoğu Rulman Sanayi
Dr. Alptekin Demiray

Pegasus Hava Yolları
Mert Köksal

SCW.AI
Haluk Atlı

Sports International
Kenan Ayduğan
Kübra Bircan Aygün
Hakan Öztürk

Tepe Betopan
Ercan Arı
Çağatay Çaparlı

Tepe Home
Ceren Evcimen

Unilever Türkiye
Arda Baş

Bölüm Başkanı'ndan

Bilkent Üniversitesi Endüstri Mühendisliği Bölümü, öğrencilerinin teknolojik ve sosyal değişikliklere uyum sağlayan, yaşam boyu öğrenen ve sorgulayan iyi endüstri mühendisleri olarak mezun olmalarını amaçlamaktadır. Karmaşık sistemlere ve problemlere bütün olarak bakabilme ve analitik düşünebilme, eğitim programının önemli amaçlarındandır. Bölüm, 2007 yılında *Accreditation Board for Engineering and Technology (ABET)* adlı bağımsız kuruluş tarafından eğitim kalitesini belgeleyen tam akreditasyonu Türkiye'de ilk alan mühendislik bölümüdür.

Eğitimde dünya çapında kalite standartlarını kullanan Endüstri Mühendisliği Bölümü, ülkemizde örnek gösterilen *Üniversite-Sanayi İşbirliği Programı*'nı 31 yıldır başarıyla uygulamaktadır. Programın hedefi mezuniyet aşamasındaki öğrencilerin kapsamlı mesleki deneyim kazandırmaktır. Altı-yedi kişilik proje ekipleri, akademik ve endüstriyel danışmanların gözetiminde firmaların çözüm bekleyen gerçek problemlerini çözmektedirler.

Bu yıl, *23. Endüstri Mühendisliği Proje Fuarı ve Yarışması*'nda 23 proje bulunmaktadır. Fuarda öğrencilerimiz, yıl boyunca projeleri üzerinde yaptıkları çalışmalarını sunmaktadırlar. Onları özverili çalışmaları için kutluyor, programa büyük katkıları olan firma yetkililerine ve danışmanlarımıza teşekkür ediyorum.

Bütün süreç boyunca yoğun ve özverili çalışmalarıyla programın hedeflerine ulaşması için büyük çaba gösteren program koordinatörleri Prof. Dr. Savaş Dayanık, Prof. Dr. Nesim K. Erkip ve Dr. Emre Uzun'a, Üniversite-Sanayi İşbirliği Öğrenci Projeleri Koordinatörü'müz Yeşim Gülseren'e, asistanlarımız, Sena Aslı Bozkurt, Kaan Çakıroğlu, Defne Tan ve emeği geçen herkese çok teşekkür ediyorum.

Prof. Dr. Bahar Yetiş Kara
Endüstri Mühendisliği Bölüm Başkanı

Chairperson's Message

Bilkent University Industrial Engineering Department strives for its students to grasp changes in technology and society and be lifelong learners and inquirers. One of the department's educational goals is that our students hold a holistic view of systems and problems backed up with analytical thinking. The department is the first engineering department in Turkey, the quality of whose education program was fully accredited by *the Accreditation Board for Engineering and Technology (ABET)* back in 2007.

For 31 years, the Industrial Engineering Department has been successfully running its exemplary *University-Industry Collaboration Program.* The program's objective is to have the department's senior students gain full-fledged industrial experience before getting full industrial positions. Six-to-seven member student groups attack real open problems of companies under the supervision of academic and industrial advisors.

Twenty-three projects are present at the *23th Industrial Engineering Project Fair and Competition.* At the fair, student groups present their year-long work and the outcomes of their projects. I congratulate them for their tireless and heart-whole hard work. I also thank the company representatives and academic and industrial advisors for their support and collaboration.

Finally, I thank course coordinators Prof. Dr. Savaş Dayanık, Prof. Dr. Nesim K. Erkip, and Dr. Emre Uzun, University-Industry Collaboration Student Projects Coordinator Yeşim Gülseren, graduate assistants Sena Aslı Bozkurt, Kaan Çakıroğlu, and Defne Tan for their relentless efforts to ensure that the program succeeds.

Prof. Dr. Bahar Yetiş Kara
Industrial Engineering Department Chairperson

Teşekkür Mektupları

Appreciation Letters

Ata Teknoloji Platformları'ndan,

Ata Teknoloji Platformları, finans, konuk ağırlama ve enerji sektörleri başta olmak üzere kurumsal şirketlerin ihtiyaç duyduğu yaşamsal (mission critical) platform, yazılım ve hizmetleri geliştiren lider teknoloji şirketlerinden birisidir. 2021 yılında halka arz olan ATP (BIST:ATATP), çatısı altında bulunan ATP Tradesoft, ATP Zenia, ATP Digital ve ATP GreenX markalarıyla, geliştirdiği yenilikçi teknolojileri rekabet ve maliyet avantajına dönüştürerek kurumsal müşterilerinin gerçek anlamda değer yaratmalarına, esnek çeviklik kazanmalarına ve inovasyon performansı ortaya koymalarına yardımcı olmaktadır.

ATP, finans, konuk ağırlama ve enerji sektörlerine dikey olarak odaklanmış marka ve profesyonel ekiplerle hizmet vermektedir. ATP'nin finans sektörüne özel yazılım çözümleri markası Tradesoft, geliştirdiği aracı kurum, fon ve portföy yönetim çözümleriyle Borsa İstanbul işlem hacminin rakip sistemler içerisindeki payının %46'sını yönetmektedir. ATP'nin restoran yönetimi ve çok kanallı sipariş teslimat çözümleri markası Zenia, lider küresel restoran markalarının 3.300'ye yakın lokasyonunda kullanılmaktadır. ATP Digital, hayata geçirdiği 500'ün üzerinde projeyle kurumsal şirketlere dijital dönüşüm konusunda uçtan uca rehberlik etmiştir. ATP'nin çevre dostu teknoloji çözümleri markası ATP GreenX, Türkiye'nin yeşil ve karbon sertifikaları ticaretini kolaylaştıran ilk dijital pazar yerini geliştirmiştir.

Türkiye, Çin ve EMEA bölgesinde 800'ün üzerinde referansı bulunan ATP, tasarladığı çözümler, gerçekleştirdiği projelerden elde ettiği uygulamalı deneyimler ve sahip olduğu süreç mühendisliği yetkinlikleriyle kurumları dijital olarak dönüştürmekte ve değişimin risklerini fırsata çevirmelerini sağlamaktadır. Ayrıca, yaptığı AR-GE çalışmalarıyla bilimsel literatüre ve hizmet verdiği sektörlerin sürdürülebilir gelişimine katkıda bulunmaktadır. Bunlarla beraber

ATP, üniversite-sanayi işbirliğine de son derece önem vermektedir.

"Hızlı Servis Restoranlarında Bozulabilir Envanter Yönetimi" isimli projemiz Bilkent Üniversitesi iş birliğiyle başarılı bir şekilde tamamlanmıştır. Proje kapsamında bozulabilir ürünlerin yer aldığı iki aşamalı bir tedarik-zinciri sisteminde belirsiz talep koşulları altında envanter seviyesini ve atık miktarını azaltmaya yönelik, sezgisel bir envanter karar destek sistemi geliştirilmiştir. Proje süresince, gösterdikleri özveri ve katkılardan dolayı ATAEN ekibindeki öğrenci arkadaşlarımıza, projeye bilgi ve deneyimleriyle değer katan Doç. Dr. Emre Nadar ve Prof. Dr. Nesim K. Erkip'e, ayrıca üniversite-sanayi iş birliğinin sağlanmasında önemli rol üstlenen Yeşim Gülseren'e teşekkür ederiz. Tüm öğrencilerimize kariyer yolculuklarında başarılar dileriz.

Ahmet Tuğrul Bayrak
Ata Teknoloji Platformları
Veri Bilimi ve İnovasyon Müdürü

Beko Küçük Ev Aletleri Direktörlüğü'nden

Bilkent Üniversitesi Endüstri Mühendisliği Bölümü tarafından yürütülen Sanayi Odaklı Bitirme Projeleri kapsamında, "Tedarikçi Karne Sistemi İyileştirme" projesinde yer almaktan büyük bir memnuniyet duyduk.

Projeye katkı sunan öğrencilerimizin analitik yaklaşımları, çözüm odaklılıkları ve yenilikçi fikirleri sayesinde mevcut sistemimizin değerlendirme mekanizmalarını daha sağlam, daha güvenilir ve daha öngörülebilir hale getirmeye yönelik önemli çıktılar elde edilmiştir. Özellikle alternatif değerlendirme yöntemleri, erken tespit sistemleri ve veri analizi çalışmaları, şirketimizin tedarikçi yönetimi süreçlerine değerli katkılar sağlamıştır.

Bu süreçte hem öğrencilerimizin gösterdiği özverili çalışmalar hem de Bilkent Üniversitesi'nin güçlü akademik desteği bizlere geleceğin mühendislerine olan güvenimizi bir kez daha pekiştirmiştir. Projeye liderlik eden değerli akademisyenlerimize, organizasyonu koordine eden mezuniyet projeleri ekibine ve projeye emeğini katan tüm öğrencilere içtenlikle teşekkür ederiz.

Üniversite-sanayi iş birliğinin güzel bir örneğini oluşturan bu çalışmanın bir parçası olmaktan dolayı gurur duyuyor, tüm öğrencilere kariyer hayatlarında başarılar diliyoruz.

Saygılarımızla,

Serdar Değirmenci
Kalite Yöneticisi
Beko - Küçük Ev Aletleri Direktörlüğü

EMEKLİLİK GÖZETİM MERKEZİ

Emeklilik Gözetim Merkezi Genel Müdürü'nden
BİLKENT ÜNİVERSİTESİ
ENDÜSTRİ MÜHENDİSLİĞİ BÖLÜMÜ BAŞKANLIĞI'NA

Emeklilik Gözetim Merkezi A.Ş. (EGM), 4632 sayılı Bireysel Emeklilik Tasarruf ve Yatırım Sistemi Kanunu uyarınca Hazine ve Maliye Bakanlığı'nın yetkilendirmesiyle kurulmuştur. Anılan Kanunda EGM'nin amacı, özel emeklilik sisteminin etkin güvenli şekilde işletilmesini sağlamak, katılımcıların hak ve menfaatlerini korumaktır.

EGM'nin temel görevlerinden bazıları; emeklilik şirketlerinin, BES aracılarının ve portföy yönetim şirketlerinin faaliyetlerinin elektronik olarak gözetimi, tespit edilen gözetim bulgularının SEDDK ve SPK'ye raporlanması, anılan idarelere gözetim ve denetim altyapısı sağlanması, emeklilik şirketlerine merkezi dijital hizmetler sunulması, Devlet katkısı tahakkuk ve ödeme süreçlerinin yönetilmesi, fon performans değerlendirme sisteminin işletilmesi ve katılımcılara bilgilendirme hizmetleri sunulmasıdır.

EGM, ülkemizi Uluslararası Özel Emeklilik Düzenleme, Denetim ve Gözetim Otoriteleri Örgütü (IOPS ve OECD) Özel Emeklilik Teknik Komitesi'nde temsil etmektedir. Uluslararası iyi uygulamalar, bilimsel araştırmalar ve ilgili literatür Kurumumuzca yakından takip edilmektedir. Üniversiteler, araştırma kurumları ve finansal teknoloji girişimleriyle iş birlikleri geliştirmek, EGM'nin stratejik öncelikleri arasında yer almaktadır.

Endüstri mühendisliğinin sanayi, enerji, finans başta olmak üzere pek çok alanda bilimsel yöntemler kullanmak suretiyle kompleks süreç ve sistemlerin analiz edilmesi, tasarlanması, iyileştirilmesi ve optimize edilmesinde kritik önemi vardır. Bu nedenle, Kurumumuzda endüstri mühendisleri istihdam edilmekte ve üniversitelerin endüstri mühendisliği bölümleriyle iş birlikleri geliştirilmektedir.

Geçen yıl olduğu gibi bu yıl da Bölümünüz son sınıf öğrencilerinin bitirme projeleri için Kurumumuzu tercih etmelerinden büyük mutluluk duyduğumuzu ifade etmek isteriz.

2024-2025 öğretim yılında Kurumumuzda gerçekleştirilen iki projeden biri olan “BES Katılımcıları için Özelleştirilebilir Portföy Öneri Sistemi” başlıklı proje ile, katılımcıların risk iştahı ve yatırım süresi dikkate alınarak kişiselleştirilmiş portföy önerileri sunan bir karar destek modeli geliştirilmiştir.

“Özel Emeklilik Sisteminde Katılımcı Risk Profillerine Uygun Fon Seçkisi Oluşturulmasına Yönelik Derecelendirme Sistemi” başlıklı diğer proje kapsamında ise, katılımcıların risk profillerine uygun olarak fon tercihlerini yönlendiren bir derecelendirme modeli geliştirilmiştir.

Her iki proje de, katılımcıların birikimlerini daha etkin yönetmelerini destekleyen, özel emeklilik sisteminin sürdürülebilir büyümesine katkı sunan ve halihazırda uygulamada yaşanan sorunlara çözüm üretmeyi amaçlayan örnek çalışmalardır. Söz konusu çalışmaların Kurumuzca katılımcılara sunulan BES Mobil, BEFAS Bilgilendirme Platformu gibi dijital hizmetlere entegre edilmesi veya emeklilik şirketlerince kullanılması potansiyeli bulunmaktadır. Mühendis adayı öğrencilerle yürütülen bu iş birliğinin, hem sektörümüzün ihtiyaçlarına yönelik çözüm üretmiş olduğu hem de genç mühendislerin mesleki gelişimine doğrudan katkı sağladığı düşünülmektedir.

Projeler boyunca öğrencilerin sergilediği yüksek motivasyon ve kararlılık, kıymetli akademisyenlerin rehberliğiyle birleşerek yüksek katma değerli sonuçların elde edilmesini mümkün kılmıştır. Projelere katkı sağlayan başta Bilkent Üniversitesi Projeler Koordinatörlüğü, proje danışmanları ve proje koordinatörleri olmak üzere tüm akademik kadroya ve projelerde yer alan tüm öğrencilere en içten teşekkürlerimizi sunarız.

Öğrencilerimizin mezuniyetini şimdiden kutlar, meslek yaşamlarında ve özel hayatlarında kendilerine başarılar dileriz.

Mustafa AKMAZ
Emeklilik Gözetim Merkezi A.Ş. Genel Müdürü

ENERJISA
Türkiye'nin Enerjisi

Enerjisa Enerji'den,

Enerjisa Enerji olarak, 1996 yılından bu yana Türkiye'nin lider elektrik dönüşüm şirketi olarak, 10 bini aşkın çalışanımızla 3 bölgede ve 14 ilde faaliyet göstermekteyiz. Herkese daha iyi bir gelecek sağlayabilmek için tüm enerjimizle çalışıyor; sürdürülebilir büyüme hedefimiz doğrultusunda topluma fayda sağlayacak projelere ve iş birliklerine odaklanıyoruz. Türkiye'nin enerji dönüşümüne öncülük ederken, çevik ve dayanıklı yapımızla daha iyi bir geleceğe hızla ilerliyoruz. En önemlisi de daha iyi bir geleceğin gençlerle mümkün olacağına inanıyoruz.

Bu doğrultuda hayata geçirdiğimiz Üniversite-Sanayi İş Birliği projesi, gençlerin geleceğin şekillenmesindeki belirleyici rolünü bir kez daha ortaya koydu. Bilkent Üniversitesi Endüstri Mühendisliği bölümü öğrencileri ve akademik kadrosu ile yürüttüğümüz "Hibrit Çalışma Düzeninde Personel Taşıma Sistemi Optimizasyonu" konulu proje sayesinde; mevcut servis güzergahlarını ve doluluk oranlarını analiz eden, Araç Rotalama Problemi (VRP) temelli matematiksel bir modelleme ortaya koyan bir çalışmaya imza attık. Projemiz, aynı zamanda İdari İşler ekiplerimizin operasyonel yükünü azaltmayı hedefleyen yenilikçi bir çözüm önerisi sundu.

Genç ekip arkadaşlarımızla dijital dönüşümü ve yenilikçi uygulamaları birlikte deneyimlemek bizler için oldukça değerliydi. Projeye emek veren tüm öğrencilere azim ve katkıları, kıymetli akademik danışmanlarına ise süreç boyunca gösterdikleri yol ve destek için içten teşekkürlerimizi sunuyor, kendilerine başarılarla dolu bir gelecek diliyoruz.

Enerjisa Enerji (İnsan, Kültür, İdari İşler Ekibi)

MEMORIAL

Memorial Sağlık Grubu'ndan,

2000 yılında kurulan Memorial Sağlık Grubu, Türkiye'de sağlık alanında birçok ilki hayata geçiren öncü kuruluşlardan biri olarak, bu yıl 25. yılını kutlamaktadır. Dünyada ve ülkemizde uluslararası kalite standartlarında sunduğu sağlık hizmetleriyle tanınan Memorial, bugün İstanbul, Ankara, Antalya, Kayseri ve Diyarbakır ve Romanya'da bulunan 11 hastanesi ile faaliyet göstermektedir. Hasta memnuniyetini merkezine alan anlayışı, uzman hekim kadrosu ve ileri tıbbi teknolojilere yaptığı yatırımlarla sağlıkta mükemmellik vizyonunu sürdürmektedir.

Bu vizyon doğrultusunda, Bilkent Üniversitesi Endüstri Mühendisliği öğrencileriyle birlikte yürüttüğümüz "Vardiya Atamaları için Karar Destek Sistemi Tasarımı İşgücü Optimizasyonu" projesiyle hemşireler ve hasta danışmanları için mevcut vardiya planlama süreçlerimizi daha etkin hâle getirmeye yönelik önemli bir çalışma gerçekleştirilmiştir. Proje, çalışan tercihlerini gözeten, eşit iş yükü dağılımını esas alan ve ani personel eksikliklerine karşı esnek çözümler sunabilen dinamik bir vardiya atama modeli geliştirmeyi amaçlamıştır.

Bu süreçte gösterdikleri özveri, analitik bakış açıları ve çözüm odaklı yaklaşımları için Bilkent Üniversitesi Endüstri Mühendisliği öğrencilerine en içten teşekkürlerimizi sunarız. Aynı zamanda, proje sürecine rehberlik eden değerli proje koordinatörüne ve katkı sağlayan tüm akademisyenlere destekleri ve yönlendirmeleri için teşekkür ederiz. Gerçek hayattaki operasyonel bir probleme akademik disiplinle yaklaşarak sundukları katkılar, bizler için son derece kıymetli olmuştur. Bu iş birliğinin, hem sağlık hizmetlerinde hem de akademik alanda verimli ve ilham verici sonuçlara vesile olduğuna inanıyoruz.

Berna Dursun
Süreç ve Verimlilik Grup Müdürü

Nestlé Türkiye'den,

Nestlé Türkiye olarak 8 farklı gıda ve içecek kategorisinde yaklaşık 800 ürünü tüketicilerimizle buluşturuyoruz. Buradaki operasyonu yönetebilmek için de her alanda verimlilik ve sürdürülebilirlik bizim için önemli unsurlar oluyor. Her fırsatta optimizasyon ve dijitalleşme olanaklarını değerlendiriyoruz. Bu noktada ise yollarımız hem endüstri hem de öğrenciler için büyük katma değer oluşturan Bilkent Üniversitesi ile kesişti. Bilkent Üniversitesi Endüstri Mühendisliği bölümünde yürütmekte olduğumuz bitirme projeleri kapsamında bu sene birisi kötü halde iadelerin azaltılması, diğeri ise araç içi doluluk oranının arttırılması konuları üzerine iki projeyi değerli öğrenci gruplarımız ve danışman hocalarımızın destekleri ile tamamladık. Üniversitenin sağladığı bu platform ile öğrenci arkadaşlarımızın gerçek konular üzerinde çalışma fırsatı bulması ve öğrencilerimizi iş hayatına hazırlamak bizim için büyük bir gurur kaynağıdır.

Bu projeler aracılığıyla, sadece arayüzler ile çözüm üretmekle kalmayıp, aynı zamanda gelişim alanlarımızı fark etme ve yeni perspektifler kazanma fırsatı buluyoruz. Akademik gelişmeleri takip etme şansımız, bu süreçte edindiğimiz deneyimlerle daha da zenginleşmektedir.

Bize sağladığı bu değerli katkılar için, özellikle Endüstri Mühendisliği Bölümü'ne, çok değerli danışman hocalarımıza ve projelerimizde emeği geçen sevgili öğrenci gruplarımıza teşekkür ederiz.

Elçin Kocaman
Nestlé Türkiye
IT İnovasyon Yöneticisi

Ortadoğu Rulman Sanayi ve Tic. A.Ş. Üretim Planlama ve Bilgi Sistemleri Müdürü'nden

Ortadoğu Rulman Sanayi ve Tic. A.Ş. (ORS) bilyalı rulman, konik makaralı rulman, silindirik makaralı rulman, makara, bilezik ve burç üretimi yapan, Ortadoğu'nun ilk, Türkiye'nin tek entegre rulman üretim firmasıdır. 1982 yılında kurulan şirket, 1986 yılında 4 milyon adet/yıl üretim kapasitesi ile seri üretime başlamıştır. Geçtiğimiz 40 yıl içerisinde üretim kapasitesi 100 milyon adet/yıla, çalışan sayısı ise 1500 kişiye ulaşmıştır. Dünya çapında yüzlerce müşterisi olan şirketin ana müşteri grubunu otomotiv, beyaz eşya ve elektrik motoru üreticileri oluşturmaktadır. Üretiminin %75'ini başta Batı Avrupa ve Kuzey Amerika ülkeleri olmak üzere sanayisi ve teknolojisi en üst seviyedeki ülkelere ihraç eden şirket, Türkiye'nin ilk 500 sanayi kuruluşu arasında yer almaktadır. Güney Kore'de kurulan ORS KOREA şirketi ile sadece rulman üretiminde değil, makine imalatında da küresel bir oyuncu olma vizyonuna emin adımlarla ilerlemektedir.

ORS, eğitime sağladığı her türlü katkıyı sosyal sorumluluğunun bir gereği olarak görmekte, birçok üniversiteyle benzer projeler sürdürmekte, her yıl yüzlerce öğrenciye proje ve staj imkânı sağlamaktadır. Bilkent Üniversitesi Endüstri Mühendisliği ile 25 yıldır yürütülen projeler ise profesyonel yönetimi, çalışma disiplini ve ortaya çıkardığı katma değer açısından ayrı bir değere sahiptir. Türkiye'deki üniversite–sanayi iş birliğinin en başarılı örneklerinden olan bu projelerin gerçekleşmesini sağlayan üniversite yönetimimiz, bölümümüzün değerli öğretim üyeleri, araştırma görevlilerimiz ve öğrenci projeleri koordinatörümüz her türlü takdiri hak etmektedir.

2024-25 akademik yılında, ORS ürünlerinin geçmiş satış verilerini anomali tespit algoritmaları ile analiz ederek satış trendlerinde beklenmeyen değişimleri tespit etmek ve gelecek 12 ayda gerçekleşecek satışları en az hatayla tahmin etmek üzerine bir proje gerçekleştirilmiştir. Bu proje, veri biliminin üretim şirketlerinde kullanımına çok başarılı bir örnek oluşturmuştur. Projede beraber çalıştığımız mühendis adaylarına katkılarından dolayı teşekkür ediyor, iş ve akademik hayatlarında kendilerine başarılar diliyoruz.

Dr. Alptekin DEMİRAY
Üretim Planlama ve Bilgi Sistemleri Müdürü
Bilkent IE 2002 Mezunu

All the best of success...

and all the best of luck!

PROJELER
PROJECTS

Algida Teslimat Kamyonu Ziyaret Sıklığı ve Rota Eniyilemesi | 1

Unilever Türkiye

Proje Ekibi
Melih Ak, Verda Arpacı, Ebru Ayan, Emir Doğan,
Muhammet Günalp Farsak, Yağmur Kuzucuoğlu, Bilge Özerdem

Şirket Danışmanı
Arda Baş
Direkt Dağıtım Müdürü

Akademik Danışman
Doç. Dr. Özlem Çavuş İyigün
Endüstri Mühendisliği Bölümü

Özet

Bu proje, yakıt giderleri, fazla mesai, verimsiz rotalama ve stok kıtlığı nedeniyle oluşan dondurma dağıtım maliyetlerini ele almaktadır. Proje, genişletilmiş bir Seyahat Eden Satış Elemanı Problemi (SESEP) yaklaşımı uygulayarak teslimat rotalarını ve satış elemanı ziyaret programlarını eniyilemektedir. Tahmin verilerini kullanan sezgisel bir yöntem, rota verimliliğini artırıp, maliyetleri düşürerek ve yeterli stok seviyelerini koruyarak aşırı stoklama olmadan ürün bulunabilirliğini sağlamaktır.

Anahtar Sözcükler: Dağıtım Eniyilemesi, Seyahat Eden Satış Elemanı Problemi, Maliyet Minimizasyonu, Satış Elemanı Ziyaret Planlaması

Algida Delivery Truck Visit Frequency and Route Optimization

Abstract

This project addresses ice cream distribution costs caused by fuel expenses, overtime, inefficient routing, and stock shortages. By applying an extended Traveling Salesperson Problem (TSP) approach, the project optimizes delivery routes and salesperson visit schedules. A heuristic method using forecast data enhances routing efficiency, provides lower costs, and maintains adequate stock levels, ensuring product availability without overstocking.

Keywords: Distribution Optimization, Traveling Salesperson Problem, Cost Minimization, Salesperson Visit Scheduling

1.1 Unilever and Problem Identification

1.1.1 Company description and system analysis

Unilever is a global leader in the fast-moving consumer goods (FMCG) sector, operating in over 190 countries and reaching approximately 3.4 billion consumers daily. Unilever Türkiye, founded in 1952, plays a key role in global operations. With over 5,000 employees and six factories, it manages brands such as Lipton, Knorr, OMO, and Algida, and serves as an export hub to more than 30 countries. Its Istanbul office oversees operations in 35 countries across the Middle East, Central Asia, and North Africa (Türkiye Investment Office, 2023a).

Algida, Unilever's flagship ice cream brand in Türkiye, is a cornerstone of its regional strategy. It operates two major production facilities—one in Çorlu established in 1990 (Algida Food Service, 2024), and another opened in 2013 with a €95 million investment, employing 300 people (Türkiye Investment Office, 2023b). Serving both domestic and export stores, Algida holds a dominant 77% share in the Turkish ice cream store, reinforcing its strategic importance within Unilever's portfolio (Çağatay, 2024).

1.2 Current System Analysis and Problem

In Algida's current system, there are two factories, two main warehouses, six direct distribution warehouses, and 82 distributor channels. Produced ice creams are first transferred to main warehouses and then transferred to local warehouses. From direct distribution centers, three types of operations take place: MT operations consist of distribution to chain stores, HT operations focus on smaller and local stores, and DT operations make deliveries to smaller warehouses. This project focus on improvements on MT channel under direct distribution.

Supplying the demand on MT channel depends on the orders given by the stores. Instead of forecasting future demands and supplying according to them, Algida prefers filling the empty spaces in the refrigerators. The Algida Sales Specialist (ASU) must first visit the stores and take their orders. Orders are then prepared for the next day and distributed by a truck. Each truck has its own region, which is mostly determined by the proximity of the stores and the drivers' routines over the years.

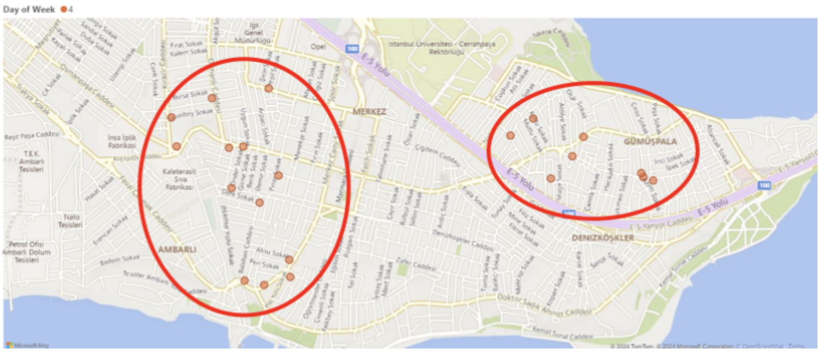


Figure 1.1: Subregions in a Region

The sales and delivery process requires that trucks serve stores exactly one day after the ASU visits. Consequently, the ASU's route directly influences truck routes. This dependency often causes inefficiencies and added costs. For example, trucks are sometimes dispatched to the same region multiple times a week—exceeding the four-visit limit—even though nearby stores are scheduled on different days. Figures 1.1 and 1.2 illustrate the current distribution pattern, each color represents a different day of delivery.

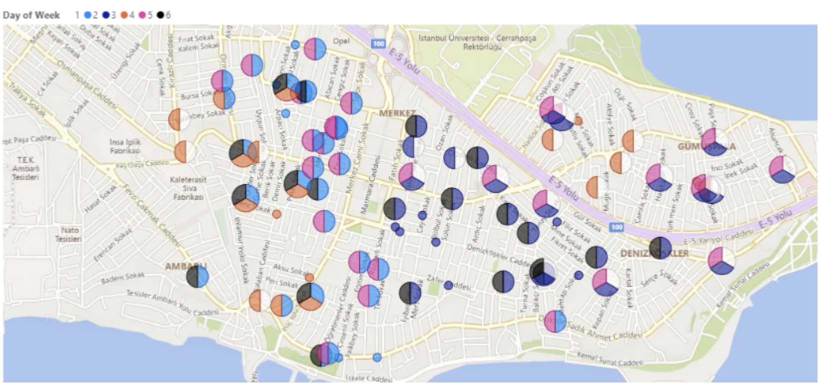


Figure 1.2: Delivery Frequency to Stores

The presence of multiple colors within the same region indicates fragmented scheduling, resulting in higher transportation costs and inefficiencies. This stems from the dependency between ASU visits and truck deliveries, as trucks are required to serve stores one day after the ASU places the order. These issues are especially prominent during summer months with high demand, sometimes leading to overtime work.

1.3 Proposed Solution Strategy

The primary objective of the project is to minimize distribution costs, with a focus on reducing travel and overtime expenses. To achieve this, past delivery data (region, truck, store info) is analyzed to generate forecasts based on seasonality and trend. Clustering is used to identify nearby stores. These feed into a mathematical model optimizing truck routing, balancing inventory and delivery frequency while minimizing costs. For efficiency, a matheuristic approach handles large instances. The combined small visit frequency model and the heuristic produce optimized visit frequencies and routes, reducing fuel and overtime costs.

1.3.1 Critical Assumptions

Some critical assumptions are made to make the problem solvable. Since our model uses daily demand data as input and deliveries are made on discrete days without any pattern, it is necessary to distribute the batch data across the days until the previous delivery. To achieve this, we assumed that demand is evenly distributed across the days between consecutive deliveries and then performed a daily demand forecast. Orders are placed at the start of the day. It is assumed that each region has a dedicated truck assigned to it, and this truck exclusively serves the store within that region. Also, when .the ASU visits a store, it places an order large enough to completely fill the capacity of the ice cream cabinet at that store.

1.3.2 Solution Approach

Forecast

In order to ensure that ice cream refrigerators remain consistently stocked, the forecasting process begins by examining historical batch delivery records to understand each store's underlying demand patterns. Since orders are typically placed to fill empty places in the refrigerators, the batch data is converted into daily demand values. After data cleaning, trend and seasonality analyses are performed to understand the recurring patterns and long-term shifts in demand. Challu et al. (2023) suggested a method for making a forecast when there is more than one layered trend for such problems. Since the project has both seasonality and weekly trends, the methods suggested in that study is used to forecast this two-layered trend. These methods

Table 1.1: Stores' Batch Error for a Region's Off-Season Monthly Forceast

Model	Metric	Average
Holt-Winters	MSE	39.18
	RMSE	6.26
Prophet	MSE	12.69
	RMSE	3.56

are Holt-Winter's, and Prophet. Prophet is a machine learning-based time series forecasting model, designed to handle missing data, outliers, and complex seasonal effects with a flexible and interpretable framework.

The evaluation of Prophet and Holt-Winter's models is conducted using historical data from 2022, 2023, and the beginning of 2024 up to October. This comprehensive dataset allows for training the models on past demand patterns, trends, and seasonality. October 2024 is reserved as the test period, where the models' forecasts are validated against actual demand data for the same month. The operational implications of Prophet's superior performance are significant in Table 1.1. Therefore, the Prophet model is used in all future forecasting operations.

Mathematical Model

The aim of the model is to minimize both the fuel costs of the trucks and the overtime costs while also ensuring that the ice cream refrigerators in the stores are never empty. Three different constraint types are used in modeling ASU's visit frequency optimization. First, TSP rooting and MTZ sub-tour elimination constraints are used to ensure the routing of trucks for each day. Second, inventory balance constraints from the deterministic inventory problem are used for each store to decide on the visits to the stores. Finally, time window constraints from the time window vehicle rooting problem are used to ensure that the stores are compatible with the goods acceptance times. The mathematical model can be seen in Appendix 1.A.

Matheuristic Approach

The purpose of the matheuristic approach is to quickly produce practical solutions for large store networks, where solving the mathematical model becomes computationally expensive in an open-source environment. K-means clustering is first used to group stores into subregions to be able to observe how many times a clusteris visited in a week. Then, TSP heuristic for multiple time window TSP suggested by Hurkala (2015) is used for the routing part of the problem. These form the basis of the 5-step matheuristic approach.

Step 1: Mathematical Model for Determining Visit Frequency:

This step uses a mathematical model to determine daily visit frequencies for each store based on each store's demand and inventory, guiding the next stages of the heuristic. This mathematical model for determining visit frequency can be seen in Appendix 1.B.

Step 2: Constructing Initial Solution: This step creates an initial schedule for store visits within specified time windows. The algorithm processes each store, checking whether the current time fits the available time window by considering the service duration and the travel time to the next store. It prioritizes the earliest start time that meets these constraints. Once a valid time window is found, the visit is scheduled, and the process moves on to the next store by adjusting the travel time.

Step 3: Variable Neighborhood Descent (VND): The variable VND algorithm improves the solution by successively applying neighborhood functions such as swapping consecutive stores, swapping two random stores, and relocating a store. Each new solution is evaluated and accepted if it offers a lower cost. This process continues until a local optimum is reached that provides the best local solution around the current one.

Step 4: Reduced Variable Neighborhood Search (RVNS): The RVNS algorithm improves solutions by exploring different initial solutions. For each one, a neighboring solution is selected using neighborhood functions, followed by VND application. When a better solution is found, the process starts over and continues until the maximum iteration, aiming to obtain an improved result.

Step 5: Feasibility Check: In this step, the feasibility of the obtained solution is checked. If any day is infeasible, one delivery from that day is canceled, and the algorithm returns to Step 2 to find another initial solution. This repeats until a feasible solution is found for each day.

1.4 Validation

The validation process checks if the solution matches real-world conditions using forecasting, the mathematical model, and the heuristic approach. Since both rely on forecasted demand, validation compares forecasted and actual data. Delivery data, which the company provides, is the basis for daily demand forecasts. The model's outputs—truck routes and ASU visits—are compared with the company's current system, where visits and routes are planned intuitively. The heuristic model, covering all stores, is validated similarly but more broadly. For validation, the model is rerun with real data. Distances are taken from Google Maps, and real fuel and labor costs are used. Known cabinet capacities are included, and unknown inventory levels are estimated using the code confirmed by the company. The validation results are logical and satisfactory. A theoretical study also improved the model by adjusting input values and checking outputs. Originally, deliveries happened only when there is no stock, but this gave unrealistic results. After advice, the threshold is changed to 70%, leading to more accurate and reliable results.

1.5 Integration and Implementation

The implementation plan ensures a smooth integration of the developed decision support system into Unilever's existing operations. During the first two weeks of April, one truck is selected for pilot testing, and a dedicated weekly schedule is created specifically for this truck. In the third week, company staff implement the plan, using the system to guide real-life operations, including optimized visit scheduling and delivery routing.

Following the pilot execution, the final week of April is allocated for evaluating the results. This evaluation focuses on the system's usability, its impact on reducing transportation costs, and improvements in operational efficiency. Based on the outcomes, potential adjustments are identified before scaling the tool across additional trucks or regions. The system's user-friendly Python-based interface ensures that Unilever personnel can easily adopt it without requiring extensive technical training, supporting its seamless integration into daily operations.

1.5.1 Decision Support System

The system is designed as a Python GUI-based decision support tool that integrates forecasting, inventory and route optimization planning for Unilever's distribution network. The first step is user authentication, where users enter their username and password and then press the "Login" button to proceed.

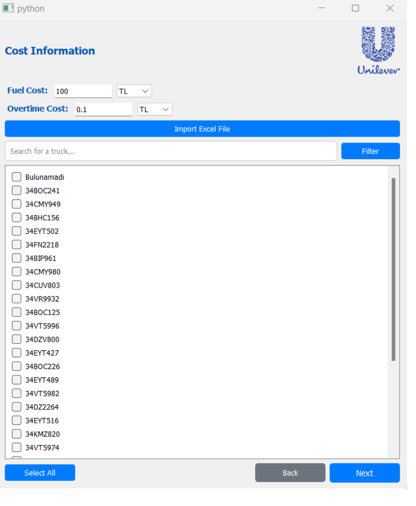


Figure 1.3: Trucks Selection Screen

After logging in, users reach the Truck Selection Page in Figure 1.3, where they choose one or multiple trucks for route analysis and optimization. The interface lists available trucks and includes a search bar for filtering. Users can also import an Excel file for past delivery data and define fuel and overtime costs. The “Select All” option simplifies selection, and clicking “Next” moves them forward.

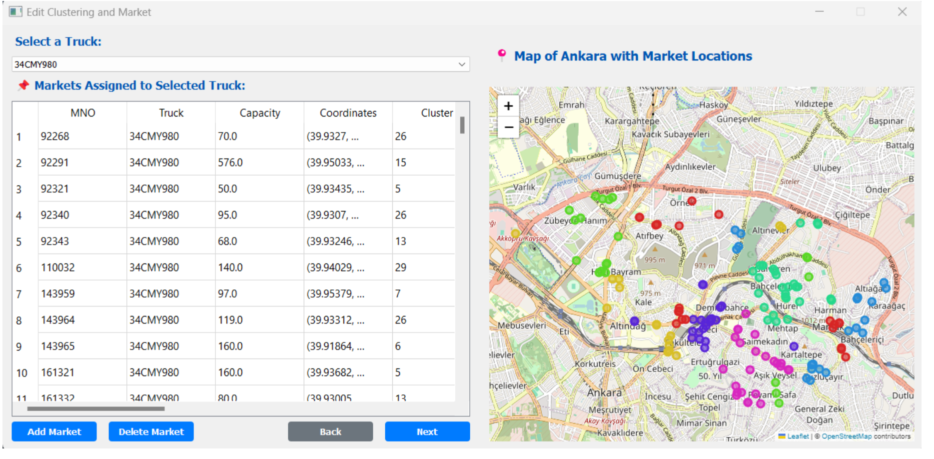


Figure 1.4: Clustering and Store Information Screen

On the Clustering Page in Figure 1.4, users select one of the previously chosen trucks. A map on the right displays the stores assigned to that truck, with regions divided into color-coded clusters. A list on the left provides store details such as store no, capacity, coordinates, cluster, and time windows. Users can manually add, remove, or edit stores to refine the assignments. Following this, the Forecast Page displays initial inventory levels, forecasted demand based on historical data, and expected stock depletion insights to optimize delivery schedules.

Finally, the Solution Page in Figure 1.5 lets users select a truck and day to view the optimized route on the map. It displays key logistics metrics such as weekly fuel and overtime costs, canceled orders, a daily breakdown of store visit sequences, and fuel consumption per trip. The Hub is also marked as the central distribution point.

1.6 Benefits to the Company

The new decision support system tackles Unilever’s cost challenges from intuition-based store selection and delivery planning by integrating demand forecasting, inventory modeling, and route optimization. Benchmarking studies across all regions demonstrates significant improvements as shown in 1.2. In September 2025, the total traveled distance in the current system

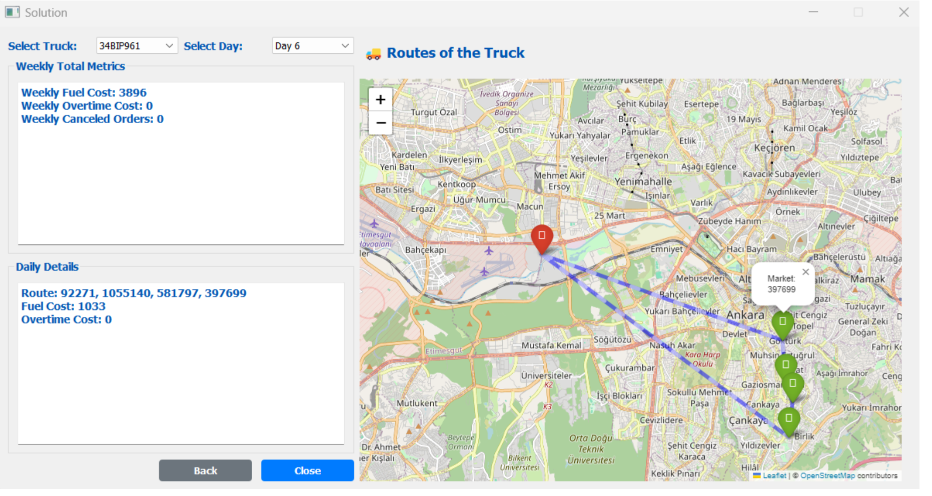


Figure 1.5: Solution Screen

is 41,756 km, whereas it is reduced to 35,225 km with the new proposed solution, reflecting a 15.6% cost reduction. In July 2025, the total traveled distance in the current system is 47,979 km, while it decreases to 41,267 km with the new proposed solution, corresponding to a 13.9% cost reduction. These reductions correspond to estimated monthly fuel savings of approximately 2,285 liters (about \$2,742) in September and 2,353 liters (about \$2,824) in July. By optimizing the routes, the system achieves a monthly reduction of approximately 3,371 kg of CO_2 emissions. Furthermore, as each route is previously traveled first by the truck and then by the ASU, the system's impact is effectively doubled .

Metric	July 2024	September 2024
Current System Distance	47,979 km	41,756 km
New System Distance	41,267 km	35,225 km
Distance Reduction	6,712 km	6,531 km
Cost Reduction	13.9%	15.6%
Fuel Saved (35L/100km)	2,353 liters	2,285 liters
Monetary Savings (\$1.2/L)	\$2,824	\$2,742
Monthly CO_2 Emission Reduction	Approximately 3,371 kg	

Table 1.2: Comparison Between Current and New Decision Support Systems

1.6.1 Conclusion

In conclusion, the developed decision support system provides a comprehensive solution to Unilever's current sales-delivery process inefficiencies. Replacing the traditional intuition-based approach with a system that combines demand forecasting, inventory management, and route optimization has led to significant cost reductions and enhanced operational efficiency. The benchmarking results clearly demonstrate that unnecessary store visits have been eliminated and delivery routes optimized without compromising the required inventory occupancy rate. The system's adaptability and ease of use enable it to be implemented across 23 regions, ensuring that these benefits are not confined to a single pilot project but can be realized throughout the entire distribution network. Beyond immediate financial gains, the environmental benefits of reduced fuel usage and lower emissions align with Unilever's broader sustainability objectives. Overall, this project not only streamlines operational processes but also provides a robust, scalable framework for long-term growth and innovation, ultimately contributing to a more efficient, sustainable, and cost-effective distribution system for Unilever.

Acknowledgment

This project was supported by TÜBİTAK BİDEB 2209/B Program under Grant 1139B412401432.

Bibliography

Algida Food Service (2024). Üretim tesislerimiz. https://www.algidafoodservice.com/hakkimizda/uretim. Erişim Tarihi: 24 Ekim 2024.

Challu, C., K. G. Olivares, B. N. Oreshkin, F. Garza Ramirez, M. Mergenthaler Canseco, and A. Dubrawski (2023). NHITS: Neural hierarchical interpolation for time series forecasting. *Proceedings of the AAAI Conference on Artificial Intelligence 37*(6), 6989–6997.

Hurkala, J. (2015). Time-dependent traveling salesman problem with multiple time windows. *Position Papers of the Federated Conference on Computer Science and Information Systems 6*, 71–78.

Türkiye Investment Office (2023a, April 17). Unilever Algida's investment in konya plant. https://www.invest.gov.tr/en/news/news-from-turkey/pages/040612-unilever-algida-turkey-konya-plant-investment.aspx. Erişim Tarihi: 24 Ekim 2024.

Türkiye Investment Office (2023b). Unilever opens second ice cream factory in turkey. https://www.invest.gov.tr/en/news/news-from-turkey/pages/270813-unilever-turkey-second-ice-cream-factory-opening.aspx. Erişim Tarihi: 24 Ekim 2024.

Çağatay, A. (2024, April 19). Türkiye'de dondurma markalarının rekabet analizi. https://anlatilaninotesi.com.tr/20240419/1082931881.html. Erişim Tarihi: 24 Ekim 2024.

Appendices

1.A Mathematical Model

Indexes	Definition
V	Representation of each stores as a node, with warehouse node 0.
E	Edges (i, j) formed by the arcs from each node i to other nodes j
T	Days of the week minus Sunday
R	Sub-regions

Parameters	Definition
d_{ij}	The distance as the crow flies between two locations (i, j) consisting of the store and the warehouse
F_i^t	Sales forecast data of i^{th} store for each t day of the week.
W_i	Ice cream refrigerator capacity of i^{th} store.
A_{ir}	Binary parameter indicating the assignment of stores to regions. Takes the value 1, if the i^{th} store belongs to the r^{th} region; 0 otherwise.
C	Ice cream box carrying capacity of the truck.
v, w	Maximum allowed visit to a store and visit to a region in a week.
α_1	Distance and time spent ratio.
α_2	Delivered box amount and time spent in the store ratio.
$[a_{ip}, b_{ip}]$	Time interval of i^{th} store can accept delivery at period $p \in \{1, 2\}$.
H	Legal weekly working hour limit.
c_1	Fuel cost per kilometer of the truck.
c_2	Hourly rate paid for overtime.

Variables	Definition
y_i^t	Binary variable indicating that the ice cream truck visited the i^{th} store on day t and made a delivery. If the truck visited the i^{th} store on day t, 1; 0 otherwise.
x_{ij}^t	Binary variable indicating whether the ice cream truck uses the road from the i^{th} store to the j^{th} store on day t. If the truck uses the road (i, j) on day t, 1; 0 otherwise.
u_i^t	The Miller-Tucker-Zemlin enumeration integer variable indicates the rank of the i^{th} store on day t. It prevents the formation of a sub-tour.
I_i^t	Continuous variable indicating that the amount of ice cream in the fridge of the i^{th} store at the beginning of day t.
D_i^t	Integer variable indicating that the amount ice cream was delivered to the i^{th} store's fridge at the end of day t.
T_i^t	Continuous variable indicating that delivery start time of i^{th} store at day t
Te_i^t	Continuous variable indicating that delivery end time of i^{th} store at day t
O^t	Continuous variable indicating that the amount of total overtime the truck had on day t.
RV_r^t	Binary variable indicating that r^{th} regions is visited at day t.

$$\min \quad \sum_{i \in V} \sum_{j \in V \setminus \{i\}} \sum_{t \in T} x_{ij}^t d_{ij} c_1 + \sum_{t \in T} O^t c_2 \tag{1.1}$$

$$\text{s.t.} \quad \sum_{j \in V \setminus \{i\}} x_{ji}^t \geq y_i^t \qquad \forall i \in V, \forall t \in T \tag{1.2}$$

$$\sum_{j \in V \setminus \{0\}} x_{0j}^t = 1 \qquad \forall t \in T \tag{1.3}$$

$$\sum_{i \in V \setminus \{0\}} x_{i0}^t = 1 \qquad \forall t \in T \tag{1.4}$$

$$\sum_{j\in V} x_{ij}^t \leq 1 \qquad \forall i \in V, \forall t \in T \tag{1.5}$$

$$\sum_{i\in V} x_{ij}^t \leq 1 \qquad \forall j \in V, \forall t \in T \tag{1.6}$$

$$\sum_{i\in V\setminus\{i\}} x_{ij}^t = \sum_{j\in V} x_{ij}^t \qquad \forall i \in V, \forall t \in T \tag{1.7}$$

$$u_i^t - u_j^t + |V| x_{ij}^t \leq |V| - 1 \qquad \forall (i,j) \in E, \forall t \in T \tag{1.8}$$

$$I_i^t - F_i^t + D_i^t = I_i^{t+1} \qquad \forall i \in V, \forall t \in T \tag{1.9}$$

$$I_i^t \leq W_i \qquad \forall i \in V, \forall t \in T \tag{1.10}$$

$$D_i^t \leq W_i y_i^t \qquad \forall i \in V, \forall t \in T \tag{1.11}$$

$$\sum_{t\in T} y_i^t \leq v \qquad \forall i \in V \tag{1.12}$$

$$\sum_{i\in V} D_i^t \leq C \qquad \forall t \in T \tag{1.13}$$

$$\sum_{i\in V\setminus\{0\}} y_i^t A_{ir} \leq |V| \times RV_r^t \qquad \forall r \in R, \forall t \in T \tag{1.14}$$

$$\sum_{t\in T} RV_r^t \leq w \qquad \forall r \in R \tag{1.15}$$

$$T_j^t \geq d_{0j}\alpha_1 x_{0j}^t \qquad \forall j \in V, \forall t \in T \tag{1.16}$$

$$T_j^t \geq T_i^t + D_i^t\alpha_2 + d_{ij}\alpha_1 - (1 - x_{ij}^t) b_{j1} \qquad \forall i,j \in V; i \neq j, \forall t \in T \tag{1.17}$$

$$Te_j^t = T_i^t + D_i^t\alpha_2 \qquad \forall i,j \in V; i \neq j, \forall t \in T \tag{1.18}$$

$$O^t + H \geq Te_i^t \qquad \forall i, \forall t \in T \tag{1.19}$$

$$a_{i1} z_{i1}^t + a_{i2} z_{i2}^t \leq T_i^t \qquad \forall i \in V, \forall t \in T \tag{1.20}$$

$$b_{i1} z_{i1}^t + b_{i2} z_{i2}^t \geq Te_i^t \qquad \forall i \in V, \forall t \in T \tag{1.21}$$

$$z_{i1}^t + z_{i2}^t \leq 1 \qquad \forall i \in V \forall t \in T \tag{1.22}$$

$$x_{ij}^t, y_i^t, RV_r^t, z_p^t \in \{0,1\} \tag{1.23}$$

$$u_i^t, D_i^t, \in \mathbb{Z}^+, u_0^t = 1 \tag{1.24}$$

$$T_i^t, Te_i^t, I_i^t, O^t \geq 0 \tag{1.25}$$

- Objective Function (1.1) minimizes the fuel cost and overtime cost in a week.
- **Routing Constraints** (1.2) **-** (1.8)**:** These constraints create a route between the visited stores and eliminates sub-tours.
- **Inventory Balance and Delivery Constraints** (1.9) **-** (1.11)**:** These constraints ensure daily inventory balance, limit storage to fridge capacity, and require truck entry when a delivery is made.
- **Trivial Constraints** (1.12) **-** (1.15)**:** These constraints limit store visits per week, ensure daily truck deliveries stay within capacity, and control regional visit frequency.
- **Time Window Constraints** (1.16) **-** (1.22)**:** These constraints ensure proper sequencing of deliveries with travel and service times,

define overtime based on the latest delivery, and enforce store-specific delivery time windows.

- **Domain Constraints** (1.23) **-** (1.25)**:** These constraints define the domain constraints.

1.B Mathematical Model for Matheuristic

$$
\begin{aligned}
\min \quad & \rho && && (1.26)\\
\min \quad & \sum_{i\in V}\sum_{t\in T} y_i^t && && (1.27)\\
\text{s.t.} \quad & M_{i,j}^t \le RV_i^t && \forall i\in R, \forall j\in R, \forall t\in T && (1.28)\\
& M_{ij}^t \le RV_j^t && \forall i\in R, \forall j\in R, \forall t\in T && (1.29)\\
& M_{ij}^t \ge RV_i^t + RV_j^t - 1 && \forall i\in R, \forall j\in R, \forall t\in T && (1.30)\\
& \sum_{i\in R}\sum_{j\in R}\sum_{t\in T} M_{ij}^t \times CD_{i,j} \le \rho && && (1.31)\\
& I_i^t - F_i^t + D_i^t = I_i^{t+1} && \forall i\in V, \forall t\in T && (1.32)\\
& I_i^t \le W_i && \forall i\in V, \forall t\in T && (1.33)\\
& D_i^t \le W_i y_i^t && \forall i\in V, \forall t\in T && (1.34)\\
& \sum_{t\in T} y_i^t \le v && \forall i\in V && (1.35)\\
& \sum_{i\in V} D_i^t \le C && \forall t\in T && (1.36)\\
& \sum_{i\in V\setminus\{0\}} y_i^t A_{ir} \le |V| \times RV_r^t && \forall r\in R, \forall t\in T && (1.37)\\
& \sum_{t\in T} RV_r^t \le w && \forall r\in R && (1.38)\\
& y_i^t, RV_r^t \in \{0,1\} && && (1.39)\\
& D_i^t, \in \mathbb{Z}^+ && && (1.40)\\
& I_i^t \ge 0 && && (1.41)
\end{aligned}
$$

- Objective (1.26) minimizes the total distance between the centers of the clusters that are visited over a week.
- Objective (1.27) minimizes the total number of visits over a week.
- **Cluster Center Constraints** (1.28) **-** (1.31)**:** These constraints ensure visits to stores across different clusters and limit the total weekly distance between visited cluster centers.
- **Inventory Balance and Delivery Constraints** (1.32) **-** (1.34)**:** These constraints ensure daily inventory balance, limit storage to fridge capacity, and require truck entry when a delivery is made.

- **Trivial Constraints** (1.35) **-** (1.38)**:** These constraints limit store visits per week, ensure daily truck deliveries stay within capacity, and control regional visit frequency.
- **Domain Constraints** (1.39) **-** (1.41)**:** These constraints define the domain constraints.

Bireysel Emeklilik Sistemi Katılımcıları İçin Özelleştirilebilir Portföy Öneri Sistemi | 2

Emeklilik Gözetim Merkezi

Proje Ekibi
Yağızalp Daşdemir, Ahmet Geçsöyler, Bilgehan Özkan
Ahmet Sayan, Tan Tezel, Doğa Işıl Tombuloğlu, Damla Uçar

Şirket Danışmanı
Hicran Aktaş Coşar
Genel Müdür Yardımcısı

Akademik Danışman
Prof. Dr. Mustafa Çelebi Pınar
Endüstri Mühendisliği Bölümü

Özet

Bireysel Emeklilik Sistemi (BES) katılımcılarının portföy yönetimi konusundaki bilgi eksikliği, fon seçimi ve zamanlama hatalarına yol açarak düşük getiri ve erken sistemden çıkışlara neden olmaktadır. Bu temel sorun, projemizin yatırımcının risk iştahı ve yatırım süresi gibi özelliklerine uygun, daha yüksek getiri potansiyeline sahip alternatif portföyler önermeyi amaçlayan bir karar destek sistemi geliştirmesine zemin oluşturmuştur. Bu doğrultuda geçmiş veriler kullanılarak matematiksel model için girdiler oluşturulmuş ve risk seviyeleri belirlenmiştir. Ayrıca arka planda modelin çalıştığı bir kullanıcı arayüzü geliştirilmiş olup farklı risk seviyelerinde geriye dönük tutarlılık testleri ile birlikte beklenen getiriler için denemeler yapılmıştır. Çeşitli risk seviyelerinde yapılan denemelerde güven aralığına bağlı olarak altın, USD ve enflasyonun üzerinde getiriler elde edilmiş ve BIST-100 endeksini %70 ihtimalle aşabilen portföyler elde edilmiştir. Bu geliştirme ile, finansal okuryazarlık eksikliği nedeniyle doğru tercih yapamayan katılımcıların yaşadığı memnuniyetsizlikten kaynaklanan erken sistemden ayrılmaların azaltılması hedeflenmektedir.

Anahtar Sözcükler: Emeklilik Sistemi, Emeklilik Fonları, Yatırımcı Riski, BEFAS, Portföy Eniyilemesi

Customizable Portfolio Recommendation System for Private Pension System Participants

Abstract

The lack of portfolio management knowledge among participants of the Individual Pension System (BES) often leads to poor fund selection and mistimed investment decisions, resulting in low returns and premature exits from the system. This core issue provided the foundation for our project, which aims to develop a decision support system that recommends alternative portfolios with higher return potential, tailored to investor-specific characteristics such as risk appetite and investment horizon. To support this, historical data was used to generate inputs for a mathematical model, and corresponding risk levels were defined. A user interface was also developed to operate the model in the background, enabling both back-testing and expected return simulations across different risk levels. In trials conducted at various risk levels, portfolios achieved returns exceeding benchmarks such as gold, USD, and inflation within defined confidence intervals. Additionally, some portfolios demonstrated a 70% probability of outperforming the BIST-100 index. This development ultimately aims to reduce early withdrawals caused by participant dissatisfaction, which stems from an inability to make sound investment decisions due to limited financial literacy.

Keywords: Pension System, Pension Funds, Investor Risk, BEFAS, Portfolio Optimization

2.1 System Analysis and the Company

Turkish private pension system known as BES (Bireysel Emeklilik Sistemi) was started in 2003. In addition, taking effect in 2013, the government announced its state contribution program to BES participants. The Turkish private pension system that was introduced is a voluntary DC pension scheme. By directing the money people deposit in the system throughout their working years into long-term investments, the program enables them to produce an income that helps them maintain their living standards in retirement. Private pension participants enter the system through two channels; voluntary enrollment (BES) and automatic enrollment (OKS). These participants who are in both the BES and OKS make deposits to the system, which is in turn invested into a variety of pension funds. All of these pension funds can be traded regardless of the participants' pension company and the funds' pension company trough the BEFAS system which was founded in 2021. The Individual Pension Fund Trading Platform (BEFAS) is a central electronic platform that is operated for buying and selling pension investment fund shares. The system allows all private pension participants to trade in all 382 pension funds offered by 15 pension companies. EGM (Emeklilik Gözetim Merkezi), the entity was created in 2003 alongside the BES under the Individual Pension Savings and Investment System Law No. 4632 with instructions of the Ministry of Treasury and Finance.The goals of EGM, mandated by law, is ensuring the effectiveness of the Turkish private pension system and protecting the rights and benefits of its participants. The company regulates pension corporations, intermediaries, and fund managers, maintaining an audit infrastructure that supports the Capital Markets Board and other authorities. It provides policy recommendations to enhance the pension system's performance (EGM, 2024).

2.2 Problem Definition

At present, private pension sector suffers from early withdrawals, which harms the sector. Early exits mainly emerge because of low real gains from investments. Due to the lack of knowledge about the BES system and the financial illiteracy, the risk-return relation cannot be accurately matched. The lack of knowledge manifests primarily in two key areas: timing uncertainty and knowledge gap. Investors struggle to determine when to adjust their portfolios, leading to missed opportunities to optimize returns with respect to timing uncertainty. Moreover, due to limited knowledge, investors often struggle with fund selection and allocation decisions, leading to inefficient portfolio distributions. This knowledge gap leads to the underutilization of the BEFAS system, diminishing individual outcomes and also undermines the overall performance of the private pension system. This underutilization and inefficiency in users' portfolio management directly impacts EGM by straining the growth and sustainability of their system. When users encounter low fund returns and underwhelming investment performance, they tend to exit the system early, shortening retention periods and create a cycle of investor dissatisfaction.

2.3 Proposed System

Our primary aim is to maximize the expected return for each of the investor risk profiles through tailored portfolio allocation suggestions. We used a variant of the foundational mathematical model for portfolio selection, the Markowitz Mean-Variance Optimization. By using this method, we obtained the ideal portfolio suggestions maximizing expected return in a given risk level. Our Markowitz Variant model utilizes MAD (Mean Absolute Deviation) for risk measures to avoid the long calculation time of the covariance. Since this model needs to work repetitively long calculation times are inefficient for the company. However, we assumed funds are independent by using MAD instead of covariance and lost this correlation information in the first part. Therefore, our model has a second step where we calculate the covariance of each portfolio we found from our mathematical model. This approach boosts the efficiency by avoiding costly one-step covariance calculations for all funds, ensuring faster execution without losing risk analysis insights. First, we identify the top 100 portfolio suggestions across various risk levels. Then, we calculate the covariance of these portfolios to preserve correlation information while ensuring a short operation time. The mathematical model works by utilizing historical data and calculating the expected returns, standard deviations and the covariance matrix of the fund returns. By using these elements we were able to construct the efficient frontier and represent the set of portfolios that are ideal for the users preferred risk and return. The historical data, standard deviations and the covariance matrix are entered as input to the model. This model allows us to create a system which is able to deliver personalized fund recommendations to BEFAS participants, ultimately meeting with EGMs goal of keeping more users in BEFAS and also helping users achieve their financial targets.

2.4 Derivation of Parameters

With the help of the data, which is provided by EGM, parameters such as fund return rates, estimated mean returns for funds, covariance matrix and fund indicators are derived with numerical operations.

2.5 Determination of the Model Attributes

The model consists of three decision variables where the first decision variable represents the weight of the fund in the portfolio and the second decision variable is a binary variable that represents whether a fund is selected for inclusion in the portfolio. This binary variable is set to 1 when the weight of the fund is greater than zero, and 0 otherwise. The second decision variable is utilized to impose a constraint on the selection of funds from a specific category, and it is used to limit the concentration of funds. Third decision variable keeps the information of deviation of the return of the funds in time t. Initially, constraints can be listed as allocation of the funds cannot exceed risk tolerance, summation of the weight of the funds is equal to one. By default, the number of funds in the portfolio is set to be between 5 and 10. However, these parameters are adjustable through the user interface. The maximum number of funds that can be allocated from the same category can also be modified, with the default value set to 3. Also, if a fund is selected, the weight of the fund is greater than or equal to zero. As an objective function, we maximize the estimated return by deriving an allocation of the funds. Expected mean returns of the funds multiplied by the weights of the funds in the portfolio. After obtaining a valid and optimal solution, parameters can be adjusted to generate several alternative portfolio suggestions along the efficient frontier.

2.6 Mathematical Model

Our model is based on the Markowitz framework to identify optimal portfolios that maximize returns for a given level of risk tolerance. Since the Markowitz model involves quadratic constraints, it is formulated as a nonlinear optimization problem, which can be time-consuming when dealing with a large number of variables. Therefore, we have adapted a linear formulation using the Mean Absolute Deviation. This linear model improved computational efficiency and successfully reached a solution. However, MAD does not retain information about the correlative changes of the funds as covariance does. Therefore, we used our model to identify the top 100 portfolios, which are likely the best within their respective risk levels. Then, as Step 2, we calculated the covariance of these portfolios separately to create an efficient frontier. As a result, we achieved portfolio suggestions without losing essential information.

Parameters

- $y_{ij} \in \begin{cases} 1 & \text{if fund i is in category j,} \\ 0 & \text{otherwise.} \end{cases}$
- r_{it} - The return rate of asset i at time t.
- μ_i - Expected return of asset i.
- R_{k} - Risk tolerance of the investor risk category k.
- Ub - The maximum number of funds that can be included in the portfolio.
- Lb - The minimum number of funds that can be included in the portfolio.
- ϵ - A sufficiently small constant for Big-M Method
- W_{max} - The maximum weight that any fund can have in the portfolio.

- W_{min} - The minimum weight that any fund can have in the portfolio if it's selected.
- C - The maximum number of funds that can be selected from each fund category.
- I - Existing number of funds in BEFAS.
- J - Existing number of fund categories in BEFAS.

Decision Variables

- w_i - Proportion of the total portfolio invested in asset i.
- $x_i \in \begin{cases} 1 & \text{if fund i is in the portfolio,} \\ 0 & \text{otherwise.} \end{cases}$
- z_t - Auxiliary variable representing the absolute deviation in time t.

Objective Function

$$\text{Maximize} \quad \sum_{i=1}^{I} \mu_i w_i$$

Constraints

$$z_t \geq \sum_{i=1}^{I} w_i r_{it} - \sum_{i=1}^{I} w_i \mu_i \qquad \forall t \in \{1, 2, \ldots, T\} \tag{1}$$

$$z_t \geq -\left(\sum_{i=1}^{I} w_i r_{it} - \sum_{i=1}^{I} w_i \mu_i \right) \qquad \forall t \in \{1, 2, \ldots, T\} \tag{2}$$

$$\frac{1}{T} \sum_{t=1}^{T} z_t \leq R \tag{3}$$

$$\sum_{i=1}^{I} w_i = 1 \tag{4}$$

$$W_{\min} \leq w_i \leq W_{\max}, \qquad \forall i \in \{1, 2, \ldots, I\} \tag{5}$$

$$\sum_{i=1}^{I} x_i y_{ij} \leq C, \qquad \forall j \in \{1, 2, \ldots, J\} \tag{6}$$

$$Lb \leq \sum_{i=1}^{I} x_i \leq Ub \tag{7}$$

$$w_i \leq x_i, \qquad \forall i \in \{1, 2, \ldots, I\} \tag{8}$$

$$w_i \geq \epsilon - (1 - x_i), \qquad \forall i \in \{1, 2, \ldots, I\} \tag{9}$$

$$x_i \in \{0, 1\}, \qquad \forall i \in \{1, 2, \ldots, I\} \tag{10}$$

2.7 Validation

To assess the performance and reliability of our recommendation model, we conducted a 12-month back-testing simulation using historical daily fund return data from EGM, covering 970 working days between 2021 and 2024. We applied a rolling-window approach, where each month the model was trained using the most recent 520 days of data, which was updated monthly by adding the latest 20 days and removing the oldest 20. This dynamic approach ensured the model remained responsive to evolving market conditions. Furthermore, we simulated an investment strategy starting with an initial investment of 100 TL, with an additional 100 TL invested at the beginning of each subsequent month. Data starting from 2021 to 2022 was used for training purposes, and testing began from January 2023. At the end of each month, an actual-to-expected return comparison was made. The results showed a strong correlation, indicating that the model accurately captured market trends over time. For high-risk investors, we assumed monthly reallocations to the riskiest portfolio recommended by the model.

2.8 Deliverables

The Private Pension Fund Portfolio Optimizer is a decision support tool developed with Gradio, designed exclusively for EGM personnel to streamline portfolio construction. The user interface allows adjustment of optimization parameters, including minimum/maximum weight per fund, diversity constraints, and bounds on the number of funds. Users can input market conditions such as inflation rate, daily risk-free return, and data periods (1/2/3 years), with an option to exclude interest-bearing funds. The system accepts twoExcel inputs—historical fund values and a structured fund category file—where unwanted categories can be deselected via listboxes before optimization. Key outputs include selectable portfolios displayed in a dropdown, visualized through efficient frontier graphs, allocation pie charts, and benchmark comparisons (Sharpe Ratio, BIST-100, gold, etc.). Results are exportable as Excel files with full fund names. While currently restricted to internal use, the design includes recommendations for future integration into EGM's public-facing website. Accompanying technical documentation and user manuals provide implementation details and step-by-step guidance, ensuring reproducibility and ease of adoption.

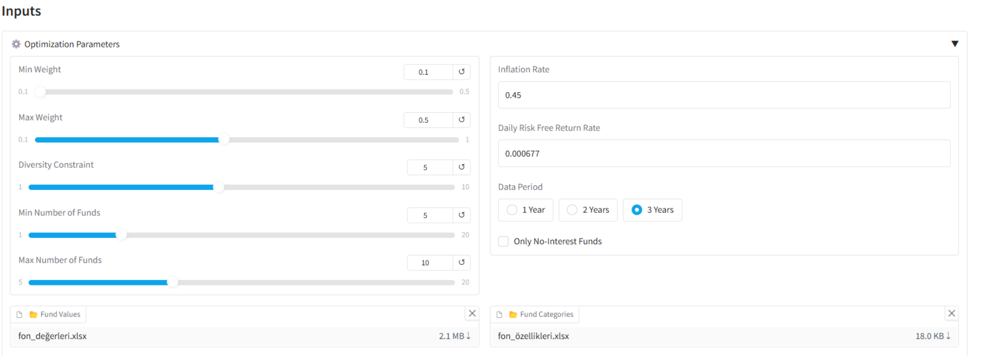


Figure 2.1: Inputting Optimization Parameters from EGM UI

2.9 Implementation and Pilot Study

Our decision support system was delivered to EGM for future integration into the BEFAS platform. As full integration requires additional time and coordination, immediate deployment into the live system was not feasible. However, to provide EGM with a clear understanding of the system's capabilities and performance, we conducted a pilot study using an extended dataset covering the period from January 2021 to March 2025.

This pilot allowed us to simulate real-world application of the model and evaluate its performance on fresh data beyond the initial development scope. The outputs generated were reviewed by EGM. This pilot study demonstrated that the system is ready for further validation and eventual integration once the necessary infrastructure and operational planning is in place.

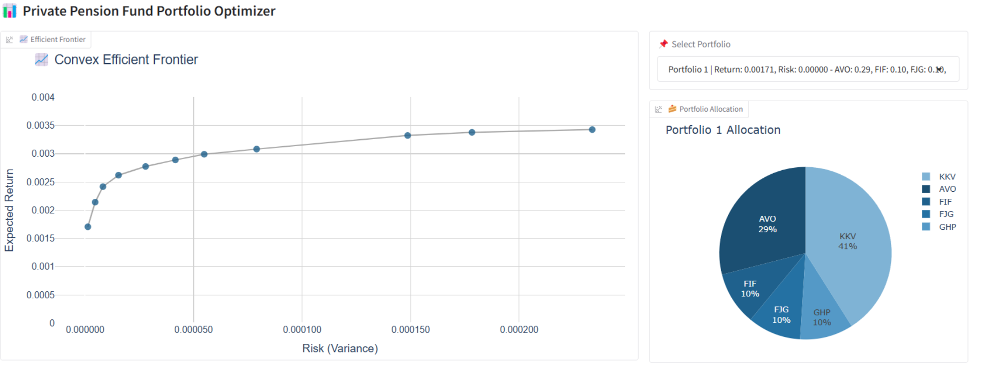


Figure 2.2: Portfolio Reccomendation, Allocations and Efficient Frontier Output

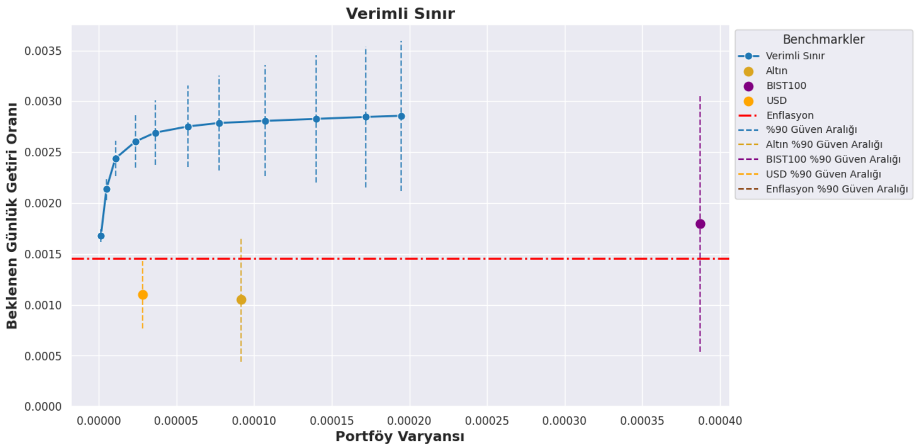


Figure 2.3: Efficient frontier with Confidence Intervals and Benchmarks

2.10 Benchmarking

In testing the success of the portfolio optimization model, we compared the model against some conventional benchmarks for investment at different risk levels and without falling into extreme cases, such as highly volatile individual stocks or risk-free money market funds, that would not provide much insight for comparison. The benchmarks include BIST-100, gold, USD/TRY, and inflation. BIST-100 was the riskier asset with a daily return variance of 0.000342 and a mean return of 0.00135. Gold, a traditionally safer investment, had the lowest mean return (0.000813) and a variance of 0.0000793. The USD/TRY exchange rate showed the modelest variance (0.0000326) with a relatively high mean return of 0.00124, making it a suitable low-risk benchmark. We included inflation since it is significant for pension fund performance. Using an annual TUIK inflation rate of 44.38% for 2024, we computed the needed daily return to keep track of purchasing power. A graph of the efficient frontier, with 90% confidence intervals (CIs), facilitated comparisons of our optimal portfolios and limit benchmarks. The benchmarks' expected returns were illustrated by dashed lines, while the portfolios were represented by their CIs. The findings suggested that, in general, our portfolios had higher expected returns compared to the benchmarks with a 90% degree of confidence, while only the very low-risk portfolios had expected returns lower than some of these benchmarks. A majority of the portfolios overlapped with the BIST-100 CI, indicating a chance of underperforming it, yet in any case, the expected returns remained higher for most of the portfolios. A wider CI for the BIST-100 indicates its higher risk. The absence of overlap with others indicates our model would be able to construct portfolios with higher expected return than lower-risk

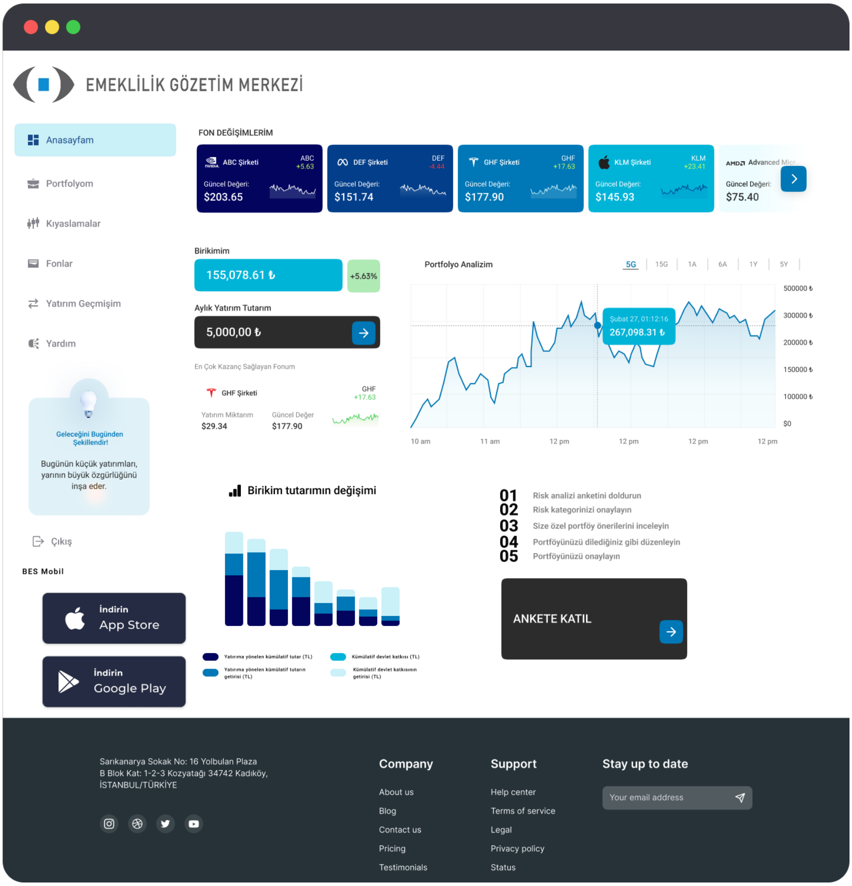


Figure 2.4: Customer Portal Recommendation Homepage

counter-part investments, validating our portfolio optimization model's efficiency across different risk categories.

2.11 Benefits to the Company

The project will provide various contributions to EGM, especially since it will help private pension participants with low financial literacy in choosing the right funds. In fund recommendations, the project's focus on providing maximum returns to each participant in line with their preferences will have a positive impact by helping to decrease the number of participants who leave the system due to low returns. Thus, our system will increase the rate of participants remaining in BES. The project's notification of participants to adjust fund distributions when necessary will also ensure more investments. Since these increased retention and investment rates contribute to a more stable and sustainable BES, it also strengthens the reputation of the system. Another potential advantage to EGM is the possibility of increased system efficiency. The proposed system design and decision assistance tools will lead to a more effective BES and make participant interactions easier. Participants, even those lacking financial knowledge, will benefit from personalized fund portfolios aligned with their risk tolerance and financial goals.

2.12 Conclusion

This project effectively addresses key challenges in the Turkish private pension system (BES) by developing a portfolio optimization model tailored to investor risk profiles. The system improves portfolio returns and reduces early withdrawals by providing personalized investment recommendations. Validation through back-testing shows that the model outperforms traditional benchmarks, ensuring better returns across various risk levels. The integration of this system into the BEFAS platform enhances user experience, increases participant retention, and promotes more investments, contributing to the overall stability of BES. Future improvements could include real-time data integration and further refinement of the user interface to meet evolving investor needs.

Bibliography

EGM (2024). Anasayfa.

3 Depo-Stok Yönetimi için Karar Destek Sistemi

İstanbul Gübre Sanayi

Proje Ekibi
Alper Zafer Aydos, Alper Dere, Emre Nihat Erol, Sevde Güney, Selin Kabaoğlu, Elif Karaman, Fahri Pulat

Şirket Danışmanı
Betül Merve Çetin
Üretim Planlama Uzmanı

Akademik Danışman
Prof. Dr. Alper Şen
Endüstri Mühendisliği Bölümü

Özet

İGSAŞ'ın farklı bölgelerde bulunan altı deposunda, stoklama ve gelen planlama kararları manuel süreçlere dayandığından, kapasite kullanılabilirliği konusunda belirsizlikler yaşanmaktadır. Bu durum, aşırı veya yetersiz stoklamaya ve sevkiyat gecikmelerine yol açmaktadır. Projemizin amacı, bir yıllık planlama ufku boyunca haftalık bazda depo kapasitelerini tahmin eden, stok yerleşimini optimize eden ve depo görünürlüğü sunan bir karar destek sistemi geliştirmektir. Elde edilen çıktılar, satış, envanter ve operasyonel planlama süreçlerinde karar almayı kolaylaştıracaktır.

Anahtar Sözcükler: Gübre, depo yönetimi, stok operasyonları, stok planlama sistemi, hücre, talep tahmini, karar destek sistemi.

A Decision Support System for Warehouse-Stock Management

Abstract

Since stock and inbound planning decisions in İGSAŞ's six warehouses located in different regions rely on manual processes, the company lacks visibility to capacity availability. This leads to overstocking or understocking and delays in shipments. The purpose of our project is to develop a decision-support system that forecasts warehouse capacities on a weekly basis over a one-year planning horizon, optimizes stock placement, and enhances warehouse visibility. The insights from the decision support system will be used by the company in planning sales, stock management and operations.

Keywords: Fertilizer, warehouse management, stock operations, stock planning system, cell, demand forecasting, decision-support system.

3.1 İGSAŞ and Problem Identification

3.1.1 Company Description and System Analysis

IGSAŞ was established in 1971 as a public organization in Kocaeli. The purpose of this company was to provide affordable fertilizers to improve agricultural productivity. The company ranked 56th in the "net sales ranking" category of the ISO 500 list in 2023, with over 800 employees. IGSAŞ sells through their more than 800 partners, which consist of dealers, industrialists, manufacturers, and distributors. Produced and imported products are kept in six warehouses with 320.000 tons of capacity (IGSAŞ, 2024).

For stock planning, the sales department evaluates global markets, seasonal needs, and consumer behavior. After that, product-based sales targets are determined. Using these targets and past sales data, the production planning department creates a plan for the procurement of materials. The procurement department is responsible for executing the purchasing operations and informing about the arrival dates of the materials. The stock and logistics department uses all this information and predicts future stock quantities. They assess the feasibility of whether a product can be stored in a specified warehouse at a specific time or not.

IGSAŞ follows a make-to-stock production approach, focusing on around 12 main products that account for approximately 80% of total sales. The company operates 5 production facilities and 8 warehouses strategically located across Türkiye to distribute products to dealers, though only 6 warehouses are within the scope of this project. Some products are also used internally as raw materials for producing other products. Warehouse inbounds consist of production, imports, and transfers from other warehouses, while outbounds include customer shipments, raw material consumption, and inter-warehouse transfers.

3.1.2 Problem Definition and Deliverables

The company mainly relies on manual processes and personal experience to estimate future stock levels, with warehouse stock management largely handled through manual calculations in Excel. For example, when deciding whether to ship a certain quantity of product to a warehouse, employees use personal judgment and manual Excel work, which is prone to errors and time-consuming. This causes limited visibility over warehouse capacities, which is critical, especially for raw material procurements arriving by cargo ships that require careful planning to avoid delays, overstocking, or stock-outs. Insufficient capacity can cause costly ship delays; to prevent this, the company often rents third-party warehouses, further raising expenses. Poor stock visibility also risks lost sales when customer demand cannot be met. Without a systematic and technical approach, operational constraints frequently arise, increasing stock inaccuracies and planning costs. Key factors to consider include seasonality, competitor pricing, product-based monthly shipping targets, warehouse stock levels at a random week t, overstocking cost, and unsatisfied demand cost.

Their main expectation from the project is to have a decision support system providing high-accuracy visibility into available capacity in its warehouses over a one-year horizon. The system provides a visual representation of the warehouse status through graphical elements such as pie charts. In pursuit of this objective, a decision support system has been developed using Excel VBA.

3.2 Proposed Solution Strategy

The solution method combines conceptual modeling with forecasting tools to estimate product inventory levels across warehouses. The method is open to refreshments on production, transfer, and sales data. This provides accurate projections for inventory planning and improved decision-making for the current system and future applications as well.

The A/F method is used for forecasting (Cleveland et al., 1990), where A represents Actual Demand and F represents the company's sales targets. By calculating the ratio of actual weekly sales to weekly targets, the A/F method constructs a probability distribution that captures the variability between expected and realized demand. This distribution is then used to adjust weekly point forecasts into more realistic and probabilistic estimates. The forecasts and the inventory management model are implemented using a combination of the A/F method and Excel VBA. Once obtained, forecasts are integrated into the model, which automatically calculates stock levels, updates results in real-time, and visualizes outputs, making the tool user-friendly for the company's planning team.

3.2.1 Forecast Method

The performance of the targets for each product in each month was calculated by dividing actual sales by the sales targets. Upon examining the resulting rates, it was observed that data cleaning was necessary. It was decided that removing a few extreme values and zeros from the dataset would yield a more accurate distribution. The cleaned data fit a single gamma distribution, with parameters 2.167 for the shape and 0.541 for the scale. This distribution represents the variability between actual sales and the company's sales targets, capturing the uncertainty and patterns observed in historical performance.

The previous year's sales were analyzed to convert monthly targets into weekly ones. The weekly sales distribution of each product across warehouses during the relevant months was calculated and applied to the following year's monthly targets. Using this approach, monthly targets were distributed into weekly values in a manner expected to better reflect actual sales patterns. Finally, the distribution obtained from the initial analysis and the weekly targets were passed to the modeling stage. The final estimations were reached by multiplying the rates generated from the A/F distribution with the weekly targets.

3.2.2 Modeling Method

The model provides an abstraction of the proposed solution approach to deliver visibility into warehouse and cell stock levels. The decision support system receives multiple inputs, where production plans, open-import shipments, and transfers from other warehouses represent inbound flows, while customer pick-ups, transfers to other warehouses, and raw material consumption represent outbound flows.

Future customer sales per warehouse are obtained from the forecast results, while all other inputs are directly fed into the model using the company's actual transactional data. The model consists of three main parts: simulation, flow equations, and cell assignment. In the first step, distinct weekly sales values for each product and warehouse are generated by applying the inverse function of the gamma distribution obtained in the forecasting stage to random probabilities. Flow equations are then used to calculate the resulting stock levels for each product-warehouse pair. Finally, based on these stock levels, products are assigned to specific cells within each warehouse to optimize space utilization.

Simulation and Flow Equations

As discussed earlier, initial stocks, production, open import orders, transfers, and raw material consumption are used as deterministic inputs to the model. At the start, the decision support system prompts the user to select a target date. Once the necessary inputs are gathered, they are stored in 4-dimensional arrays indexed by product, warehouse, week, and year. The model first calculates the total product quantities between the current and target weeks, then computes warehouse stock levels by summing initial stocks and inbounds, and subtracting outbounds.

Since customer sales are uncertain, a simulation approach is used to capture real-world variability and better prepare for different sales scenarios. The simulation runs 100 times by generating random sales values using the gamma inverse function with parameters from the forecasting step. After simulation and flow calculations, the system presents confidence intervals and related metrics to the user, offering a clearer view of the expected variability in stock levels. A flow chart of this process is shown in Figure 3.1.

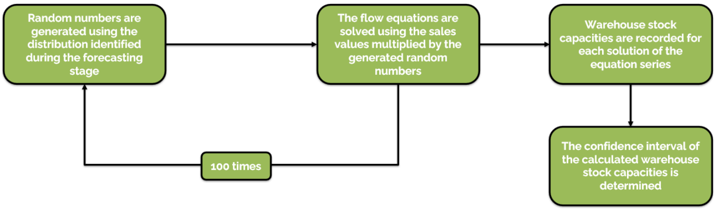


Figure 3.1: Flowchart of the Simulation Process

Cell Assignment Model

The mean values of the simulation runs for warehouse stock levels are used as inputs to the cell assignment model. The model assigns product quantities to cells within each warehouse while satisfying capacity limits and ensuring that only one product type is stored per cell. Initially, products are already placed in certain cells, and moving them can be costly. However, the current allocation may cause excessive cell usage. To balance cost and space, the model prioritizes keeping the initial assignments when it is cheaper than reallocating products to other cells with more available capacity. Below are the parameters and variables used in the cell assignment model.

Table 3.1: Sets and Indices

Index	Definition
W	Set of warehouses $W = \{1,2,3,\ldots,6\}$

continued from last page

Index	Definition
c	Set of cells $c \in c_w$ at warehouse $w \in W$
P	Set of products $P = \{1,2,3,\ldots,12\}$

Table 3.2: Decision Variables

Decision Variables	Definition
$x_{p,w,c}$	Quantity of product $p \in P$ at warehouse $w \in W$ on cell $c \in c_w$.
$y_{p,w,c}$	$\begin{cases} 1, & \text{if product } p \text{ is assigned to cell } c_w \text{ in warehouse } w \\ 0, & \text{otherwise.} \end{cases}$

Table 3.3: Parameters

Parameters	Definition	#
$k_{p,w}$	The current quantity of product $p \in P$ at warehouse $w \in W$.	(1)
f_p	Storage factor for product $p \in P$ to calculate the volume in the cell.	(2)
$T_{w,c}$	Capacity of cell c_w, i.e., the maximum amount of any product that cell c_w can hold.	(3)
$u_{p,w,c}$	$\begin{cases} 0.5, & \text{if cell initially used by product } p \text{ in warehouse } w \\ 1, & \text{otherwise.} \end{cases}$	(4)

The cell distribution model aims to minimize number of used cells in warehouse for the available products while obeying the capacity and product storage conditions.

$$\min \sum_{p \in P} \sum_{w \in W} \sum_{c \in c_w} u_{p,w,c} \cdot y_{p,w,c} \tag{0}$$

subject to:

$$f_p \cdot x_{p,w,c} \leq T_{w,c} \cdot y_{p,w,c} \quad \forall p \in P, w \in W, \text{ and } c \in c_w. \tag{1}$$

$$\sum_{p \in P} y_{p,w,c} \leq 1 \quad \forall w \in W, \text{ and } c \in c_w. \tag{2}$$

$$\sum_{c \in c_w} x_{p,w,c} = k_{p,w} \quad \forall p \in P \text{ and } w \in W. \tag{3}$$

$$y_{p,w,c} \in \{0,1\} \quad \forall p \in P, w \in W, \text{ and } c \in c_w. \tag{4}$$

$$x_{p,w,c} \in int \quad \forall p \in P, w \in W, \text{ and } c \in c_w. \tag{5}$$

- Objective (0) minimizes the number of used cells which is indicated by the binary variable y by also taking into account the initial assignment plan.
- Constraint (1) ensures that cell capacity requirement is obeyed if the cell is assigned to a product.
- Constraint (2) prevents any cell being filled by distinct SKUs.
- Constraint (3) ensures that all of the products at the warehouse are assigned to cells.
- Constraint (4) and (5) stands for defining binary and integer variables.

3.2.3 Utilized Platforms and Softwares

The primary goal of the project is to develop a decision support system that provides high-accuracy visibility into warehouse capacities over a one-year horizon. The system displays warehouse status through graphical elements such as pie charts, enabling actionable insights. Built using Excel VBA, the system prompts users to enter key inputs, including the current and target year-week combinations for inventory forecasts at both warehouse and storage cell levels. Once inputs are provided, the integrated Solver runs the necessary simulations, and the results are transferred to designated Excel sheets for visualization and further analysis. The decision support interface and the resulting pie chart are shown in Figure 3.2.

3.3 Validation Approach

The backtesting method was used during the validation phase to assess the alignment between the system's predictions and the actual operational results. Weekly forecasts and actual customer sales for a specific warehouse were compared to evaluate prediction accuracy. The analysis was conducted by cumulatively summing weekly forecasts and actual sales for particular products over a five-week period. For Product 1, the gap between the cumulative forecast and actual sales narrowed to just 0.3%. Given that this product represents 60% of total product sales, such a low error rate indicated a high level of predictive accuracy. Based on the evaluations presented during the most recent meeting with the company, the estimates were considered valid and reliable in light of the observed performance.The results are summarized in Figure 3.3.

3.4 Integration and Implementation

To integrate our solution approach, a pilot study was conducted at the IGSAŞ Kocaeli warehouse. This pilot study used current data from 2025 to evaluate the effectiveness of our decision support system. The simulation was run for different weeks using Excel VBA, and the results were compared with the product groups available in the warehouse for each respective week. The findings revealed that the system demonstrated 90% accuracy in forecasting for a period of one month and 70% accuracy over a period of three months. Notably, the system showed high forecast accuracy for product groups that constitute a significant portion of the market share, ensuring that the most critical inventory items are well-managed and replenished in a timely manner. This pilot study serves as a proof of concept for the potential scalability and reliability of our approach in real-world warehouse operations. As a result of the plan obtained, procurements are carried out according to the warehouse conditions for different target weeks, with the system running continuously. The decision support system is designed for long-term use, as it can be executed regularly to provide an effective solution even as the warehouse conditions change. This ensures that the system remains adaptable to dynamic operational requirements and continues to optimize inventory management and procurement decisions over time.

3.5 Benchmarks and Benefits

Implementing an integrated decision support system that combines warehouse capacity management with supply and demand planning brings ma-

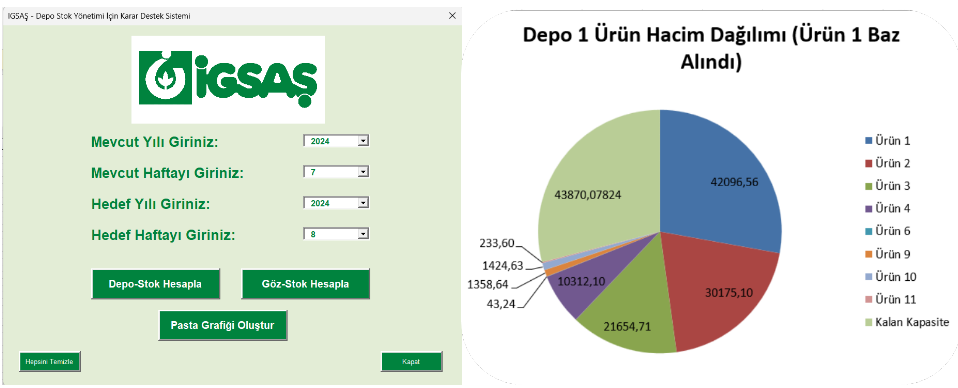


Figure 3.2: Decision Support System (left) and pie chart

Week Number	Product Type		
	Product 1	Product 3	Product 7
Week 1+2	53%	26%	10%
Week 1+2+3	51%	15%	13%
Week 1+2+3+4	21%	12%	7%
Week 1+2+3+4+5	0,3%	5%	5%

Figure 3.3: Percentage Error for Particular Products and Warehouses.

jor improvements to operational efficiency and financial performance. By blending historical sales, import, procurement, and production data with forecast projections, the system makes planning more data-driven, accurate, and flexible across short- and long-term horizons. It allows decision-makers to quickly simulate multiple scenarios, improving responsiveness and reducing the risk of errors from manual estimations.

Historical analyses reveal the substantial financial burden caused by stock uncertainty and planning inefficiencies. In 2024, reactive decision-making led to the unplanned rental of warehouse space for approximately 14,887 tons of product, incurring an annual cost of 163,757 USD. Inaccurate stock projections triggered the unplanned transfer of 10,748 tons of inventory between warehouses, resulting in additional transportation costs of 38,682 USD. Operational disruptions in vessel planning due to unforeseen warehouse capacity constraints created further losses of approximately 40,248 USD, driven by port charges and supplementary freight expenses. Altogether, stock-related inefficiencies imposed a financial impact exceeding 242,000 USD per year.

Addressing these challenges, the newly developed system introduces high-accuracy forecasting capabilities, achieving approximately 90% accuracy over a one-month horizon and maintaining strong 70% accuracy over three months. This high prediction accuracy drastically reduces operational uncertainty, allowing the company to proactively manage inventory levels, warehouse capacities, and logistics operations with greater precision and foresight.

Future stock projections at the warehouse and storage-cell levels help prevent both overstock and stockouts. Automated calculations based on product volume and density minimize inefficient space use, while accurate capacity planning reduces the need for emergency warehouse rentals and costly last-minute transportation, enhancing operational stability. The system also strengthens vessel operation planning by providing early visibility into warehouse stocks, enabling more precise shipment allocations, reducing port charges, minimizing demurrage risks, and shortening unloading times. Reliable stock availability lowers sell-out risks, boosts customer satisfaction, and secures revenue otherwise lost due to stockouts. Additionally, visibility into future warehouse capacity allows the company to act on market-driven purchasing opportunities, such as bulk acquisitions during favorable pricing periods, directly contributing to margin improvement.

While the system may not completely eliminate all operational losses, it is projected to significantly mitigate them, contributing to an estimated annual benefit of 242,687 USD. Even in the face of unexpected operational challenges, the system enables the company to proactively manage uncertainty, minimize risks, and maintain much greater control over inventory and logistics operations. By embedding predictive analytics and intelligent decision-making into core processes, the company positions itself to achieve stronger operational stability, financial performance, and strategic agility in a dynamic market environment.

3.6 Conclusions

The aim of the project was to establish warehouse capacity visibility and integrate demand planning processes to minimize stock-related inefficiencies. A robust decision support system was developed, leveraging historical data and predictive models to generate forward-looking stock projections and simulate capacity scenarios. Through the decision support system, operational teams can proactively manage inventory levels and optimize warehouse utilization. Throughout the project, regular alignment meetings were held, and a pilot implementation was successfully conducted. The pilot results strongly validated the system's effectiveness, demonstrating significant reductions in unplanned warehouse rentals and transportation costs, along with marked improvements in operational agility.

Acknowledgment

This project was supported by TÜBİTAK BİDEB 2209/B Program under Grant 1139B412408382

Bibliography

Cleveland, R. B., W. S. Cleveland, J. E. McRae, and I. Terpenning (1990). Stl: A seasonal-trend decomposition procedure based on loess. *Journal of Official Statistics 6*(1), 3–73.

IGSAŞ (2024). Tarihçemiz. https://www.igsas.com.tr/kurumsal/tarihcemiz. Accessed: 20-Oct-2024.

4 Depolar Arası Yatay Sevkiyat Miktarlarının Azaltılması

Nevzat Ecza Deposu

Proje Ekibi
Fatma Azra Altınsoy, Pınar Çakıl, Süleyman Doran,
Ahmet Said Kargın, Ahmet Seyfi Özkan, Ozan Sazak, Mert Timur

Şirket Danışmanı
Harika Karpuzcu Dilik
Genel Müdür Yardımcısı

Akademik Danışman
Prof. Dr. Alper Şen
Endüstri Mühendisliği Bölümü

Özet

Ankara bölgesindeki yerel depolar arasında yaşanan envanter yetersizlikleri ve yatay sevkiyatlar, Nevzat Ecza Deposu'nun operasyonel verimliliğini olumsuz etkilemektedir. Projenin amacı, talep tahmin doğruluğunu artırmak ve ürünlerin merkez depodan yerel depolara daha etkin bir şekilde dağıtılmasını sağlayan bir karar destek sistemi geliştirmektir. Bu amaçla R programlama dili kullanılarak ARIMA, STL ve yeniden örnekleme yöntemleriyle tahmin modelleri oluşturulmuş; günlük dağıtım kararları ise Örnek Ortalaması Yaklaştırması tabanlı bir eniyileme modeli ile alınmıştır. Geliştirilen sistem, pilot uygulama kapsamında yatay sevkiyat oranlarını yaklaşık %11 oranında azaltmış; stok dağıtım doğruluğunu ve hizmet seviyesini ise önemli ölçüde artırmıştır.

Anahtar Sözcükler: Yatay Sevkiyat, Güvenlik Stoğu, Talep Tahmini, Envanter Yönetimi, Stok Besleme Optimizasyonu, Örnek Ortalama Yaklaşımı

Minimizing Inter-Warehouse Lateral Shipments

Abstract

At Nevzat Pharmaceutical Wholesale, the lack of a forecasting-based inventory allocation system has resulted in inefficient stock distribution and high rates of lateral transshipments among local warehouses in the Ankara region. This project aims to enhance service levels and reduce operational costs by developing a fast, user-friendly decision support system that forecasts demand and optimizes distribution. The system is implemented using R and Shiny, integrating ARIMA, STL decomposition, and resampling techniques for demand forecasting, and Sample Average Approximation (SAA) for inventory optimization. Results from a pilot study demonstrate that the new system reduced lateral transshipments by approximately 11% and significantly improved allocation efficiency

Keywords: Lateral Transshipments, Safety Stock, Demand Forecasting, Inventory Management, Stock Replenishment Optimization, Sample Average Approximation (SAA)

4.1 Company Description

Nevzat Pharmaceutical Wholesale is one of Turkey's leading pharmaceutical distributors, with over 60 years of experience in the healthcare supply chain. The company operates six central and fourteen local warehouses across major cities, including Ankara, Samsun, Antalya, Adana, Trabzon, and Erzurum. Each region has a designated central warehouse supported by local warehouses that serve geographically assigned pharmacies.

The central warehouses also host executive units, whereas local warehouses focus solely on storage and direct distribution to pharmacies. The scope of the project is limited to the Ankara region, where the central warehouse located in Balgat coordinates five local warehouses: Sincan, Keçiören, Kapadokya, Cebeci, and Konya.

4.2 System Description

In the Ankara region of Nevzat Pharmaceutical Wholesale, the inventory network consists of a central warehouse and six local warehouses. Products are supplied to the central warehouse in accordance with the company's orders placed with pharmaceutical manufacturers, after which they are distributed to the local warehouses. Pharmacies place their orders through local warehouse call centers, and they are served by the geographically closest warehouse. If a product is out of stock at a local warehouse, the system first checks the central warehouse and, if unavailable, checks other local warehouses. If a warehouse cannot meet its own demand, another local warehouse fulfills the demand through the central warehouse, which is called the lateral transshipment process.

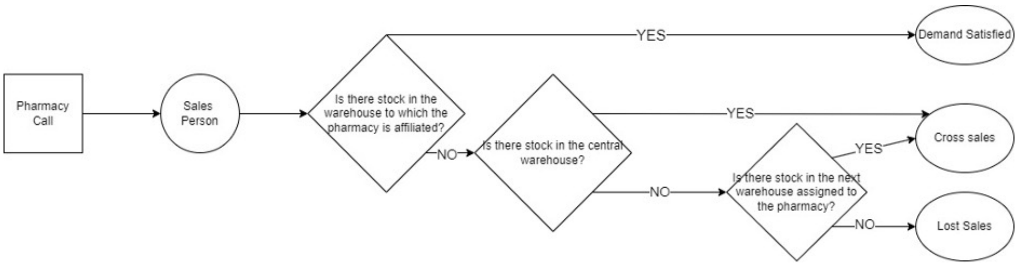


Figure 4.1: Lateral Transshipment Process

In such cases, the product is first shipped to the central warehouse, then re-handled and repackaged before being sent to the pharmacy. This results in additional labor, higher logistics costs, increased packaging waste, and elevated risk of product damage. The company aims to maintain 21 days of inventory in each warehouse and centralize the replenishment process for newly arrived stock.

4.3 The Engineering Problem

Currently, the company's ERP system (BOYUT) allocates inventory of the local warehouses based on the past 60 days of sales data of each product. The ERP system uses the average of the data as the forecast for the future sales amounts of the warehouses. This methodology fails to consider seasonal effects, product-specific trends, or campaign-driven fluctuations; hence, it does not reflect the actual and dynamic demand patterns of each local warehouse. Using this forecast methodology for future sales amounts results in inefficiency for the allocation of the inventory of the local warehouses.

Analysis of sales data between 2021 and 2024 reveals high volatility in product demand across warehouses and throughout the year. Products like Ecopirin 100 mg show multiple annual peaks that differ per warehouse. Consequently, the uniform distribution method leads to inventory imbalances—some warehouses run out of stock while others hold excess. These mismatches result in frequent lateral transshipments and lost sales. For instance, only 53% of Keçiören's demand was met locally in this period, while 84% of the central warehouse's output went to non-local pharmacies. This underlines the need for a dynamic, data-driven forecasting and allocation system.

4.4 Model and Proposed System

To address frequent and inventory mismatches in the Ankara region, the project consists of two main components; demand forecasting and inventory allocation optimization.

4.4.1 Demand Forecasting

Three methods were employed to forecast demand for each product and warehouse:

- **STL Decomposition:** used for products having seasonal or trending historical sales data (Cleveland et al., 1990)
- **ARIMA:** applied to products with relatively regular demand (Saadeddin, 2025).
- **Resampling:** used when patterns are irregular or data is sparse (Dunn, 2022).

Historical sales data from 2021 to 2024 were cleaned and aggregated weekly. Campaign-driven outliers and discontinued products were excluded to increase model reliability. A loop in RStudio selects the best forecasting method per product and warehouse and generates three-week demand forecast output and generates 400 demand samples.

4.4.2 Inventory Allocation Model

Samples generated from the forecast output are fed into Sample Average Approximation (SAA)-based optimization model, which determines the optimal distribution amount among warehouses . The objective below aims to minimize the expected cost considering different scenarios.

$$\min \frac{1}{T} \sum_{t \in T} \Big(\sum_{i \in I} C_1 S_{iit} + \sum_{i \in A} C_2 S_{1it} + \sum_{i \in B} C_3 S_{1it} + \sum_{i,j \in I, i \neq j} C_4 S_{ijt} + \sum_{i \in I} C_5 S_{xit} \Big)$$

- S_{iit}: Quantity of shipment from local warehouse i to locality i in scenario t
- S_{ijt}: Quantity of lateral shipment from local warehouse i to locality j in scenario t
- S_{1it}: Quantity of lateral shipment from the central warehouse to locality i in scenario t
- S_{xit}: Unmet demand from location i in scenario t

The model satisfies operational constraints such as:

- Retaining 20% of incoming inventory as safety stock at the central warehouse
- Allowing lateral transshipments only when surplus exists
- Fulfilling demand in compliance with good distribution practices (GDP)

The model is executed daily for each SKU using the `glpk` solver in R. The detailed version of the model can be seen in the appendix.

4.4.3 Tools and Implementation

The entire system is developed in **RStudio** using forecasting and optimization libraries (Team, 2021). A **Shiny dashboard** serves as the interface, allowing users to input arriving products and view recommended allocations interactively (Chang et al., 2021).

4.4.4 Assumptions and Constraints

- Intercity lateral shipments are excluded due to time delays
- All warehouses are assumed to be fully staffed
- Product deliveries are entered into the system by 7:00 AM, and distribution starts at 9:00 AM
- Costs are estimated based on distance and loss projections in the absence of net cost data

4.5 Verification and Validation

To ensure the accuracy and practicality of the proposed decision support system, verification and validation steps were conducted throughout the development process.

For verification, the model was tested under various input scenarios to evaluate its logical behavior. Continuity tests showed that the model adapts proportionally to changing inventory levels, distributing products effectively whether supply is scarce or abundant. Consistency tests confirmed that changes in key parameters, such as demand variance and initial inventory, produced expected results. For example, when the standard deviation in the Sincan warehouse was increased, the model allocated more stock to mitigate uncertainty. Similarly, high initial inventory values led to reduced allocations, preventing overstocking. Cost parameters were also calibrated to reflect operational realities and maximize service levels.

For validation, the model was tested using real sales and inventory data from February 14–27, 2025. Forecasts were generated using ARIMA, STL decomposition, or resampling depending on product demand patterns. The best-fitting model was automatically selected based on historical accuracy, and 400 demand scenarios were simulated to support optimization.

Operationally, the system was installed on a company computer, where daily inventory data was uploaded. The system generated optimal allocation decisions through an interactive Shiny dashboard. Face validation was conducted with the industrial advisor production planning, who confirmed that the assumptions and logic aligned with the real system.

Performance of the model was also benchmarked against the company's current policy. For product 11854, the new system eliminated lateral transshipments entirely (0% vs. 4%), while for product 1001, the rate was reduced from 11% to 6%. These results indicate a significant improvement in allocation efficiency and support the feasibility of full-scale implementation.

4.6 Deliverables and Benefits

As final output of the project, a user-friendly decision support system (DSS) has been developed to assist Nevzat Pharmaceutical Wholesale in daily inventory allocation for its warehouses.

İlaç Kodu	Bilgi	Depo 1	Depo 2	Depo 3	Depo 4	Depo 5	Depo 8
11854	Gelen_miktar	2720					
	Dağıtılacak_İlaç_Miktarı	544	143	276	319	1192	245
	Koli_Sayisi	300					
	Ortalama_Talep_Tahmini	447.09	368.52	363.16	515.82	575.15	405.14
4200	Gelen_miktar	1848					
	Dağıtılacak_İlaç_Miktarı	370	0	367	727	385	0
	Koli_Sayisi	600					
	Ortalama_Talep_Tahmini	774.40	1127.93	967.41	998.97	867.81	605.23
1586	Gelen_miktar	35000					
	Dağıtılacak_İlaç_Miktarı	7000	5449	4570	8153	5925	3902
	Koli_Sayisi	500					
	Ortalama_Talep_Tahmini	338.16	466.90	385.88	734.47	511.89	325.90
26592	Gelen_miktar	3000					
	Dağıtılacak_İlaç_Miktarı	600	440	528	589	499	345
	Koli_Sayisi	300					
	Ortalama_Talep_Tahmini	336.70	337.02	408.98	459.93	385.06	261.76
496	Gelen_miktar	3000					
	Dağıtılacak_İlaç_Miktarı	600	1321	508	0	571	0
	Koli_Sayisi	20					
	Ortalama_Talep_Tahmini	624.67	761.70	686.81	583.38	795.31	569.07
8094	Gelen_miktar	3000					
	Dağıtılacak_İlaç_Miktarı	600	1566	0	626	209	0
	Koli_Sayisi	20					
	Ortalama_Talep_Tahmini	784.12	1080.98	989.02	1141.82	893.26	540.15

Figure 4.2: Decision Support System Output

The system uses four years of historical sales data and applies the most accurate forecasting method (ARIMA, STL, or resampling) for each product and with forecasting output, it generates 400 demand scenarios. Based on these forecasts, the DSS optimizes stock allocation among the central and local warehouses using a Sample Average Approximation (SAA) model (Verweij et al., 2003).

The DSS interface requires the product code and the quantity of incoming stock as input. In return, it provides:

- Suggested distribution to the central and 5 local warehouses
- Forecast method used and expected demand values
- Current inventory levels per warehouse
- Key performance metrics such as expected cost, service rate, and lateral transshipment rate

Benchmarking was conducted using company data between February 14–27, 2025. The DSS was tested on 12 products and outperformed the company's existing distribution system. For example, Keçiören Warehouse's lateral transshipment rate decreased from 38% to 33% by using DSS. Across all tested products, the DSS reduced lateral transshipments, unmet demand, and unnecessary handling. Moreover, the system decreases employee workload and supports the company's ESG goals by minimizing waste and breakage during distribution.

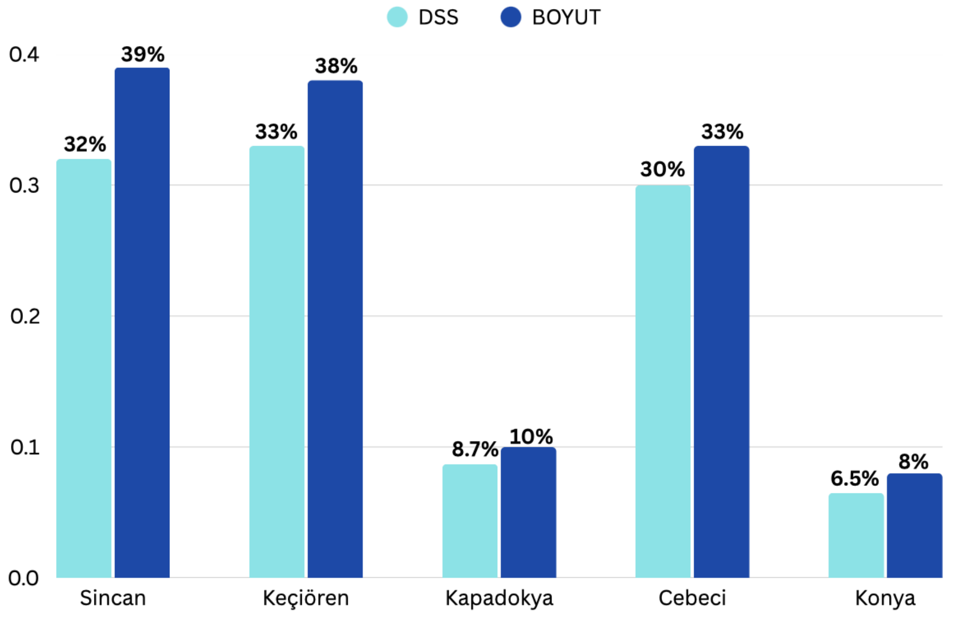


Figure 4.3: Lateral Transshipment Comparison Based on Warehouses

4.7 Integration and Implementation

The developed decision support system (DSS) is implementing on a standalone company computer, independent of the existing ERP system. Daily warehouse inventory levels and newly arrived product quantities is manually entered by the operations team using Excel files created from supplier invoices.

The DSS operated daily to generate optimized stock allocations based on forecasted demand and real-time inventory data. While the DSS does not update ERP records directly, it supports the allocation decision process before invoice-based stock entry.

To ensure a smooth transition, weekly coordination meetings were held with the company, and the system were tested under real operational conditions. The interface is designed to be simple: the user uploads the Excel file having the newly arriving products' codes and quantities, then receives allocation outputs along with current stock levels, forecast method used and expected demand forecast.

The DSS is ready for operational use and supports the company in reducing lateral transshipments and improving daily distribution efficiency.

4.8 Conclusion and Future Work

This project has led to the development of a fully functional decision support system for warehouses, specifically tailored to the operational structure of Nevzat Pharmaceutical Wholesale. By integrating product-level demand forecasting with cost-based inventory optimization, the system supports more informed daily allocation decisions and significantly minimizes lateral transshipments. Throughout the project, close collaboration with the company has ensured that the model reflects real-world constraints and practical needs. The decision support tool has been successfully prepared for pilot use and is designed to integrate seamlessly into existing workflows without disrupting current ERP operations.

Looking ahead, the collaboration between the project team and the company is expected to continue. As sales patterns evolve, new warehouses are added, or operational practices shift, the system will be automatically updated and refined. Forecast frequencies, optimization logic, and interface features can be adapted over time based on company feedback. This dynamic relationship ensures that the tool remains relevant and scalable for future needs.

The project provides a strong foundation for further automation and data-driven planning efforts within the company and marks a critical step toward smarter pharmaceutical logistics.

Bibliography

Chang, W. et al. (2021). *Shiny: Web Application Framework for R*. RStudio, PBC.

Cleveland, R. B., W. S. Cleveland, J. E. McRae, and I. Terpenning (1990). Stl: A seasonal-trend decomposition procedure based on loess. *Journal of Official Statistics 6*(1), 3–73.

Dunn, T. (2022). An introduction to statistical learning with the tidyverse and tidymodels. https://bookdown.org/taylordunn/islr-tidy-1655226885741/. [Online; Accessed: Feb. 15, 2025].

Saadeddin, Z. (2025). Arima for time series forecasting: A complete guide. https://www.datacamp.com/tutorial/arima. [Online; Accessed: Feb. 15, 2025].

Team, R. (2021). *RStudio: Integrated Development for R*. RStudio, PBC.

Verweij, B., S. Ahmed, A. J. Kleywegt, G. Nemhauser, and A. Shapiro (2003). The sample average approximation method applied to stochastic routing problems: A computational study. *Computational Optimization and Applications 24*, 289–333.

Appendix: Mathematical Model

Table 4.1: Sets, Variables, and Parameters Used in the Model

Type	Symbol	Description
Indices	$A = \{2, 3, 5\}$	Set of warehouses located in Ankara
	$B = \{4, 8\}$	Set of warehouses located outside of Ankara
	$I = \{1, 2, 3, 4, 5, 8\}$	Set of all warehouses
	$T = \{1, \ldots, 400\}$	Set of scenario indices
Decision Variables	Q_i	Quantity allocated to local warehouse i
	S_{iit}	Quantity of shipment from local warehouse i to locality i in scenario t
	S_{ijt}	Quantity of lateral shipment from local warehouse i to locality j in scenario t
	S_{1it}	Quantity of shipment from the central warehouse to an in-town locality i in scenario t

	S_{xit}	Unmet demand from location i in scenario t
Parameters	D_{it}	Demand in locality i in scenario t
	C_1	Cost parameter for meeting the demand in the warehouse's region
	C_2	Cost parameter for meeting the demand of an Ankara warehouse from the central warehouse
	C_3	Cost parameter for meeting the demand of a warehouse outside Ankara from the central warehouse
	C_4	Cost parameter for lateral transshipment
	C_5	Cost parameter for unmet demand
	I_i	Initial inventory at warehouse i
	Q	Total available supply to be allocated

$$\min \frac{1}{T}\sum_{t\in T}\Big(\sum_{i\in I} C_1 S_{iit} + \sum_{i\in A} C_2 S_{1it} + \sum_{i\in B} C_3 S_{1it} + \sum_{i,j\in I, i\neq j} C_4 S_{ijt} + \sum_{i\in I} C_5 S_{xit}\Big)$$

$$S_{1it} + \sum_{j\in A, j\neq i} S_{jit} + S_{iit} + S_{xit} = D_{it}, \qquad \forall i \in A,\ \forall t \in T \tag{1}$$

$$S_{1it} + S_{iit} + S_{xit} = D_{it}, \qquad \forall i \in B, \forall t \in T \tag{2}$$

$$S_{11t} + S_{x1t} = D_{1t}, \qquad \forall t \in T \tag{3}$$

$$\sum_{i\in A} S_{1it} + \sum_{i\in B} S_{1it} + S_{11t} \leq Q_1, \qquad \forall t \in T \tag{4}$$

$$\sum_{j\in A, i\neq j} S_{ijt} + S_{iit} \leq Q_i + I_i, \qquad \forall i \in A,\ \forall t \in T \tag{5}$$

$$S_{iit} \leq Q_i + I_i, \quad \forall i \in B \qquad \forall t \in T \tag{6}$$

$$\sum_{i\in I} Q_i = Q + I_1 \tag{7}$$

$$Q_1 \geq (Q + I_1)\cdot\frac{1}{5} \tag{8}$$

$$S_{xit} \leq \sum_{j\in I} S_{xjt}\cdot\frac{D_{it}}{\sum_{k\in I} D_{kt}} \qquad \forall i \in I,\ \forall t \in T \tag{9}$$

$$S_{ijt}, S_{xit}, Q_i \geq 0, \qquad \forall i, j \in I, \forall t \in T \tag{10}$$

5 | Gecikme Yayılımını Enazlayan Sağlamcı Uçuş Çizelgelemesi

Pegasus Hava Yolları

Proje Ekibi

İrem Aslan, Yakup Kaan Baycan, Dilara Demir,
Ahmet Can Gökçe, Kaan Gürler, Elifnaz Özcan, Burak Ünal

Şirket Danışmanı
Mert Köksal
Ağ Planlama Uzmanı

Akademik Danışman
Prof. Dr. M. Selim Aktürk
Endüstri Mühendisliği Bölümü

Özet

Pegasus Hava Yolları'nın mevcut çizelgeleme sürecinde geçmiş gecikme verilerinin kullanımına yönelik geliştirme alanları bulunmaktadır; bu durum, bazı gecikmelerin diğer uçuşlara yayılmasına neden olabilmektedir. Bu sorunu çözmek amacıyla geliştirdiğimiz matematiksel model, geçmiş sezonlardaki gecikme senaryolarını analiz edip tampon süreleri eniyileyerek toplam gecikme süresini en aza indiren bir çizelgeleme yaklaşımı sunmaktadır. Geliştirdiğimiz çözüm, Pegasus Hava Yolları'nın operasyonel kısıtlarını, şirketin merkezi olan Sabiha Gökçen Havalimanı'nın kapasitesini ve uçuşların uygulanabilirliğini girdi olarak almakta ve gecikme yayılımını önleyen yeni bir uçuş çizelgesi üretmektedir. Kullanıcı dostu bir arayüz ile şirketin kullanımına sunulan model, ağ planlama uzmanlarının belirleyebileceği farklı stratejiler doğrultusunda gecikme yayılımını enazlayan sağlamcı bir çizelgeyi çıktı olarak vermektedir.

Anahtar Sözcükler: Sağlamcı Planlama, Tampon Zaman Yönetimi, Zamanında Kalkış Performansı, Gecikme Yayılımı, Matematiksel Model, Gecikme Enazlama

Robust Flight Scheduling Minimizing Delay Propagation

Abstract

Pegasus Airlines' current scheduling process offers opportunities to incorporate historical delay data better, as some delays may propagate to subsequent flights. To address this issue, we have developed a mathematical model that analyzes past seasons' delay scenarios and optimizes buffer times to minimize total arrival delay, offering an optimized scheduling approach. Our solution takes into account Pegasus Airlines' operational constraints, the capacity of its hub, Sabiha Gökçen Airport, and the feasibility of flights as inputs, and generates a new flight schedule that minimizes delay propagation. The model, presented to the company through a user-friendly interface, provides a robust schedule that minimizes delay propagation based on different strategies that can be defined by network planning specialists.

Keywords: Robust Planning, Buffer Time Management, On-Time Departure Performance, Delay Propagation, Mathematical Model, Delay Minimization

5.1 Company and System Analysis

5.1.1 Company History

Pegasus Hava Taşımacılığı A.Ş. was founded as a joint venture between Aer Lingus Group, Silkar Yatırım ve İnşaat Organizasyonu A.Ş., and Net Holding A.Ş. in 1990, and started its operations with two commercial planes. Later on, in 2005, Esas Holding acquired Pegasus, and domestic operations to six destinations were initiated, making Pegasus Türkiye's 4th biggest airline. Sabiha Gökçen Airport was selected as the main hub for the fleet. In 2006, international flights started with Stuttgart, followed by Nicosia and Vienna. İzmir, Dalaman, Bodrum, Gaziantep, Malatya, and Kayseri were added to the domestic network. In 2007, Pegasus expanded its fleet significantly with a $3.2 billion investment, marking one of the biggest private aviation investments in Türkiye. Between 2006 and 2010, while Türkiye's domestic flight market grew by 15%, Pegasus achieved a 42% increase in its passenger numbers. Pegasus became the first airline to integrate Groundlink's End-to-End Network Solutions System into its fleet in 2011 (Pegasus Airlines, 2024).

5.1.2 Current System Analysis

Planning is crucial for airline operations, and Pegasus Airlines follows a structured approach to scheduling. Their planning process consists of three main stages: Flight Schedule Generation, Aircraft Scheduling, and Crew Scheduling. Flight Schedule Generation involves designing the network, assigning flight frequencies, and setting specific schedules twice a year for summer and winter seasons. Pegasus operates from its central hub at Sabiha Gökçen Airport (SAW), which serves 143 destinations. Aircraft Scheduling covers fleet assignment and aircraft routing, ensuring optimal aircraft usage while maintaining passenger satisfaction and minimizing delays. However, due to project constraints, fleet assignment is not applied. Maintenance is performed on the SAW during the night, so maintenance scheduling is also not included. Crew scheduling, which ensures proper flight staffing, is also beyond the scope of our project.

5.2 Problem Definiton

Generally, delay types can be separated into two categories: chronic delays and abnormal delays (anomalies). Abnormal delays are random, one-off incidents caused by severe weather, tarmac accidents, or late passengers. Chronic delays are caused by problematic airports with high congestion levels, short buffer times, scheduling issues, miscalculated ground times, and repeating ground services issues; they stem from planning errors and can be prevented through better scheduling. The main goal of our problem is improving the On-Time Performance of flights. Our objective is to develop a robust model that minimizes delay propagation. Delay propagation refers to the delay times affecting consequent flights like a chain reaction, causing subsequent flights to be delayed.

A critical aspect regarding delay propagation is setting proper buffer times between flights. If buffer times are too short, the schedule becomes more sensitive to delays and operational variability; if buffer times are too long, the Aircraft Utilization Rate decreases, leading to inefficient use of resources. Therefore, it is essential to balance the Aircraft Utilization Rate and schedule robustness by adjusting the buffer times appropriately.

Currently, the Network Planning Department creates its schedules by working with an external software development company and using simulation software developed by Lufthansa. Nonetheless, this outdated software does not fully meet Pegasus' objectives. With the software, it is only possible to select different parameters, such as FIFO and LIFO, and the software transforms these rotations into Gantt Charts. While it is useful to see aircraft availability, it does not consider robustness or past delay data while creating schedules. As a result, buffer times are minimized to maximize utilization, making schedules highly vulnerable to delay propagation. Once a flight is late, then all of the later flights end up late as well. Thus, while Lufthansa's software helps visualize rotations, it lacks decision support mechanisms and produces schedules prone to propagated delays.

5.3 Proposed Solution and Methodology

5.3.1 Critical Assumptions

This project is based on several critical assumptions guiding the scheduling process. The number of aircraft assigned to Sabiha Gökçen Airport (SAW), Pegasus Airlines' main hub, is fixed for the season. Although the fleet consists of similar narrow-body aircraft, differences in seating capacities are considered significant to ensure accuracy in future cost analyses. Minimum Turn Time (MTT) is assigned based on aircraft type and departure/arrival airports, following Minimum Ground Time values from the Industrial Advisor. The flight schedule initially covers one day and, if feasible, extends to a week (approximately 3,500 flights).

The study focuses solely on chronic delays, excluding anomalies, while maintaining the current tariff structure, allowing aircraft to operate both domestic and international flights within a day. Previously established MTT values remain unchanged per the academic advisor's guidance. Slack time between consecutive flights is the difference between planned and minimum turn times; if the preceding flight's arrival delay exceeds slack, the excess becomes propagated delay. Delay codes define "Delay Scenarios," where arrival delay per scenario informs slack reallocation. Independent Arrival Delay is the delay experienced within a scenario, refined through further analysis. Initially, the average delay per scenario (in minutes) serves as the Independent Arrival Delay. To minimize total arrival delay, the probability of each scenario occurring is determined as the ratio of its observed occurrences to the total observations.

5.3.2 Major Constraints

The major constraints in this project are categorized into Company Regulations and Relevant Engineering Standards. Company regulations require that all scheduled flights be executed while ensuring aircraft maintain route consistency by returning to their originating hub. The number of aircraft assigned to Sabiha Gökçen Airport must remain fixed, and slack reallocation must preserve both passenger and aircraft connection feasibility. Additionally, block times must remain constant, as even minor adjustments are not permitted per Industrial Advisor guidance. Engineering standards dictate that aircraft cannot operate without passengers, except for ferry flights used for positioning or maintenance. Departures and arrivals must adhere to predetermined airport time slots, ensuring compliance with scheduling constraints and operational feasibility.

5.3.3 Objective

Qualitative improvements depend on the problem's objectives, with the primary goal being Minimizing Total Expected Arrival Delay. This project aims to create a robust flight schedule by optimizing buffer time management to reduce delay propagation. The objective function achieves this by adjusting slack times between consecutive flights, ensuring delays are absorbed locally rather than spreading across the network like a snowball effect.

5.3.4 Conceptual Model

The proposed solution is designed to be a complementary tool for the currently used Lufthansa Scheduling Tool: The schedule that is created with the Lufthansa software is the input to our model, and the decision-maker chooses the better-performing schedule. The representation of this process is shown in Figure 5.1.

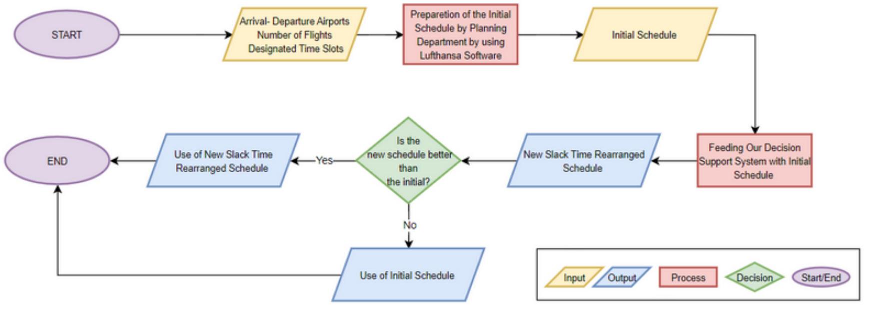


Figure 5.1: Conceptual Flow Chart

The updated schedule is created by the model we proposed via the Decision Support System, which takes planned block times, initial slack (buffer) time values, available SAW slots, delay scenarios, and independent arrival delay amounts as inputs, then gives the improved schedule with modified buffer and block times, therefore with better expected total arrival delay amount. The representation of inputs and outputs to the Decision Support System can be seen in Figure 5.2.

5.3.5 Mathematical Model

The mathematical model, detailed in the appendix, includes parameters, sets, decision variables to adjust buffer (slack) times, an objective function to minimize the expected total arrival delay, and constraints to express the limitations of the company and the problem requirements. The mathematical model used in this project reallocates slack times to improve schedule

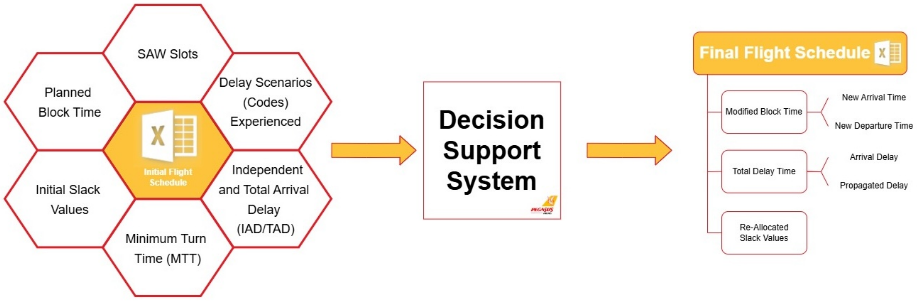


Figure 5.2: Conceptual Model

robustness by minimizing expected total arrival delay. The model shifts flight departure and arrival times within defined limits, adjusting slack and block times accordingly. Delay propagation is incorporated through predefined delay scenarios, where each scenario's probability and independent arrival delay (IAD) inform the calculation of propagated delay (pd) and total arrival delay (tad). The objective function minimizes the expected total arrival delay, while constraints regulate aircraft and passenger slack adjustments, ensure feasibility, and maintain operational constraints set by Pegasus. A key parameter, δ defines the time granularity of schedule adjustments and is set to 5 minutes, reflecting Pegasus Airlines' policy of scheduling flights in 5-minute intervals. This enables integer shift variables to align with real-time planning. A mathematical model adapted from Barnhart and Cohn (2004) is utilized to adjust flight departure and arrival times within a limited time interval, aiming to enhance schedule robustness against delay propagation. The model reallocates slack times and updates block times to generate a more resilient flight schedule.

5.4 Validation

The validation process assesses the model's compatibility with Pegasus Airlines' current system and its effectiveness under real operational conditions. We compared model outputs with actual flight data, focusing on key metrics like flight timings, delay rates, and schedule efficiency. Initially, small-scale tests were conducted on daily flight schedules to evaluate the model's accuracy and adaptability in short-term operations. These tests allowed direct comparisons with the current system to identify any discrepancies.

Flight and delay data from September 2024, provided by Pegasus Airlines' Operations Control Center, were analyzed to support this process. The dataset included aircraft types, schedules, airports, and categorized delay codes. Key delay patterns across major airports, particularly Istan-

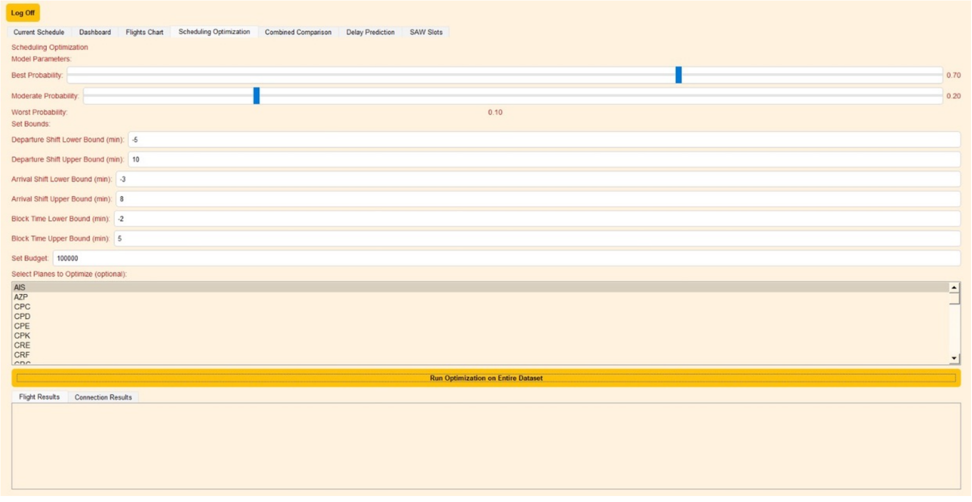


Figure 5.3: Scheduling Optimization Panel of the User Interface

bul Sabiha Gökçen, were identified, and quantile analysis of total delay times was performed to capture departure point variability. These findings guided the creation of realistic delay scenarios for the model.

To further examine robustness, we performed scenario analysis, testing the model under various delay scenarios to determine how well it manages Independent Arrival Delay (IAD), Propagated Delay (PD), and Total Arrival Delay (TAD). Feedback from the industrial advisor was incorporated to align the model with real-world operational requirements.

Experiments were conducted using ten aircraft under two different probability settings for quantitative validation. In the first case, equal probabilities were assumed for all delay scenarios, and the model reduced total arrival delays by 11.07% through strategic slack reallocation while keeping ground times fixed. In the second case, historical delay distributions were applied based on the earlier analysis, enabling the model to reflect airport-specific patterns better. This led to even greater improvements, as the model optimized slack allocation more effectively by considering real-world delay patterns. These validation steps confirm that the model enhances schedule reliability, reduces delay propagation, and remains feasible for practical implementation within airline operations.

5.5 User Interface

An interactive and comprehensive user interface has been developed by Pegasus Airlines to facilitate the adoption of the robust scheduling model. This interface serves as a bridge between raw operational data and our optimization engine, empowering planning department control over schedule

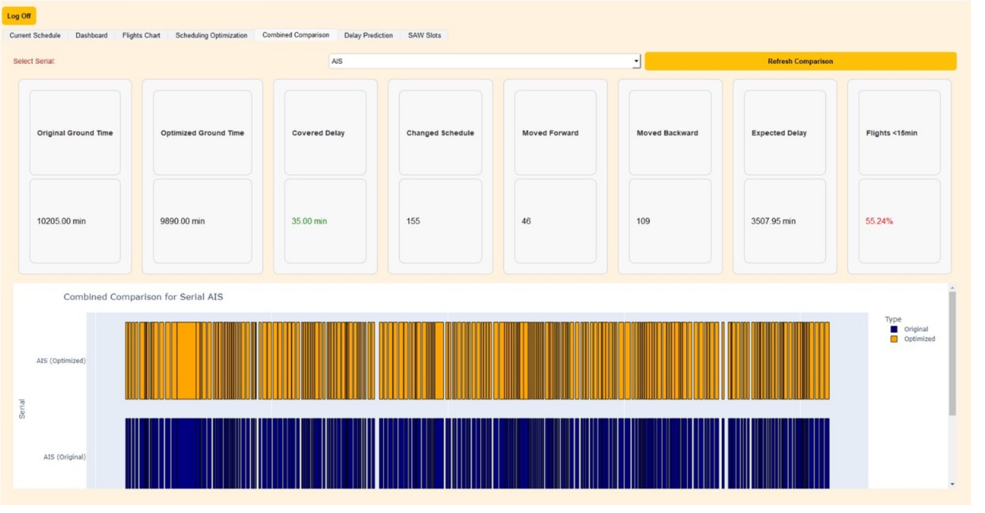


Figure 5.4: Combined Comparison Panel of the User Interface

adjustments. It begins with a rapid upload and cleansing process, preparing a month of flight history in seconds. A live dashboard then displays key metrics—flight number, average delay, and on-time performance—on color-coded cards to highlight issues. An interactive timeline visualization enables the user to recap flight operations and turnaround times for specific aircraft, mark peak periods, and identify inefficiencies. In the optimization panel, users can modify parameters such as delay probabilities, time flexibility, and budget constraints to simulate best-case and worst-case operational scenarios. The Scheduling Optimization Panel of the User Interface is shown in Figure 5.3.

This enables planners to test different planning assumptions and generate schedules that remain effective under varying levels of uncertainty. The results are compared with the initial schedule, as well as the performance gain, which are shown in the Combined Comparison Panel of the User Interface, shown in Figure 5.4.

Add-on features consist of a delay forecasting option for rapid what-if analyses, and a slot observation heatmap for Sabiha Gökçen Airport in order to ease ground congestion. In general, the interface is utilized for data-driven, effective scheduling with minimum effort.

5.6 Implementation and Pilot Study

As part of the pilot study, the functionality and accuracy of the new scheduling model were tested. In particular, its real-life performance was observed and compared with past data. These comparisons are seen as a critical step in evaluating the accuracy and effectiveness of the scheduling and allow the results to be analyzed from a more objective perspective. In the meeting held with the industrial advisor on February 14, 2025, it was noted that Pegasus possesses alternative tools to support the implementation process. The industrial advisor performed this comparison and observed the feasibility of the scheduling. This provided an essential opportunity to assess the model's compatibility with Pegasus' current operations and identify areas for improvement. As part of forward planning, the senior project team visited the Istanbul office on February 19, 2025. During this visit, detailed discussions were held regarding the pilot study's scope, data characteristics, comparison metrics, and analysis methods. Using operational parameter settings initially determined by Pegasus Airlines based on industrial advisor feedback, the pilot study validated the model's practical applicability. Additionally, Pegasus Airlines independently adjusted parameters and tested the system on datasets beyond September 2024, consistently achieving improved scheduling outcomes through the developed interface and optimization model. The timeline for future meetings and implementation strategies was also finalized during this visit.

5.7 Benchmarking and Benefits

The benchmarking process evaluates the proposed model's performance against Pegasus Airlines' current system under different operational scenarios. It aims to quantify benefits, identify shortcomings, and provide an optimized, implementable schedule. Key performance metrics (KPIs) used for comparison include total delay time, operational costs, on-time performance (OTP), and total ground time. Benchmarking ensures reliability by considering flight characteristics such as time, seasonality, and location. Benchmark data were collected from Pegasus Airlines to establish a reference point. The model's performance was tested under varying conditions, including different weather scenarios and seasonal fluctuations. Improvements in delay reduction, flight regularity, and cost optimization were quantitatively measured. Finally, benchmarking results were compiled into a detailed report outlining the model's benefits and its potential value for Pegasus Airlines. By optimizing buffer times and addressing chronic causes of delay, the model aims to reduce propagated delays, reduce costs, and enhance customer satisfaction. The system also reduced reliance on external scheduling software, cutting costs and increasing accessibility within the Network Planning Department. Unlike existing tools, which minimize buffer times and fail to adapt to historical data, our model strategically optimizes slack to enhance schedule flexibility and resilience. The model ensures a more robust and passenger-friendly scheduling approach by improving operational efficiency and reducing passenger misconnections. Benchmarking with September 2024 operational data demonstrated that, using the ±15-minute flexibility bounds defined through industrial advisor feedback, the schedule produced by our model achieved improvements of up to 9.06% in departure delay performance compared to the existing system. It should be noted that this improvement is expected if the delay distributions observed in September 2024 materialize similarly in future operations. This validated the model's ability to enhance operational robustness while aligning with Pegasus Airlines' planning practices.

5.8 Conclusions and Recommendations

This project aimed to improve Pegasus Airlines' flight scheduling by reducing delay propagation through a scenario-based optimization model. Historical data and delay possibilities are utilized to develop a robust scheduling system, enhancing on-time performance while staying compatible with current planning operations. The interface of the solution being used is very user-friendly and allows planners to visualize flight data, change parameters, and easily generate optimized schedules. The model enhances flexibility by reallocating slack time and minimizing delay propagation. It was developed and validated using parameters defined by Pegasus Airlines, achieving up to a 9.06% improvement in departure delay performance. The system is now ready for seamless integration into Pegasus Airlines' scheduling operations.

Acknowledgment

This project was supported by TÜBİTAK BİDEB 2209/B Program under Grant 1139B412401230.

Bibliography

Barnhart, C. and A. Cohn (2004). Airline Schedule Planning: Accomplishments and Opportunities. *Manufacturing & Service Operations Management 6*(1), 3–22.

Pegasus Airlines (2024). Pegasus Airlines. Flypgs.Com. Accessed November 6, 2024 from https://www.flypgs.com/pegasus-hakkinda/genel-bakis.

Appendix: Mathematical Model

Table 5.1: Model Sets & Parameters

Notation	Description
F	Set of flights
A	Set of aircraft connections: $A = \{(i,j) \vert i,j \in F\}$
S	Set of scenarios
T	Set of SAW slots
D	Set of days
$saw\_flights \subseteq F$	Subset of flights departing from SAW
l_{xi}, u_{xi}	Lower and upper bounds of x_i (shift amount of departure time) for a flight $i \in F$
l_{yi}, u_{yi}	Lower and upper bounds of y_i (shift amount of arrival time) for a flight $i \in F$
l_i, u_i	Lower and upper bounds of total shift amount of block time of a flight $i \in F$
Dep_Port_i	Departure airport of flight $i \in F$
Arr_Port_i	Arrival airport of flight $i \in F$
STD_i	Scheduled time of departure of flight $i \in F$
$day_i \in D$	Day of flight $i \in F$
IAD_{is}	Initial independent arrival delay of flight $i \in F$ in scenario $s \in S$
$aSlack_{ij}$	Initial ground slack for connection $(i,j) \in A$
$cost_{ij}$	Cost associated with changing ground slack for $(i,j) \in A$
budget	Total budget for schedule adjustments
p_s	Probability of scenario $s \in S$
$slot\_cap_{td}$	Maximum number of flights that can depart in slot $t \in T$ on day $d \in D$
δ	Time granularity for schedule adjustments, in minutes (set to 5 based on operational scheduling practice)

Decision Variables

$x_i \in \mathbb{Z}$,	Departure shift of flight $i \in F$ in 5-minute increments
$y_i \in \mathbb{Z}$,	Arrival shift of flight $i \in F$ in 5-minute increments
$aSlack'_{ij} \geq 0$,	Updated ground slack for $(i,j) \in A$
$pd_{ijs} \geq 0$,	Propagated delay from flight $i \in F$ to flight $j \in F$ in scenario $s \in S$
$tad_{is} \geq 0$,	Total arrival delay for flight $i \in F$

in scenario $s \in S$

$z_{itd} \in \{0,1\}$, 1 if flight $i \in F$ is assigned to slot $t \in T$ on day $d \in D$

Objective Function

$$\min \sum_{s \in S} p_s \sum_{i \in F} tad_{is} \tag{5.1}$$

Constraints

$$aSlack'_{ij} = aSlack_{ij} - \delta y_i + \delta x_j, \quad \forall (i,j) \in A \tag{5.2}$$

$$pd_{ijs} \geq tad_{is} - aSlack'_{ij}, \quad \forall (i,j) \in A, \quad \forall s \in S \tag{5.3}$$

$$tad_{is} \geq IAD_{is} + \delta x_i - \delta y_i, \quad \forall i \in F, \quad \forall s \in S \tag{5.4}$$

$$tad_{js} \geq pd_{ijs} + IAD_{js} + \delta x_j - \delta y_j, \quad \forall (i,j) \in A, \quad \forall s \in S \tag{5.5}$$

$$\delta(y_i - x_i) \geq l_i, \quad \forall i \in F \tag{5.6}$$

$$\delta(y_i - x_i) \leq u_i, \quad \forall i \in F \tag{5.7}$$

$$y_i = x_i, \quad \forall i \in F \tag{5.8}$$

$$\sum_{(i,j) \in A} cost_{ij}(aSlack'_{ij} - aSlack_{ij}) \leq \text{budget} \tag{5.9}$$

$$\sum_{t \in T} z_{itd} = 1, \quad \forall i \in saw\_flight \quad \forall d \in D \tag{5.10}$$

$$\sum_{i \in saw\_flights} z_{itd} \leq slot\_cap_{td}, \quad \forall d \in D, \quad \forall t \in T \tag{5.11}$$

$$STD_i + \delta x_i \in [t, t+10], \quad \forall i \in saw\_flights \, \forall t \in T \, \forall d \in D \tag{5.12}$$

- Objective (5.1) is to minimize the expected total arrival delay.
- Constraint (5.2) updates the slack between two flights when their departure and arrival times are changed.
- Constraint (5.3) equates the excess total arrival delay of a flight to the successor flight as propagated delay.
- Constraint (5.4) equates the excess independent arrival delay of a flight to the successor flight as total arrival delay.
- Constraint (5.5) equates the sum of propagated delay from the previous flight and excess independent arrival delay, to total arrival delay.

- Constraints (5.6) & (5.7) are the bounds for the δ-minute time shifts.
- Constraint (5.8) ensures that the total time shift for departure and arrival are equal to each other, in order to keep the block time constant.
- Constraint (5.9) is the budget constraint for the adjustments.
- Constraint (5.10) ensures that every flight departing from SAW airport must occupy one slot.
- Constraint (5.11) ensures that the slot capacity is not exceeded.
- Constraint (5.12) is the matching of slot assignment and departure time.

Hızlı Servis Restoranlarında Bozulabilir Envanter Yönetimi | 6

Ata Teknoloji Platformları

Proje Ekibi
Elif Serra Baştopçu, Emirhan Candan, Fatih Selim Erdem,
Buket Satır, Ayşe Selin Türker, Utku Yamaç, Çağdaş Yenilmez

Şirket Danışmanları
Ahmet Tuğrul Bayrak, Veri Bilimi Müdürü
Bekir Berker Türker, Kıdemli Veri Bilimi Uzmanı

Akademik Danışman
Doç. Dr. Emre Nadar
Endüstri Mühendisliği Bölümü

Özet

Bu proje, kısa raf ömrü, değişken talep ve operasyonel karmaşıklığın neden olduğu israf ve stok yetersizliklerini azaltmak amacıyla, hızlı servis restoranlarında bozulabilir ürünlerin envanter yönetimini geliştirmeyi hedeflemektedir. Ele alınan sistem, depo sevkiyatları ve mutfak hazırlıklarını kapsayan iki aşamalı yapısıyla, bozulabilirlik kısıtları ve acil sipariş imkânı gibi özellikleriyle standart envanter problemlerinden ayrılmaktadır. Stokastik optimizasyon modelinin hesaplama zorlukları nedeniyle, iki aşamalı baz stok politikası ile tek endeksli politikanın birleştiği sezgisel bir çözüm önerilmiştir. Bu yaklaşım, belirsiz talebi modelleyen gelişmiş tahminleme teknikleriyle desteklenen simülasyon-optimizasyon yöntemiyle uygulanmıştır. Önerilen çözüm, fazla siparişleri ve stok seviyelerini azalttı. Mutfakta oluşan et israfının %23,25 oranında düşmesi sonucunda günlük et kullanım maliyetlerinde %8,39 azalma sağlandı.

Anahtar Sözcükler: Envanter yönetimi, bozulabilirlik, çok aşamalı sistemler, simülasyon optimizasyonu, acil sevkiyat.

Perishable Inventory Management in Fast Food Restaurants

Abstract

This project aims to improve inventory management for perishable items in fast-food restaurants, where short shelf lives, random demand fluctuations, and operational complexity contribute to waste and stockouts. Unlike standard inventory problems, this project involves a two-echelon structure—storage deliveries and kitchen preparations—along with perishability constraints and the option of emergency orders. Due to the computational complexity of solving the stochastic optimization model, a heuristic approach was proposed, combining a two-echelon base-stock policy for inventory control with a single-index policy to manage emergency orders. A simulation-optimization model was used to optimize the heuristic's parameters, supported by advanced forecasting techniques to model uncertain demand. The proposed solution reduced unnecessary orders and excess inventory. As a result of a 23.25% reduction in kitchen-generated meat waste, daily meat usage costs decreased by 8.39%.

Keywords: Inventory management, perishability, multi-echelon systems, simulation-optimization, emergency order.

6.1 Company Description

Founded in 1997 as a subsidiary of Ata Holding, Ata Teknoloji Platformları (ATP) delivers IT solutions across Turkey, China, and Europe, serving over 700 clients at 3,200+ global locations—mainly in the quick-service restaurant sector. In 2021, ATP invested in a Burger King branch at Galataport, Istanbul, to observe customer behavior and test its technologies in a real-world setting. With over 30,000 monthly visitors, the pilot site plays a key role in validating and refining ATP's digital solutions through direct operational insights. (ATP, 2024).

6.2 System Analysis and Problem Definition

6.2.1 System Analysis

The system follows a two-echelon structure. The first echelon is the storage area, receiving raw materials via regular and emergency shipments. Regular orders follow a fixed schedule with set order and delivery days, while emergency orders are placed as needed, arriving in one day at a 25% higher unit cost. Shipment costs are proportional ordering costs, with no fixed ordering fee. All raw materials come from a single supplier. Limited storage capacity restricts order volume, making accurate forecasting crucial to minimize emergency shipments.

Based on forecasted demand, raw materials are moved from storage to the second echelon, the kitchen, where they are prepared and assembled into final products. The restaurant uses two assembly strategies depending on the product and demand: stock-based assembly, where preparation and assembly are done in advance based on forecasts, and order-based assembly, where raw materials are prepared in advance but assembled after the order is received.

Perishability is a major constraint. Raw materials in storage are discarded if unused by their expiration dates. Once transferred to the kitchen, items like meat are cooked and held for a limited, type-specific time. If not assembled into final products within this period, they are discarded per disposal rules. A First-In, First-Out (FIFO) policy is used in both storage and the kitchen to reduce spoilage. Meat and bread demonstrate the highest waste rates, making them key targets for optimization.

Inventory is counted manually at the end of each day, with no real-time tracking during operations. This limits responsiveness and underscores the importance of proactive planning. The lack of real-time visibility limits the early detection of stockouts or overstocking, increasing the risk of waste or emergency orders.

The current forecasting system estimates future revenue using a method similar to a similar moving average—e.g., Monday's forecast is based on the average revenue of the last four Mondays. These revenue projections are converted into raw material needs using predefined ratios. Though practical, this approach overlooks short-term fluctuations and broader time-series patterns like trends and seasonality, limiting its ability to adapt to dynamic demand.

6.2.2 Problem Definition

The current system faces major inventory management challenges due to forecasting inaccuracies, manual processes, and the perishability of key products. The current forecasting method, based on simple historical averages, often overestimates demand and misses key time-series patterns like trends and seasonality, leading to excess inventory and waste. Inventory decisions are manual, with no standardized reordering policies or real-time tracking across the two echelons, limiting responsiveness and efficiency. Perishability adds complexity, especially for meat products, which are frequently discarded if not assembled into final products shortly after cooking. ABC and waste-based analyses show that meat products contribute most to both sales (51.86%) and waste (47.41%), making it the project's focus.

6.3 Proposed Solution Approach

6.3.1 Critical Assumptions

The model operates daily using a rolling-horizon approach with a two-week planning horizon. Each day spans 12 hours, divided into 24 consecutive 30-minute time buckets. Frozen items are assumed to have long shelf lives and do not expire in storage, while freshly prepared meat must be assembled into final products within 60 minutes after cooking or is discarded as waste. All shipments are assumed to arrive on time with standard quality, and items in the same shipment and product group share identical expiration dates. A consistent FIFO policy is applied in both the storage and the kitchen to minimize spoilage. Preparation times are negligible and independent of workforce availability, which is beyond the model's scope. Once raw materials are transferred from storage to the kitchen, they cannot be returned.

6.3.2 Major Constraints

The restaurant operates 12 hours a day. Regular replenishment orders for meat products are scheduled twice weekly, on Tuesdays and Fridays. Tuesday orders have a two-day lead time, while Friday orders have a four-day lead time (e.g., a Tuesday order is available on Thursday). Additionally, emergency orders can be placed any day and arrive with a one-day lead time. At the end of each day, products that exceed their expiration dates, or meat not assembled into final products within 60 minutes after cooking, are discarded as waste.

6.3.3 Objectives

The primary objective is to improve the inventory management system by enhancing accuracy, responsiveness, and alignment with operational needs. This includes improving forecast accuracy and minimizing inventory costs, which comprise lost sales, replenishment, and waste. The approach reduces costs and boosts customer satisfaction by ensuring sufficient product availability.

6.3.4 Conceptual Model

To address challenges from demand uncertainty, perishability, and the two-echelon inventory structure, a sequential decision-making model is developed. The model uses a policy function to determine order quantities, trigger emergency replenishments, and guide kitchen decisions based on the system's current state, which includes the minimal necessary historical data.

As shown in Figure 6.1, the mathematical model builds on data-driven product aggregation, grouping the most demanded meat types into a single product to reduce variability and improve forecast accuracy. This aggregation approach lowers the mean absolute percentage error (MAPE) by 32.35% compared to individual forecasts.

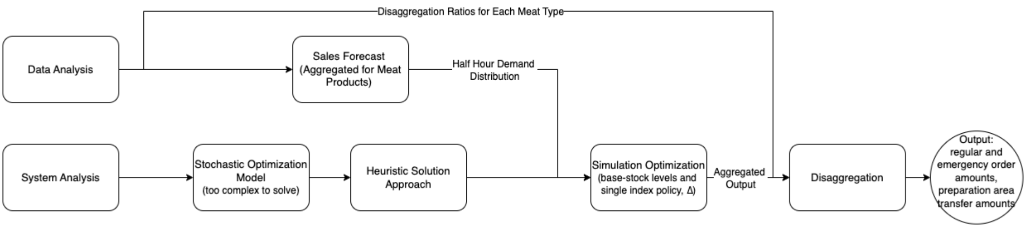


Figure 6.1: Conceptual Model

Given the computational complexity of the stochastic optimization model, a heuristic solution is used, combining a two-echelon base-stock policy for regular orders and a single-index policy for emergency replenishments. These policies are optimized through a simulation-optimization framework. Finally, a disaggregation method translates aggregated outputs into detailed product decisions by leveraging historical sales ratios.

6.3.5 Mathematical Model

The mathematical model aims to minimize expected total inventory cost by distinguishing between regular and emergency replenishments, as shown in objectives (6.1) and (6.2); see the appendix. Inventory dynamics are modeled for both storage and kitchen areas. Constraints (6.3)–(6.6) maintain interday and intraday balance in storage, while constraints (6.7)–(6.9) manage kitchen area inventory, incorporating perishability and disposal. Capacity limits are enforced via constraints (6.10) and (6.11), lost sales are tracked by constraint (6.12), and constraint (6.13) ensures non-negativity. The model captures the complexities of a two-echelon perishable inventory system under demand uncertainty and varying lead times.

The stochastic optimization model is computationally intensive due to several interacting factors. Inventory pipeline dynamics expand the state space, and nonlinear waste constraints further complicate decision-making. The model also operates on different time scales—daily in storage and half-hourly in the kitchen—creating interdependencies. Additionally, the large number of time periods increases dimensionality. These factors make exact optimization impractical, necessitating heuristic or simulation-based methods.

6.3.6 Solution Method

Heuristic Solution Approach

To manage the stochastic optimization model's complexity, we propose a two-echelon single-index policy with state-independent base-stock levels (TESIP). Each echelon operates with base-stock levels, (de Kok et al., 2018). For echelon 1, we define two base-stock levels, because there are two regular orders each week. One applies on Tuesday (denoted by S_{1T}), based on the inventory position on Tuesday, and the other on Friday (denoted by S_{1F}), based on the inventory position on Friday. For echelon 2, there is more than one base-stock level (denoted by S_{2i}) to handle varying demand conditions, such as rush hours or weekends. After setting these base stock levels, single-index policy parameter Δ governs expedited orders. If the realized sales in a day exceed Δ, then $\max(\text{realized sales} - \Delta, 0)$ units of raw material are ordered on an expedited basis, (Scheller-Wolf et al., 2007). This design balances responsiveness to demand fluctuations with a manageable decision structure.

Simulation-Optimization

The simulation optimization model addresses inventory decisions under uncertainty by integrating forecast outputs, demand distributions, and policy evaluation. Daily forecasts are generated using various models, including classical time series and machine learning techniques. The method with the lowest MAPE is selected, and its forecasts are used for further analysis. These daily forecasts are then disaggregated into half-hour intervals using historical sales patterns and refined through Kernel Density Estimation (KDE) to capture intraday and interday fluctuations.

To define base-stock levels for both storage (echelon 1) and kitchen (echelon 2), 1000 demand samples are generated per half-hour period. Quartile-based bounds set the search range for TESIP policy parameters. Five candidate values per decision variable form the grid for policy tuning, with the number of scenarios shown in Figure 6.2. Four TESIP configurations are tested, each with two base-stock variables for echelon 1 (Tuesday and Friday orders) and one emergency threshold Δ. Configurations vary by the number of base-stock variables for echelon 2, dividing the 12-hour day into 1 to 4 intervals, each with a distinct base-stock level. K-Means clustering groups half-hour periods based on sales patterns, replacing manual grouping and enabling data-driven alignment of echelon 2 base-stock levels with demand trends.

Simulation over a 14-day horizon with 1000 replications shows that increasing decision variables improves performance but increases computation

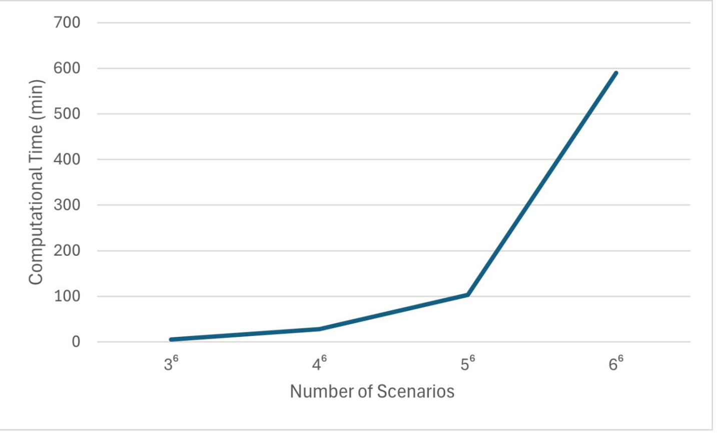


Figure 6.2: Computational Time vs. Number of Grid Search Values per Decision Variable

time. Figure 6.3 compares cost and computation time across configurations. Based on this analysis, the 7-variable configuration—consisting of two base-stock levels for echelon 1, four for echelon 2, and one Δ parameter—is selected for its balance between accuracy and computational efficiency.

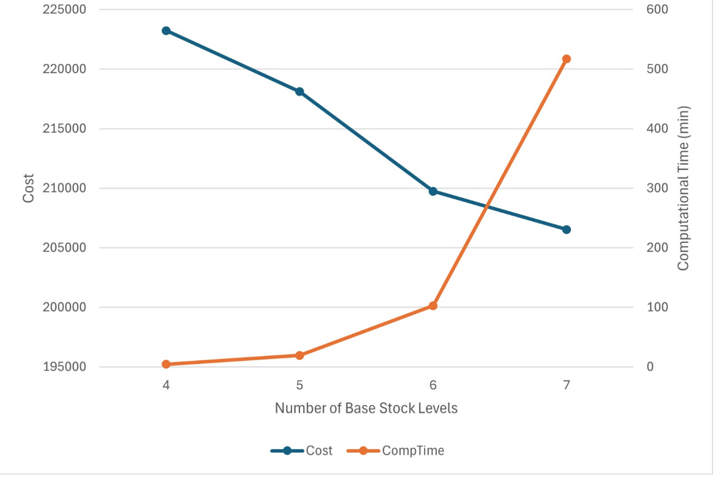


Figure 6.3: Cost vs. Computational Time for Different Numbers of Base-Stock Levels

The objective of the simulation-optimization model is to minimize total cost, including regular order, emergency order, and lost sales. The model captures key operational constraints: regular orders are placed at the start of designated order days, while emergency orders are placed at day-end—except on days regular shipment scheduled. In the kitchen, inventory is replenished each period and discarded if unsold within one hour, with all remaining inventory disposed of at the end of each day.

The model outputs aggregated decisions: for echelon 1, meat order quantities via regular and emergency channels; for echelon 2, meat preparation amounts per half-hour. Overall, the model incorporates perishability, capacity constraints, and lost sales, serving as a flexible, robust decision-support tool for dynamic inventory planning.

Disaggregation

The disaggregation process involves breaking down aggregated sales data into product-level quantities for two decisions. Using the sales data from the past three months, product sales proportions are calculated. For kitchen decisions, product sales proportions for each half-hour interval are applied to the aggregated simulation outputs to determine time-specific product quantities. For storage decisions, only overall product proportions from the last three months are used to allocate regular and emergency orders.

6.4 Validation

The simulation-optimization model and forecasting methods were tested on company servers for reliability and applicability. Simulations used the expected average inventory as the initial condition. The simulation optimization procedure took three hours, while forecasts were obtained in 30 minutes. The simulation computed product quantities over a 14-day period, which were then disaggregated into specific product types. This resulted in obtaining regular order quantities, expected emergency orders, and product volumes for the entire period.

Validation of the storage area used data from June 17–30, 2024, during which the selected forecasting model achieved an MAPE of 8.5%. Results showed that the decision support system maintained the expected sawtooth inventory pattern, balancing consumption with scheduled replenishments (Tuesdays and Fridays). Optimized base-stock levels prevented stockouts while keeping inventory levels low.

The kitchen area was validated separately using sales data from February 10–23, 2025. The selected forecasting model for this period had a MAPE of 22%. The simulation validated the system's ability to manage short shelf-life items, effectively enforcing perishability constraints and disposal rules.

6.5 Benchmarking and Benefits

To evaluate the effectiveness of the proposed solution approach, a benchmarking analysis was conducted on forecasting accuracy, inventory performance, waste reduction, and managerial workload.

For forecasting, the simple moving average model currently in use resulted in a MAPE of 32%, whereas the selected forecasting model achieved a lower MAPE of 22% during the 14-day benchmark period (February 10–23, 2024). The same period was used for validation of the kitchen area.

For the storage area representing echelon 1, the proposed decision support system enabled a reduction of up to 70.33% in excess inventory without causing stockouts during the tested period. The extent of this reduction depends on the buffer allocated to each item—higher buffer levels reduce the risk of lost sales but also limit the potential for inventory minimization. This outcome was primarily driven by the correction of systemic over-ordering, which resulted from extended ordering cycles and high forecast errors due to disaggregated product-level demand estimations. In addition, the optimization of safety stock levels based on actual replenishment lead times, the reduction of kitchen waste, and the implementation of a structured inventory policy contributed significantly. Managers' tendency to avoid emergency orders—due to performance evaluation concerns—further emphasized the value of a proactive replenishment strategy.

For the kitchen area representing echelon 2, the proposed decision support system reduced waste costs by 32.71% compared to the current system during the 14-day benchmark period. Because managerial initiatives are taken during operations to respond to deviations between actual demand and forecasts, a direct comparison based on waste ratios was not feasible; therefore, the overall results of the two systems were compared directly.

In addition to reducing waste and excess inventory, the benchmark also evaluated the time and effort required by branch managers. The proposed decision support system reduced the daily workload from one hour to just 8-10 minutes by automating calculations and eliminating the need for manual processing across multiple reports.

The structure of the proposed decision support system allows for seamless implementation across 800 Burger King branches in Turkey. By simply updating sales data, inventory levels, storage capacities, and shipment constraints, the system can be adapted to different locations with minimal adjustments.

6.6 Implementation and Pilot Study

The main code for the decision support system runs automatically each night over approximately three hours on a dedicated server. Two options are available for using the system: users can either work directly with the Excel outputs or access the user interface to adjust parameters. The main components of the interface are the echelon 1 page, displayed in a calendar view, and the echelon 2 decisions page, presented in a tabular format; see Figure 6.4. Sales and inventory data are updated automatically everyday. Users only need to import a file for new shipment orders into the system;

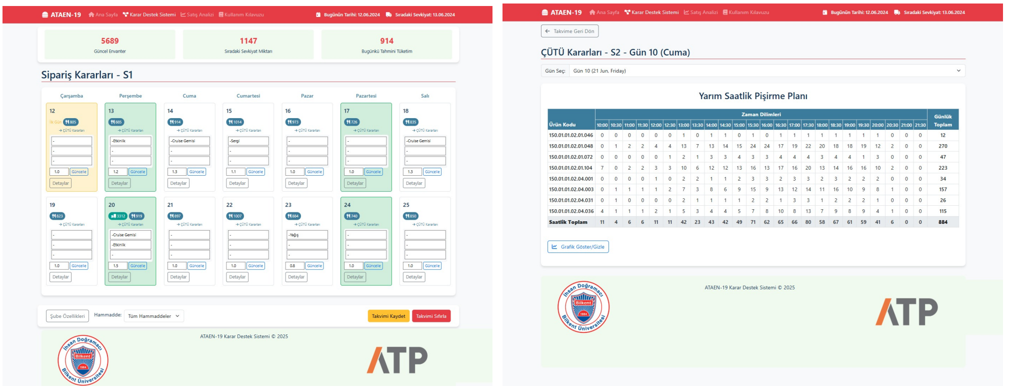


Figure 6.4: User Interface: Echelons 1 (left) and 2 Order Planning

no other inputs are required. The system generates decisions based on simulations with 1,000 replications, but results from 100 replications are also stored as a precaution, as the difference in confidence intervals between 1,000 and 100 replications is not significant.

The pilot study plan was divided into two phases. The first phase, held on April 9–10, 2025, focused on analyzing initiative-based decisions, evaluating reporting outputs, counting waste, and gathering feedback to improve the UI and simulation modules. The second phase was conducted on April 24, 2025, to test the implementation of the refined system. The project team reviewed the TESIP decisions and waste quantities collaboratively with managers and shift supervisors for each period. These decisions were adjusted to align the system outputs with operational practices. As a result, a 23.25% reduction in meat waste costs and an 8.39% reduction in daily meat usage costs were achieved, validating the system's effectiveness in real-world operations.

6.7 Conclusion

The project met expectations at Galataport BK and showed potential for other branches by improving forecasts, reducing waste and workload. A decision support system based on forecasting techniques and simulation-optimization reduced kitchen-generated meat waste costs by 23.25%, excess storage inventory by 70.33%, daily meat costs by 8.39%, eliminated stockouts, and lowered managerial daily workload from one hour to 8–10 minutes.

The system is easily adaptable across branches with minimal customization. Future work could focus on integrating real-time inventory tracking, expanding the system to non-meat products, and developing adaptive forecasting models that incorporate external factors such as tourism trends or local events, further enhancing operational efficiency.

Bibliography

ATP (2024, September). Atp first half & 2nd quarter 2024 results presentation. Accessed: 30 March 2025.

de Kok, T., C. Grob, M. Laumanns, S. Minner, J. Rambau, and K. Schade (2018). A typology and literature review on stochastic multi-echelon inventory models. *European Journal of Operational Research 269*(3), 955–983.

Scheller-Wolf, A., S. Veeraraghavan, and G.-J. van Houtum (2007). Effective dual sourcing with a single index policy. *Manufacturing & Service Operations Management 9*(2), 144–162.

Appendix: Mathematical Model

Sets:

Symbol	Explanation
T	Set for time periods, $T = \{1, 2, \dots, 24\}$
K	Set for echelons, $K = \{1, 2\}$, where 1 and 2 indicates storage and preparation, respectively
DD	Set for days, $DD = \{1, \dots, 14\}$
SD	Set for delivery days, $SD = \{1, 4, 8, 11\}$
Π	Set of admissible policies
π	Any admissible control policy, $\pi \in \Pi$

Decision Variables:

Symbol	Explanation
$O^{\pi}_{d-LT_d}$	The quantity of a regular order placed on day $(d - LT_d)$ that arrives on day d, $d \in SD$
$Q^{\pi}_{t,d}$	Quantity transferred to the preparation area in time t on day d, $t \in T, d \in DD$
$I^{\pi}_{k,t,d}$	Inventory level in the echelon k at time t on day d, $k \in K, t \in T, d \in DD$
E^{π}_{d-1}	The quantity of an emergency order placed on day $(d-1)$ that arrives on day d, $d \in DD \setminus SD$
$L^{\pi}_{t,d}$	Lost sales quantity due to unfulfilled demand in time t of day d, $d \in \mathrm{DD}$, $t \in \mathrm{T}$

Parameters:

Symbol	Explanation
$D_{t,d}$	Random variable for demand at time t on day d, $t \in T, d \in DD$
CB	Regular ordering cost for each raw material
CE	Emergency order cost for each raw material
CL	Cost of lost sales for each raw material
SS	Maximum storage capacity
II	Initial inventory for raw material in storage area
A	Maximum shipment capacity
LT_d	Lead time for day d, $d \in SD$

Objective Function:

$$z^{\pi} = \mathbb{E}[\sum_{t \in T} \sum_{d \in DD} \left(CE \cdot E^{\pi}_{d-1} + CL \cdot L^{\pi}_{t,d} + CB \cdot O^{\pi}_{t,d-LT_d} \right)] \tag{6.1}$$

$$Z^* = \min_{\pi} z^{\pi} \tag{6.2}$$

Policy Function:

The policy $\pi(S_{k,d,t})$ determines actions based on the current state $S_{k,d,t}$, including inventory levels $(I_{k,d,t})$, regular orders given in the last LT_d days (O_{d-LT_d}) and expedited orders given a day before (E_{d-1}).

Constraints:

Each decision given by the policy π must satisfy the following constraints:

Inventory Balance in Storage Area:

$$I^{\pi}_{1,1,d} = I^{\pi}_{1,t_{max},d-1} + E^{\pi}_{d-1} - Q^{\pi}_{1,d}, \forall d \in DD \setminus SD \tag{6.3}$$

$$I^{\pi}_{1,24,0} = II \tag{6.4}$$

$$I^{\pi}_{1,t,d} = I^{\pi}_{1,t-1,d} - Q^{\pi}_{t,d}, \forall t \in T \setminus \{1\}, \forall d \in DD \tag{6.5}$$

$$I^{\pi}_{1,1,d} = I^{\pi}_{1,i,t_{max},d-1} + O^{\pi}_{d-LT_d} - Q^{\pi}_{1,d}, \forall d \in SD \tag{6.6}$$

Inventory Balance in Preparation Area:

$$I^{\pi}_{2,t,d} = \max(Q^{\pi}_{t,d} - \max(D^{\pi}_{t,d} - I^{\pi}_{2,t-1,d}, 0), 0), \forall t \in T,\ \forall d \in DD \tag{6.7}$$

$$I^{\pi}_{2,0,d} = 0, \forall d \in DD \tag{6.8}$$

$$I^{\pi}_{2,i,t_{\max},d} = 0, \forall d \in DD \tag{6.9}$$

Capacity Constraints:

$$I^{\pi}_{1,t} \leq SS, \qquad \forall t \in T, \forall d \in DD \tag{6.10}$$

$$O^{\pi}_{d-LT_d} \leq A, \qquad \forall t \in T, \forall d \in SD \tag{6.11}$$

Lost Sales Constraint:

$$L^{\pi}_{t,d} \geq D^{\pi}_{t,d} - (I^{\pi}_{2,t-1,d} + Q^{\pi}_{t,d}), \forall t \in T \setminus \{1\},\ \forall d \in DD \tag{6.12}$$

Non-negativity and Integer Constraints:

$$Q^{\pi}_{t,d}, O^{\pi}_{d}, I^{\pi}_{k,t,d}, E^{\pi}_{d}, L^{\pi}_{t,d} \in \mathbb{R}_{+} \cup \{0\}, \qquad \forall t \in T, \forall d \in DD, \forall k \in K \tag{6.13}$$

7 İlaç Üretiminde Toplam Değiştirme Süresi Azaltımı ile Çizelgeleme Optimizasyonu

SCW.AI

Proje Ekibi
Bürge Çevik, İpek Mocul, Rana Mutlum, Eda Tatar,
Önder Kutay Toker, Ulaş Uludağ, Eren Fehmi Yaygel

Şirket Danışmanı
Haluk Atlı
Ar-Ge ve İleri Analitik Direktörü

Akademik Danışman
Mis. Dr. Öğr. Üyesi Andrea Pizzuti
Endüstri Mühendisliği Bölümü

Özet

Bu proje, ilaç üretim sektöründe faaliyet gösteren SCW.AI firmasının dijital sistemine entegre edilmek üzere, sıra bağımlı ve paralel hatlarda üretim planlaması problemini ele almaktadır. SCW.AI, ilaç üreticilerine yönelik üretim sahası dijitalleştirme çözümleri geliştiren bir teknoloji ve danışmanlık şirketidir. Projenin temel amacı, üretim hattında iş emirlerinin yerleşimini planlayarak toplam değiştirme süresini en aza indirmektir. Bu ana hedefin yanında, geciken iş emri sayısının ve toplam gecikme süresinin azaltılması da projenin hedeflerindendir. Problem, bu yapıya uygun geliştirilen sezgisel bir algoritma ile çözülmüştür. Elde edilen çözüm sonuçları, SCW.AI müşterilerinin üretim sahalarında kullanılmak üzere firmanın dijital sistemine entegre edilmiştir.

Anahtar Sözcükler: Çizelgeleme, İlaç üretimi, Paralel hat dengelemesi, Değiştirme süresi azaltımı.

Minimizing Total Changeover Time in Pharmaceutical Manufacturing Scheduling

Abstract

This project addresses the sequence-dependent parallel line scheduling problem to be integrated into the digital solutions of SCW.AI, a company operating in thepharmaceutical manufacturing industry. SCW.AI is a technology and consultancy firm that develops shop floor digitalization solutions for pharmaceutical producers. The primary objective of the project is to minimize the totalchangeover time by assigningwork orders toproduction lines. In addition to this main goal, the project also aims to reduce the number of delayed work orders and the totaltardiness. The problem is solved using aheuristic algorithm specifically developed for this structure. The resulting solution is integrated into SCW.AI's digital system to be used in the production environments of its clients.

Keywords: Scheduling, Pharmaceutical manufacturing, Parallel line balancing, Changeover time minimization.

7.1 Company Information

Supply Chain Wizard is a management and technology consulting firm founded by Evren Ozkaya in 2014, specializing in end-to-end supply chain solutions for the pharmaceutical industry. The company serves major pharmaceutical manufacturers and contractors across North America, Europe, the Middle East, and Asia. In 2017, it launched the "Digital Factory" platform, which integrates IoT devices to optimize production processes. In 2022, Supply Chain Wizard AI (SCW.AI) was established, offering a SaaS version of the platform with expanded capabilities, helping manufacturers achieve cost savings and quality improvements. SCW.AI has been recognized on the Inc. 5000 list for its rapid growth and currently serves over 4,000 users worldwide, with 80% of its products being pharmaceuticals (SCW.AI, 2024).

7.2 Current System

The Scheduler Tool helps optimize job shop and labor scheduling by creating just-in-time schedules aligned with work order due dates and shelf-lives. It supports efficient labor allocation, real-time tracking of OTIF (on-time and in full), maintenance, and schedule compliance, aiming to reduce costs by over 20% and improve capacity utilization by up to 50%. It also analyzes scheduling discrepancies to boost efficiency and customer satisfaction.

The tool incorporates several objective functions that help users optimize their production schedules based on their specific needs. These include minimizing costs, maximizing service, reducing excess inventory, and maximizing OTIF delivery when all work orders cannot be met on specified dates. Custom objectives are also available for specific company requirements. However, the tool does not have an objective function dedicated to minimizing changeover time.

7.3 Problem Definition

The current Scheduler Tool used by the company supports optimization based on several objectives. However, it lacks a strategy to minimize changeover time, which is a critical factor in pharmaceutical production due to strict regulations and the complex process of switching between different products. Changeover time, which includes both setup and cleanup processes, significantly impacts the ability to meet deadlines and minimize makespan. Therefore, a new approach is needed to minimize changeover time while improving the on-time completion of work orders. This approach considers the varying setup and cleanup times, which differ by product family and type, as each product has specific requirements in pharmaceutical production. The aim of this project is to develop and integrate a changeover time minimization algorithm into the existing Scheduler Tool by creating a new algorithm that also seeks to enhance the ability to meet work order due dates.

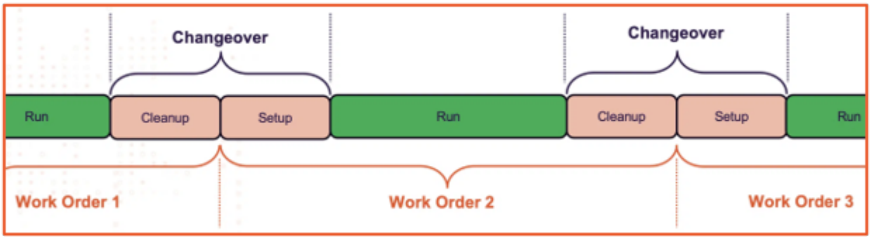


Figure 7.1: Changeover times between consecutive work orders

7.4 Proposed Solution Strategy

The SCWCO Parallel Line Balancing project addresses a scheduling problem whose objective functions may vary depending on different Key Performance Indicators (KPIs). After discussions with the company, the primary objective has been clearly defined as the minimization of total changeover time. Additionally, the approach takes into account due date satisfaction and total tardiness as secondary performance measures to ensure alignment with operational priorities and client expectations.To address this challenge, a custom-designed heuristic algorithm was developed, specifically tailored to handle the sequence-dependent nature of tasks and the structure of parallel production lines.

Following the solution development, a user-friendly interface is designed to visualize and interact with the proposed model. In the final stage, the solution is integrated into SCW.AI's digital production platform, Digital Factory, enabling SCW.AI clients to benefit from optimized production scheduling through the company's existing systems.

7.4.1 Assumptions

- Work orders cannot be divided into smaller work orders or same product's work orders cannot be merged.
- A work order begins with setup and ends with cleanup.
- A work order in the process cannot be stopped to start another work order and restarted from the point it was interrupted.
- At most one work order per time can be processed on a single line.
- If a task is not completed by the end of the shift, it will resume from where it left off when the next working period begins.
- The inventory costs arising from producing products ahead of time will be disregarded.

7.4.2 Major Constraints

- The number of production lines is predetermined.
- Not every product can be manufactured on every line, but the same product can be produced on multiple lines. The production time for each product varies depending on the line used.
- Production is family and sequence-dependent, meaning changeover times vary between products.
- The daily working hours and total working days for each production facility are predetermined.

7.5 Solution Approach

A Mixed Integer Linear Programming (MILP) model was initially developed to minimize changeover time, but due to the problem's NP-hard nature and runtime constraints, a heuristic algorithm was developed. The developed decision support system enables users to input parameters specific to their operations, such as the number of lines, daily working hours, and permissible lateness, and it delivers customized solutions accordingly.

7.5.1 Heuristic Algorithms

The developed heuristic algorithm consists of Initialization with Grouping Algorithm followed by a Multi-Phase Local Search Algorithm. Details of this heuristic approach will be explained below and a diagram showing the steps of the algorithm can be seen in Figure 7.2.

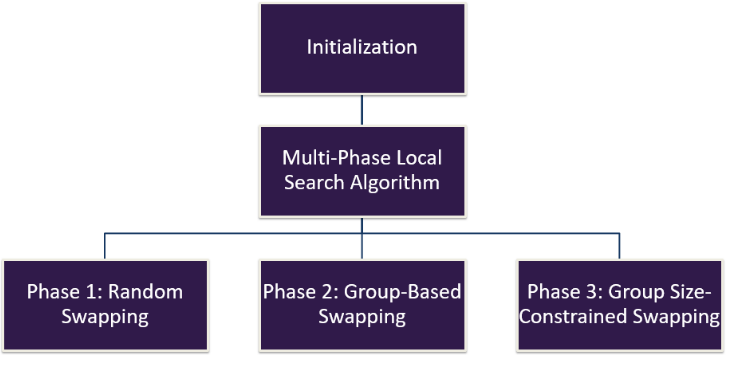


Figure 7.2: Diagram of heuristic algoritm's steps

Initialization with Grouping Algorithm

The process starts by grouping jobs according to their product types. This is because the lowest changeover time, namely minor changeover time, occurs when jobs of the same product type are scheduled consecutively. Within each group, jobs with earlier due dates are prioritized.

The product type with the earliest average due date is selected first, as it introduces tighter scheduling constraints. Since all production lines are initially empty, the algorithm assigns the work orders of the first product type to the fastest compatible line. The goal is to place as many jobs as possible of this product type on that line. If a job is scheduled to exceed the maximum allowed delay, the remaining jobs are assigned to the second-fastest compatible line. At this stage, all changeover times remain minor.

Once the first product type is fully assigned, the algorithm proceeds to the next one. It first attempts to find an idle and compatible line to avoid major changeover time, which occurs when different product types are scheduled consecutively. If no idle line is available, the algorithm consults the changeover time matrix and selects the line that minimizes the transition cost.

If all jobs are successfully assigned, the initial solution is complete. If not, the algorithm increases the allowable delay by a predefined ratio and restarts the process, effectively overcoming infeasibility issues.

Multi-Phase Local Search Algorithm

The initial solution was enhanced using an iterative job assignment heuristic, named theMulti-Phase Local Search Algorithm. This approach is inspired by the neighborhood-based techniques discussed by Choi and Choi (2002), where local search is used to iteratively improve scheduling solutions through operations like swaps and insertions.

The heuristic consists of three phases. In Phase 1, Random Swapping, individual jobs are randomly moved to different positions or swapped across lines, favoring lines already producing the same product type. In Phase 2, Group-Based Swapping, groups of consecutive jobs with the same product type are treated as single units and moved or swapped. In Phase 3, Group-Size Constrainted Swapping, group sizes are randomly limited to 2 to 4 jobs per line to increase mobility and allow finer adjustments.

These three phases are repeated a total of three times combining group-level and individual-level improvements besides enabling a more comprehensive exploration of the solution space.

After each adjustment, the heuristic recalculates key performance measures such as total changeover time, total tardiness, penalties due to maximum allowed delay, and due date satisfaction ratio. These metrics are aggregated into an objective function, where each component is weighted based on user-defined preferences. If the new solution yields a better objective value, the change is accepted and becomes the new baseline; otherwise, it is discarded and the algorithm continues with the previous solution. This mechanism ensures that only beneficial changes are retained, guiding the search process toward higher-quality solutions.

The process continues for a predefined number of iterations, ultimately returning a detailed schedule for each job, including start and finish times, assigned production lines, and any tardiness.

7.6 Verification and Validation

7.6.1 Verification

The verification process tested the algorithm using company data to simulate real-world conditions. The solver was run multiple times with different datasets to determine appropriate coefficients and maximum iterations.

Coefficients for changeover time, tardiness, and due date satisfaction were set based on trials and remained constant across all tests. Consistency testing involved increasing the number of work orders, product types, and modifying parameters like production lines to ensure results aligned with theoretical expectations. Several test cases were used to evaluate different job numbers, product types, and production lines. In complex scenarios with 500 and 1000 work orders, the heuristics still performed well, reducing tardiness and improving due date satisfaction. All outputs were completed within the company's 10-minute execution time limit.

Figure 7.3 illustrates the improvements achieved at each stage of the algorithm. The changeover time consistently decreased throughout the process, and due date satisfaction steadily increased. These results highlight that Multi-Phase Local Search Algorithm runs properly.

Case	Metric	Initial Solution	First Heuristic	Second Heuristic	Third Heuristic	Final Result
Number of Jobs: 100 Number of Lines: 5 Product Type Size: 10	Changeover (h)	104.5	103.98	98.93	98.93	98.58
	Total Tardiness (h)	476.37	453.67	199.56	199.56	220.55
	Due Date Satisfaction	81%	83%	85%	85%	85%
	Exceeding Tardiness	0	0	0	0	0
Number of Jobs: 100 Number of Lines: 10 Product Type Size: 10	Changeover (h)	84	84	75.6	75.6	75.6
	Total Tardiness (h)	84.79	44.75	132.15	6.27	0
	Due Date Satisfaction	93%	96%	95%	99%	100%
	Exceeding Tardiness	0	0	2598	0	0
Number of Jobs: 100 Number of Lines: 5 Product Type Size: 20	Changeover (h)	229.5	181.27	178.05	177.35	172.02
	Total Tardiness (h)	439.47	453.38	438.17	349.16	371.9
	Due Date Satisfaction	77%	84%	90%	91%	91%
	Exceeding Tardiness	0	404.13	1485.68	355.04	486.54
Number of Jobs: 500 Number of Lines: 5 Product Type Size: 10	Changeover (h)	474.63	474.63	473.98	473.98	473.98
	Total Tardiness (h)	11165.86	11157.79	9542.96	8344.61	8335.27
	Due Date Satisfaction	87%	87%	87%	87%	87%
	Exceeding Tardiness	0	0	0	0	0

Figure 7.3: Verification results

7.6.2 Validation

The validation phase aimed to ensure that our algorithm calculates and evaluates key performance indicators (KPIs) in alignment with the company's existing system. To achieve this, we obtained a sample result from the company's current scheduling algorithm and used it as the initial solution input for our algorithm. In addition, we were provided with the corresponding KPI values used by the company for performance evaluation.

By processing the company's solution through our developed heuristic, we observed the consistency of metric calculations between the two systems. Furthermore, our algorithm not only replicated the company's KPI calculations accurately but also achieved significant improvements across key measures such as total changeover time, total tardiness, and due date satisfaction. These findings confirm that the proposed solution maintains compatibility with the company's performance evaluation framework.

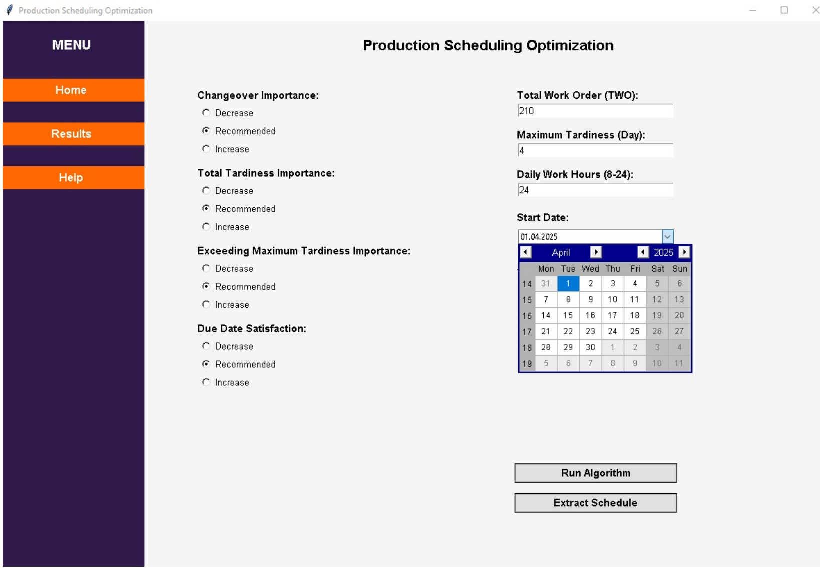


Figure 7.4: Home page of the user interface

7.7 Deliverables

The main deliverable is a heuristic-based optimization algorithm designed to minimize changeover time while meeting work order due dates. It addresses large-scale scheduling challenges in the pharmaceutical industry and provides efficient production schedules. A decision support system created by Python allows data input and preference adjustment, generating an Excel schedule and Gantt chart. A pilot study is conducted to validate the system and support integration into existing software.

7.7.1 User Interface

ThePython-based interface is designed to simplify scheduling by allowing users to input work orders and adjust key parameters such as changeover time, total and exceeding tardiness, and due date satisfaction. Based on these inputs, the system runs the optimization algorithm and generates anExcel file that includes job-line matchings, start and end times, product types, and performance metrics. A Gantt chart is also provided to help visualize the schedule.

7.8 Benchmarking and Benefits

The benchmarking process was conducted using two datasets with 250 work orders provided by the company. These datasets were processed and run in the company's system using two different methods. The results were then compared with the outcomes generated by our proposed algorithm

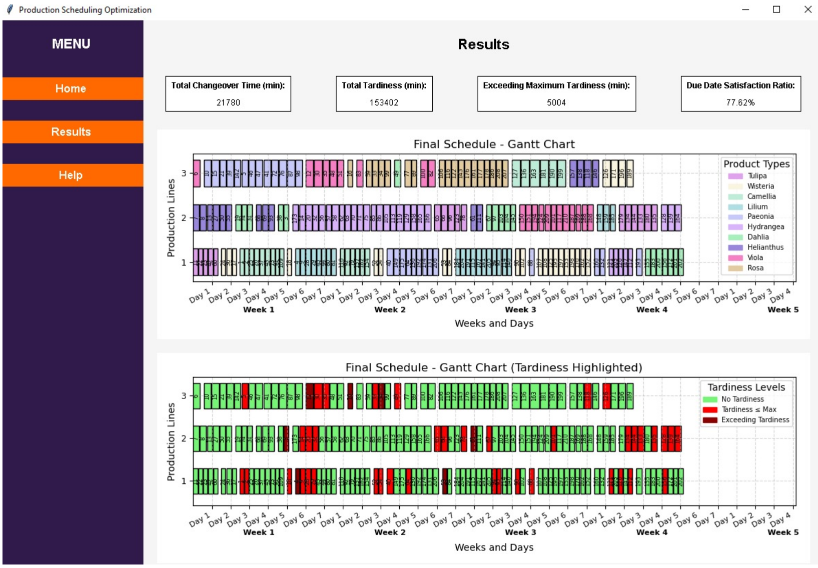


Figure 7.5: Results page of the user interface

to evaluate how well our approach performed compared to the company's current methods. The company provided the key performance indicator results related to the performance of their current system. By comparing these KPIs with the results obtained from our algorithm, improvements were evaluated and the effectiveness of the new optimization strategy was assessed.

Figure 7.6 presents a comparison between the company's current system and the proposed system. The level of improvement may seem quite significant; however, it is important to note that the company's current system does not include any algorithm aimed at minimizing changeover time. These improvements are a result of introducing a new system specifically designed to address this issue.

The proposed scheduling solution significantly enhances SCW.AI's capabilities by introducing an optimization approach focused on minimizing changeover time which is an objective previously unavailable in the company's existing Scheduler Tool. The algorithm's execution time is 360 seconds, which was allowed by the company, and despite being longer than

Metric	Company's Current System	Our System	Improvement (%)
Total Changeover Time (h)	582.25	259	40%
Total Tardiness (h)	9173.21	805.35	51%
Due Date Satisfaction Ratio	0.72	0.9	36%
Exceeding Total Tardiness (h)	4543.03	2.17	100%
Makespan (day)	27.7	24.45	11%
Execution Time (s)	20	360	-94%

Figure 7.6: Benchmarking results

the current tool's 20 seconds, it delivers substantial operational advantages. Evaluations show that the algorithm reduces total changeover time by up to 40%, total tardiness by up to 51%, and increases due date satisfaction rates by 36%. These improvements directly impact operational performance by increasing on-time delivery and reducing downtime between jobs, which in turn leads to better resource utilization and higher overall efficiency. As the approach is fully compatible with the company's existing Digital Factory platform, these benefits are achieved without requiring additional infrastructure, offering a highly practical and impactful improvement to SCW.AI's scheduling capabilities.

7.9 Conclusion

This project addressed SCW.AI's requirement of minimizing changeover time in pharmaceutical production scheduling. The custom heuristic approach, supported by a decision support system, was developed to minimize changeover time. In addition to achieving this primary goal, the solution also improved other key performance metrics such as on-time delivery, total tardiness, and exceeding tardiness. These improvements not only align with SCW.AI's operational goals but also increase the value delivered to its clients.

Acknowledgment

This project was supported by TÜBİTAK BİDEB 2209/B Program under Grant 1139B412409517.

Bibliography

Choi, I.-C. and D.-S. Choi (2002). A local search algorithm for jobshop scheduling problems with alternative operations and sequence-dependent setups. *42*(1), 43–58.

SCW.AI (2024). About scw.ai. https://scw.ai/company/about-us/. [Online; accessed April 8, 2025].

8 Kart Üretiminde Kurulum Sürelerine Göre Teslimat Takvimi Çizelgelemesi

Meteksan Savunma

Proje Ekibi
Ahmet Emir Abay, Aras Bozyel, Mert Çağman, Çağan Dal,
Yiğit Eren Peker, Salih Orkun Şenel, Mukadder Nihan Yıldız

Şirket Danışmanı
Eda Şenol
Üretim Planlama Mühendisi

Akademik Danışman
Prof. Dr. Oya Karaşan
Endüstri Mühendisliği Bölümü

Özet

Bu projenin temel amacı, Meteksan Savunma'nın üretiminde toplam kurulum süresini en aza indirmek için ideal bir üretim sıralaması oluşturmaktır. Meteksan Savunma'nın üretim sistemi incelenmiş ve analiz edilmiştir. Sistem analizi sonrasında, mevcut sistemdeki problem açıklanmış ve kapsamı ortaya konmuştur. Çözüm olarak iki ayrı matematiksel model ve bir sezgisel model geliştirilmiştir. Bu çözümler bir karar destek sistemiyle kullanıma hazır hale getirilmiştir. Son bölümde ise, projenin çıktıları ve teslim edilecekleri olan karar destek sistemi, kullanım kılavuzu ve üretim çizelgesini planlamak için hazırlanmış modeller sunulmuştur.

Anahtar Sözcükler: Üretim Planlama, Çizelgeleme, Matematiksel Modelleme, Kurulum Süresi Optimizasyonu, Sezgisel Yöntem

Delivery Schedule Planning in Card Production Based on Setup Times

Abstract

The main objective of this project is to create an ideal production sequence to minimize the total setup time in Meteksan Savunma's production. The production system of Meteksan Savunma was examined and analyzed. After the system analysis, the problem in the existing system was explained and its scope was revealed. Two mathematical models and a heuristic algorithm were developed. These solutions are made ready for use with a decision support system. In the last part, the outputs and deliverables of the project, namely the decision support system, the user manual and the models for planning the production schedule are presented.

Keywords: Production Planning, Scheduling, Mathematical Modeling, Setup Time Optimization, Heuristic Method

8.1 Company Description

Meteksan Savunma is an Ankara-based company specializing in high-tech defense systems. It was established in 2006 by Bilkent Holding to contribute to the defense industry and fund the Bilkent University. The main product portfolio of Meteksan Savunma consists of radar systems, control and command units, electro-optic, surveillance, and communication systems. Also, the electronic circuit boards to be embedded in these systems are produced by Meteksan Savunma. All of these products are developed, designed, produced, and tested in their 1500 m^2 headquarters located near Bilkent Cyberpark. To achieve the lowest possible error margins, Meteksan Savunma utilizes high-tech labs, equipment, and a test facility at Bilkent Lake. Currently, Meteksan Savunma proceeds its activities with 320 employees (Meteksan, 2024).

8.2 System Analysis and Problem Definition

8.2.1 System Analysis

Meteksan Savunma's production system involves a type-setting machine that processes around 150 types of circuit boards. There are three main production stages: Setup phase, type-setting phase, and post-typesetting phase. The setup phase involves placing the materials of cards in the type-setting machine. The setup process is monitored by production planning engineers. After the setup process, the machine places the components on the cards. Then, the production moves on by post-typesetting processes.

Meteksan Savunma's production processes are monitored with the SAP system. The production planning team consists of four engineers, one planning technician, and five warehouse technicians. Despite the ERP system, production delays can occur due to exceptional situations or potential changes. Due to the lack of any mathematical model, the company relies on experience and intuition.

8.2.2 Problem Definition and Scope

The production planning department faces some challenges with managing total setup time due to the lack of any mathematical model. Production planning department uses a heuristic method to plan the schedule. The heuristic used is similar to earliest due date which is a well-known algorithm in the scheduling literature. A mathematical model is needed to minimize total setup time and create a production plan following due dates, and increasing production efficiency.

The project's objective is to reduce production inefficiencies caused by setup processes. The project's scope includes circuit boards, their due dates, demanded amounts, and production times. Production time was considered as setup and processing times. Each setup time is dependent on the card that was produced previously. Ultimately, their similarity affects each setup time and, hence, the total setup time. The goal is to create a production plan that minimizes the total setup time.

Meteksan Savunma requested a matrix that displays the resemblance between each card according to their bills of materials. Bills of materials are stored in a database that is ready to be updated anytime. Also, it is asked to be connected to the decision support system for operational efficiency. Besides, the decision support system was aimed at providing production plans using different models and a heuristic algorithm for different needs. The project scope is finalized by providing a user manual to guide future uses.

8.3 Solution Approach

8.3.1 Model Development

Project team developed mathematical models that minimizes the total setup time and total overtime hours to optimize the production planning of electronic cards for Meteksan Savunma. The model takes into account various critical parameters such as similarity rates based on the bill of materials (BOM) between cards, processing times, delivery dates and setup times.

Two different models were implemented. The primary model aims to minimize the total setup time, if it is possible to meet the delivery deadlines.

The second model relaxes this constraint by minimizing total overtime hours when deadlines are tight. OR-Tools solver was chosen because it is open source to ensure that the model can be used without requiring a license. In addition, an intuitive Tabu Search Algorithm was developed to obtain faster and near-optimal results on large data sets.

8.3.2 Mathematical Models

Model Minimizing Total Setup Time

Decision Variables:

- $x_{ij} \in \{0,1\}$: A binary variable representing whether job j is produced immediately after job i (1 if true, 0 otherwise).
- $s_i \in \mathbb{R}^+$: The start time of job i, where $i \in P$.
- $c_i \in \mathbb{R}^+$: The completion time of job i, where $i \in P$.

Parameters:

- $P = \{1, 2, \ldots, n\}$: Set of jobs to be scheduled.
- $P_0 = P \cup \{0\}$: Set of jobs including the dummy job 0.
- $st_{ij} \in \mathbb{R}^+$: Setup time required when switching from job i to job j.
- $pt_i \in \mathbb{R}^+$: Processing time for job i.
- $D_i \in \mathbb{R}^+$: Due date for job i.
- $M \in \mathbb{R}^+$: A large constant used to model conditional constraints.

Objective: Minimize the total setup time, which is given by:

$$\text{Minimize} \quad \sum_{i \in P_0} \sum_{j \in P_0, j \neq i} st_{ij} \cdot x_{ij}$$

Constraints:

- Each job is produced exactly once:

$$\sum_{i \in P_0, i \neq j} x_{ij} = 1 \quad \forall j \in P_0$$

- Each job is followed by at most one other job:

$$\sum_{j \in P_0, j \neq i} x_{ij} \leq 1 \quad \forall i \in P_0$$

- Start time and setup time relation:

$$s_j \geq c_i + st_{ij} - M \cdot (1 - x_{ij}) \quad \forall i \in P, j \in P, i \neq j$$

- Completion time constraint:

$$c_i = s_i + pt_i \quad \forall i \in P$$

- Due date constraint:

$$c_i \leq D_i \quad \forall i \in P$$

- Initial job timing:

$$c_0 = 0, \quad s_0 = 0$$

Domain Restrictions:

$$x_{ij} \in \{0, 1\} \quad s_i \geq 0, \quad c_i \geq 0 \quad \forall i, j \in P_0$$

Model Minimizing Total Overtime Hours

Decision Variables:

- $x_{ij} \in \{0, 1\}$: A binary variable representing whether task j is scheduled immediately after task i (1 if true, 0 otherwise).
- $s_i \in \mathbb{R}^+$: The start time of task i, where $i \in P_0$.
- $c_i \in \mathbb{R}^+$: The completion time of task i, where $i \in P_0$.
- $o_i \in \mathbb{R}^+$: The overtime required for task i, where $i \in P$.

Parameters:

- $P = \{1, 2, \ldots, n\}$: Set of tasks to be scheduled.
- $P_0 = P \cup \{0\}$: Set of tasks including the dummy task 0.
- $st_{ij} \in \mathbb{R}^+$: Setup time required when switching from task i to task j.
- $pt_i \in \mathbb{R}^+$: Processing time for task i.
- $D_i \in \mathbb{R}^+$: Due date for task i.
- $M \in \mathbb{R}^+$: A large constant used to model conditional constraints.

Objective To minimize total overtime hours.

$$\text{Minimize} \quad \sum_{i \in P} o_i$$

Constraints:

- Each job is produced exactly once:

$$\sum_{i \in P_0, i \neq j} x_{ij} = 1 \quad \forall j \in P_0$$

- Each job is followed by at most one other job:

$$\sum_{j \in P, j \neq i} x_{ij} \leq 1 \quad \forall i \in P_0$$

- Start time and setup time relation:

$$s_j \geq c_i + st_{ij} - M \cdot (1 - x_{ij}) \quad \forall i, j \in P, i \neq j$$

- Completion time constraint:

$$c_i = s_i + pt_i \quad \forall i \in P$$

- Overtime calculation:

$$o_i \geq c_i - D_i \quad \forall i \in P$$

- Initial job timing:

$$c_0 = 0, \quad s_0 = 0$$

- Domain Restrictions:

$$x_{ij} \in \{0, 1\}, \quad s_i \geq 0, \quad c_i \geq 0, \quad o_i \geq 0 \quad \forall i, j \in P_0$$

8.3.3 Heuristic Method

The preferred heuristic method for the project is the Tabu Search Algorithm. Tabu Search Algorithm is developed to decrease the run time if necessary. Tabu Search Algorithm starts with a reasonable solution and systematically explores the neighborhood of a current solution while maintaining a short-term memory of previously visited solutions to prevent cycling. Upon visiting the neighbors, the algorithm determines tabus to avoid revisiting these neighbors and implementing certain solutions. This approach allows the algorithm to escape local minima and continue improving towards a global or near optimal solution (Khoo, 2006).

8.4 Verification

8.4.1 Verification of Mathematical Models

The verification of two mathematical models is done to make sure that two models are accurate and outputs correct results. To verify the models, a procedure is followed. Initially, models were transitioned from Gurobito OR-Tools, and outputs were compared to ensure consistent results. A primary dataset of 5 cards was used for manual verification, ensuring the solver accurately minimizes total setup time and total overtime hours while maintaining the correct sequence. Extreme scenarios, such as tight deadlines and large setup times, were tested to validate the models' robustness and its ability to construct and minimize total overtime hours and total setup time effectively. Additionally, each constraint was systematically removed to confirm its functionality in each model. These steps verified the models' accuracy while delivering feasible and optimized solutions such as outputting the correct sequence. Also, running times of this model for both solvers are tested and running time comparison tables are made for different card numbers in both solvers.

8.4.2 Verification of Heuristic

Verification of the heuristic algorithm is done by checking the outputs of the heuristic algorithm and comparing them with optimal solutions. Additionally, the inputs are changed to test the accuracy of the algorithm. The algorithm is run with extreme data and the obtained results are examined. In addition, to verify all models together, the same data sets are used for input and outputs are compared. It was observed the heuristic algorithm could find solutions close to the main model. The verification of Tabu Search Algorithm ensured that the outputs of the heuristic algorithm are as expected. Also, it is observed that no matter which datasets are included in the inputs, Tabu Search Algorithm outputs a result within two seconds until 50 different card types. Outputs of the total setup time minimization model and Tabu Search Algorithm were compared, and it was detected that results differ after the sample of ten cards.

8.5 Validation

To ensure models and the heuristic algorithm meet Meteksan Savunma's operational needs and integrate into the existing production workflow, the validation phase is essential to test the credibility of the models and the heuristic algorithm. According to real data, some inputs such as setup time between two electronic cards and processing times of them are calculated by the project group with methods that are agreed with the company by using bill of materials (BOM). Also, real due dates are used as an input data. Then, these inputs are be used in the models and the heuristic algorithm. With the given real data (January 2025), the model that minimizes total setup time output an optimal solution with 11 card types in 1 month horizon, meaning that the due dates of cards are counted as 1 month, only including working hours. Therefore, there were no need to use the model which minimizes total overtime hours. Additionally, heuristic is also used with the same inputs. The output of both the model and the heuristic algorithm is total setup time and the production sequence. The results are analyzed and examined by industrial advisor, and it is determined as applicable and logical.

8.6 Integration and Implementation

The implementation starts with the pilot study. Arrangements were made after the pilot study was completed and feedback was received. The arrangements include formatting of the decision support system and modifications in the model. The first phase of the implementation started with preparation. All the cards were recorded as entities in the database. Their similarities and processing times were computed according to their bill of materials (BOM) data. After all the data was placed in the required files, the model was ready to run using the data provided as parameters. The second phase is the pilot study. A proper Excel file was created and uploaded to the decision support system and run with Tabu Search Algorithm. The outcome of the decision support system was discussed and analyzed with the industrial advisor.

The third phase is the feedback phase. According to the feedback, the errors were fixed. The industrial advisor requested formatting changes in the outputs. The user manual was updated according to user needs. The model, the decision support system, database, and user manual were modified. The fourth and last phase is the finalization phase. The final arrangements were made according to the feedback and observations. The project is finalized for use in the system with the finalized models, decision support system, and user manual. An additional decision support system was developed to calculate setup and processing times.

8.7 Benefits and Benchmarking

The project provides improvements to the Meteksan Savunma's production system by reducing total setup time in the feeding process of the typesetting machine. In the current system, the production schedule is created

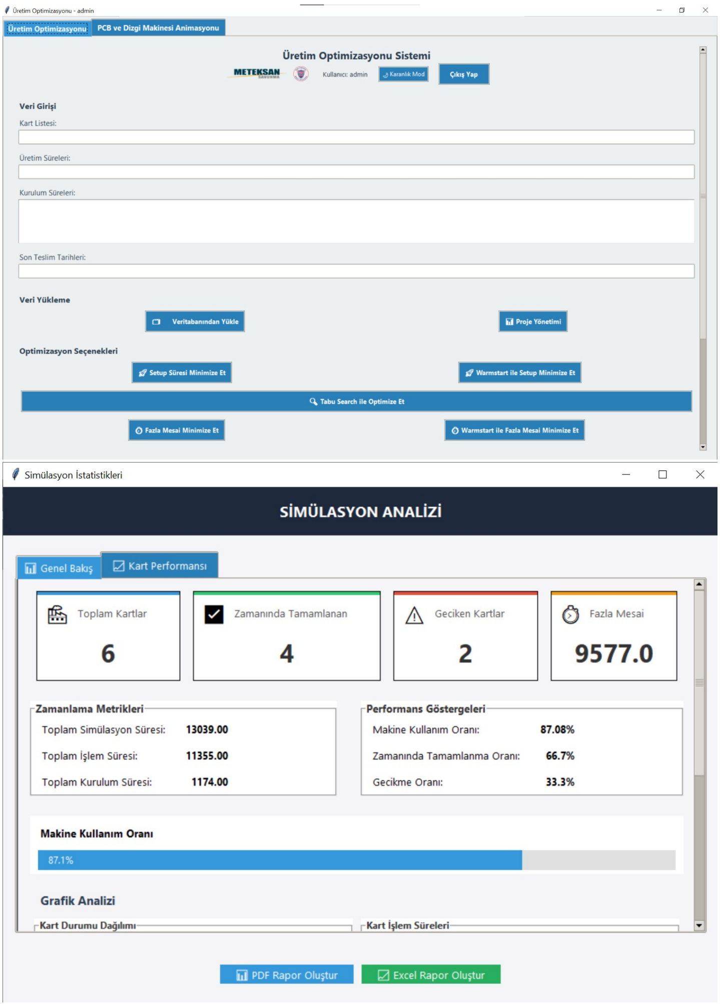


Figure 8.1: Main and Output Analysis Screens of the Decision Support System

manually with a focus on due dates with little consideration on material similarities between cards. This results in longer setup times and inefficiencies in the production flow. With the implementation of the models, production becomes smoother and faster, which enables Meteksan Savunma to produce more cards in the same period of time.

Additionally, the system is designed for long-term flexibility. The user-friendly Python-based interface and the structured SQL database make it easy for the production planning team to manage and update production data. New card types can be added, or existing ones removed, directly through the SQL database. The main screen and the output analysis screen of the decision support system are included in the following figures.

Using the user-friendly decision support system, data can be loaded from

Excel files or retrieved directly from the database. Optimization methods can be easily run, and the results can be viewed in a user-friendly manner. This flexibility allows the system to adapt to new product types. This eliminates those with manual intervention and minimizes debugging.

Faster and more reliable scheduling also helps Meteksan Savunma accept urgent orders with tight deadlines which is supporting customer satisfaction and maintaining a competitive edge in the market.

When tested with real production data from January 2025, the mathematical model reduced the total setup time by 24.66%, while the Tabu Search Algorithm achieved a 23.92% reduction. These improvements show that the value of the mathematical optimization system over the current manual planning approach.

8.8 Conclusion

The models and the decision support system met expectations of Meteksan Savunma by significantly improving production planning efficiency. Validation processes, including real data validation and expert assessments, confirmed the practical applicability of the model and its potential for significant operational improvements.

Using historical production data, the comparative analysis showed that optimized planning can deliver a 24.66% reduction in total setup time compared to existing planning method. This improvement directly translates into increased production efficiency, and improved profitability for Meteksan Savunma.

The enhancement of the heuristic algorithm, the expansion of the system's database capabilities, and the carrying out of comprehensive pilot studies to ensure smooth integration into daily production workflows have been carried out. Overall, the project successfully delivered a practical and effective planning optimization tool that aligns well with the Meteksan Savunma's strategic objectives.

Bibliography

Khoo, F. F. C. . E. M. . H. (2006, November). A multi-objective tabu search for a single-machine scheduling problem with sequence-dependent setup times. *European Journal of Operational Research).*

Meteksan (2024). Meteksan savunma, about us. Accessed: Oct. 22, 2024. https://www.meteksan.com/.

9 Müşteri Talep Yönetimi Süreçlerinin İyileştirilmesi

Hayat Finans

Proje Ekibi
Yavuz Eren Arslan, Faisal Baraka, Timurhan Bulut,
Begüm Ecerkale, Helin Arya Gündoğdu, Yusuf Özkan, Özgü Şimşek

Şirket Danışmanları
Aylin Gücüyener, Suzan Öztürk
ve Açelya Tanışman
Süreç Yönetimi

Akademik Danışman
Prof. Dr. Nesim K. Erkip
Endüstri Mühendisliği Bölümü

Özet

Hayat Finans çağrı merkezinde müşteri talep yönetiminin ilk aşaması, gelen şikayetlerin sınıflandırılmasıdır. Bu sınıflandırma, talebin ilgili departmana yönlendirilmesi ve çözüm sürecinin başlatılması için kritik öneme sahiptir. Ancak mevcut durumda müşteri temsilcilerinin şikayetleri elle sınıflandırması, hatalara ve çözüm süresinin uzamasına yol açmaktadır. Ayrıca çağrı yoğunluğunun gün içindeki değişkenliği, belirli saatlerde temsilci yetersizliği veya fazlalığına neden olmaktadır. Bu sorunlara çözüm olarak makine öğrenmesine dayalı bir sınıflandırma algoritması geliştirilmiş, çağrı tahmini ve vardiya planlaması için optimizasyon modelleri oluşturulmuştur. Pilot uygulamada proje çıktıları test edilmiş; sistemin iş yükünü azalttığı, vardiya planı doğruluğunu artırdığı ve hizmet kalitesini iyileştirdiği görülmüştür. Pilot çalışmanın ardından programların tam zamanlı kullanım için kurulumları gerçekleştirilmiştir.

Anahtar Sözcükler: Çağrı Merkezi, Sınıflandırma, Vardiya Planlama, Makine Öğrenmesi, Tahminleme, Müşteri Memnuniyeti.

Improvement of Customer Demand Management Processes

Abstract

At Hayat Finans call center, the first stage of customer demand management is the classification of incoming complaints. This classification is critically important for directing the request to the relevant department and initiating the resolution process. However, under the current conditions, the manual classification of complaints by customer representatives leads to errors and prolongs the resolution time. Additionally, fluctuations in call volume throughout the day cause either a shortage or a surplus of representatives at certain hours. To address these issues, a machine learning-based classification algorithm has been developed, along with optimization models for call forecasting and shift planning. In the pilot study, the project outputs were tested; it was observed that the system reduced the workload, improved shift planning accuracy, and enhanced service quality. Following the pilot study, the programs were installed for full-time use.

Keywords: Call Center, Classification, Shift Scheduling, Machine Learning, Forecasting, Customer Satisfaction.

9.1 About The Company

Founded in 1937, Hayat Holding is a global player with over 67 companies and more than 20,000 employees operating in various sectors like port management and FMCG. Hayat Finans, as the financial investment of the holding, in March 2023, has started providing free-of-charge services through the Hayat Finans mobile app and internet banking. It currently operates as Turkey's first digital bank. Their core activities include private banking services, commercial banking, SME banking, retail banking, investment banking and treasury transactions.

9.2 System Analysis

Since there isn't a physical branch, Hayat Finans interacts with and serves its customers through digital channels. These include the mobile application, website, call center, "Bize Yazın" feature in the app, customer contact form, and email. To ensure any customer demand is met efficiently and effectively, Hayat Finans also provides a 24/7 call center, staffed with 50 customer representatives, and seven back-office workers who resolve requests/complaints, namely agents. There are three distinct job definitions which are carried out by customer representatives, simultaneously. The first is operational complaint recording. This is the main task of customer representatives, it continues 24/7 non-stop. Second job is to make video calls with registering customers in order to verify their national identity cards. This task is performed during weekdays only during business hours. The last is the sales calls for corporate affairs. Customer representatives are assigned by the team leader to do corporate calls when needed, therefore, it is not exactly scheduled.

When a complaint arrives, firstly, the complaint information is entered into the system by a customer representative in the call center. Then it is manually selected by agents in the back office or assigned by their supervisors to be solved. After assignment, agents first provide control of the problems, then the majority of these problems are allocated to the actual departments where they will be solved. The assignment to other departments is also done manually by agents. The flow chart of the processes after a complaint arrives can be seen in Figure 9.1.

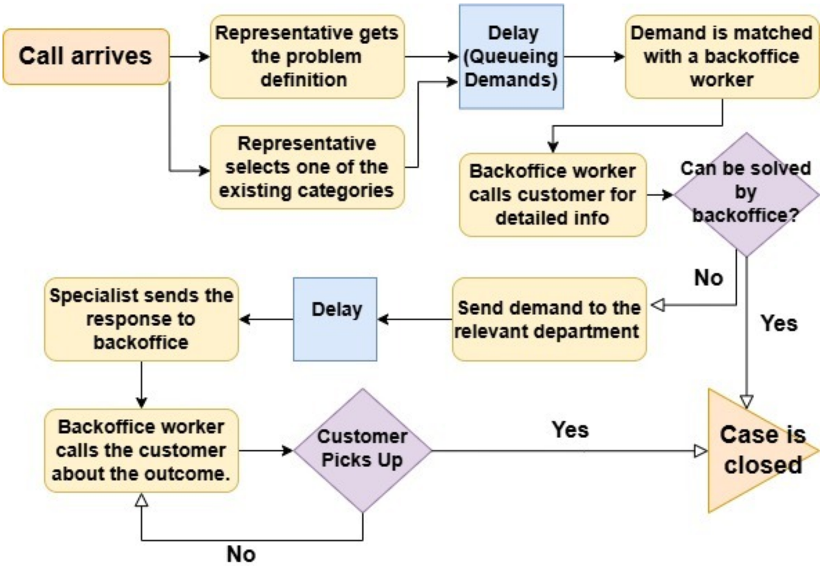


Figure 9.1: Flow chart of processes.

9.3 Problem Definition

While responding to a call, customer representatives are responsible for selecting complaint categories and typing descriptions instantly, leading to errors in classification and descriptions. This causes challenges for agents to detect the core of the problem correctly before sending these to other departments. Additionally, since call arrival rates vary throughout the day, overstaffing during off-peak hours and understaffing during peak hours for customer representatives are observed. These inefficiencies result in difficulties in responding to customer calls in a timely manner, which may pose a regulatory compliance risk. Furthermore, the inability to accurately categorize complaints prolongs resolution times, reducing customer satisfaction. As the customer base continues to grow, the need to utilize representative resources more efficiently becomes increasingly critical.

9.4 Proposed Solution System

Given the diverse nature of the problem, the solution approach has been structured into separate components, each focusing on a specific part of the problem.

The first solution approach is based on machine learning algorithms developed to improve the correct classification and assignment of customer complaints. First, complaint descriptions are cleaned up, removing numbers, punctuation, unnecessary characters and extra spaces. In addition, common typos, keywords and important phrases (e.g. "potential customer") are identified from historical data. After this cleaning and word detection, the machine learning model is trained with historical data to provide accurate category suggestions to call center agents. This speeds up the process without the need for a second customer call. K-Means and Logistic Regression algorithms also work in parallel in this process, helping to identify the new categories needed (Scikit-Learn Developers, 2024a). As shown in Figure 9.2, a user-friendly interface was designed by analyzing the existing system interface and Excel files. When the required fields are filled in, the algorithm presents the suggested categories on the screen. The user can approve these suggestions and save the complaint to the system with the "Save and New" button. If the suggested categories are not suitable, the user can delete these suggestions and make a manual selection. Complaints are automatically saved in an Excel file, while manual category selections are noted in the system for future training of the model. Thus, the model improves with real user preferences and becomes capable of providing more accurate and intelligent recommendations.

The other solution approach is based on the effective utilization of customer representatives throughout the day through a forecast program for call arrivals and shift scheduling with three mathematical models.

The forecast program uses RandomForest Regressor from the Sklearn library to estimate the number of incoming calls on an hourly basis (Scikit-Learn Developers, 2024b). The program investigates historical call arrival data with respect to parameters such as total number of customers at the time, days of the week, national holidays, and campaign periods. The user is asked to type the time interval for forecast, estimated number of customers for that period, and whether there will be an ongoing campaign during that period. If a campaign is present, the model predicts a higher

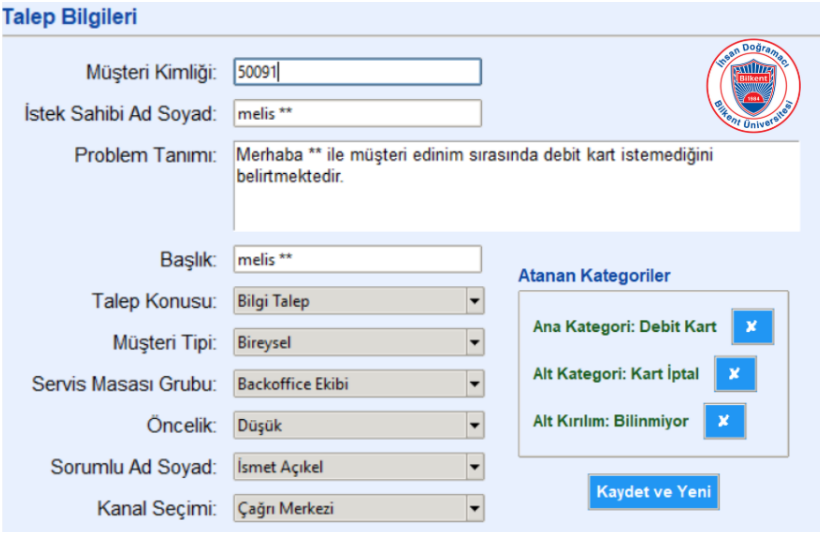


Figure 9.2: Interface of machine learning algorithm.

volume of incoming calls compared to regular periods. Similarly, an increase in the number of customers leads to higher call volumes, while call volumes tend to decrease during national holidays. In addition, the model captures variations across weekdays, reflecting typical patterns in call volume observed throughout the week. Figure 9.3 shows the interface of the forecast program.

The output of the forecast program is then inputted to the shift scheduling program. Along with the forecasted call arrival rates, the user is asked to input estimatedservice rates, estimated efficiency percentage of the call center, the maximum acceptable probability that a customer waits in the queue, the maximum amount of time in the queue if they wait in the queue, and finally, the maximum number of representatives that will be eligible to work on the given day. An open-source Python code, which executes three different mathematical models, finds the shift plan that minimizes understaffing and overstaffing.

Figure 9.3: Interface of the forecast program.

The first mathematical model, presented in Appendix 9.A, determines the number of required customer representatives as the call center is an example of M/M/s queueing system (Pinsky and Karlin, 2011). Arrival rates are provided by the forecast program and other required parameters are entered by the user. Constraints (9.6) and (9.7) ensures the expected waiting time in the queue and the waiting probability does not exceed respective limit parameters. The model finds the least amount of representatives for an hour that satisfies these constraints, namely the requirement of an hour. An open source Python code implementing a heuristic approach is used to solve the model: starting from one server, the algorithm incrementally increases the number of servers until both the expected waiting time and waiting probability fall within the specified limits. The loop terminates once a feasible solution is found.

The company uses a five-block shift system, therefore the requirements of each hour should be met through only five intervention points. Shift scheduling model in the Appendix 9.B determines the shift with minimum number of total customer representatives while constraint (9.10) ensures that the requirement of each hour is covered.

The last mathematical model, presented in Appendix 9.C, provides a solution for cases where the number of available customer representatives is insufficient to fully cover the hourly requirements. In this case, the requirement coverage constraint of the shift scheduling model is relaxed, meaning that the model can now assign fewer representatives than the requirement. The objective is to minimize total squared deviation between requirements and assignments while constraint (9.13) ensures total assigned customer representatives for the given day cannot exceed the user input and constraint (9.14) ensures at least one representative works each hour. An open source Python code is used to solve this problem by iteratively adjusting assignments to minimize squared deviation while satisfying the remaining constraints.

As a result, the mathematical models described above generate two separate shift plans: one representing the minimum number of customer representatives needed, and the other representing the maximum allowable staffing levels. These two plans are displayed in the system as the "Minimum Personnel" and "Maximum Personnel" shift schedules, respectively. Figure 9.4 shows an example Minimum Personnel Plan generated by the last mathematical model. Using these outputs, the final shift schedules are prepared and integrated into the workforce management system.

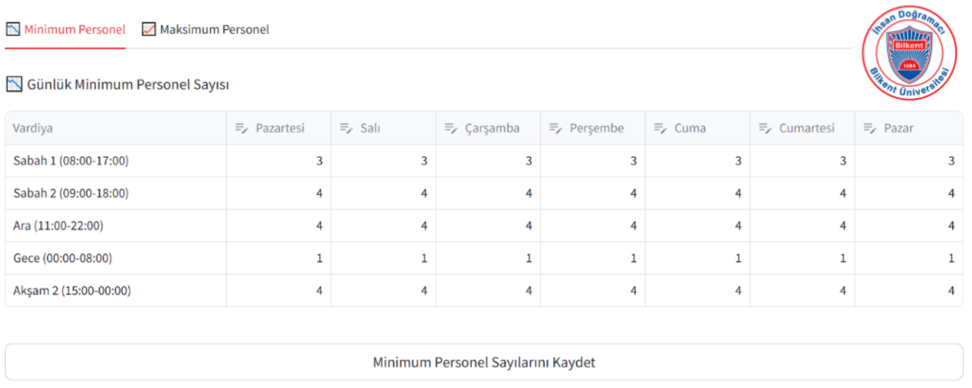


Figure 9.4: Interface of the shift scheduling program.

9.5 Verification and Validation

All the components of proposed solution system were tested individually to ensure they worked properly. The classification algorithm was tested with extreme cases, and consistency checks were made. Similarly, the forecasting, queueing and shift scheduling models were verified by modifying the parameters, such as arrival rates, and checking the output. These tests ensured the results were logical, feasible, and consistent.

For validation, expert opinions were considered to ensure the models matched real world needs. The classification algorithm was discussed with company advisors to confirm alignment with operational requirements. Its results were compared with historical data, and speed tests were performed to ensure it produced outputs quickly and consistently.

The forecasting model was validated by checking that it captured the main factors affecting call arrival rates and that its assumptions matched real-world conditions. Model outputs were compared with past data, and it was confirmed that inputs could be updated regularly to maintain accuracy. This ensured the forecasts were reliable enough to support the shift scheduling system.

For the shift scheduling models; validation included calibration of parameters, adjusting key inputs such as available customer representative limit or the limit of waiting time in the queue, and checking the stability of the generated solution. The results indicated that the models worked properly under varying input conditions and were reliable for practical use.

9.6 Integration and Implementation

All of the programs discussed in Section 9.4 are designed in a way that ensures maximum ease-of-use and ease-of-implementation. Respective files and detailed user manuals are uploaded into a link that is provided by Hayat Finans IT department. However, since information security is a heavily regulated and critical issue for banks, the uploaded programs were installed on a third-party computer that is not connected to the company's internal systems for the purpose of pilot study.

Pilot study is designed in such a way that the classification algorithms are run with at least 20 calls of data each day, and the shift scheduling models are run every Wednesday, when the call center team leader builds the shift plan for the upcoming week. After one month of initial implementation, the outcomes were reviewed to identify areas for improvement and to resolve any faults in the systems. Key performance indicators (KPIs), such as changes in response time and manual workload, were tracked and compared before and after implementation to measure improvements. Furthermore, feedback was gathered from industrial advisors to identify any areas for further enhancement, ensuring the system was adjusted before full-scale deployment.

Following the pilot study, the programs were finalized for full-scale deployment based on the feedback and performance evaluations gathered during the testing phase. All programs underwent an additional review by the information security team to ensure compliance with internal policies. The classification algorithms were implemented in collaboration with the artificial intelligence team, while the forecasting and shift scheduling programs were integrated into the main workforce management software with the support of the system development team. Following the deployment, all programs were fully integrated into daily operations and are actively used by the call center team.

9.7 Benefits to the Company

The proposed solution system provides tangible improvements in both complaint classification and shift scheduling processes.

The classification algorithms significantly improved operational efficiency during the pilot study. The time required to record a complaint decreased by 32.7%, as cases were categorized instantly. Additionally, the error rate in complaint classification decreased by 9.1%, leading to more accurate and relevant task assignments to departments. Since the model continuously updates itself with real user feedback, its classification accuracy is expected to further improve over time.

The shift scheduling models enabled a better match between representative availability and hourly call demand. As shown in Figure 9.5, compared to the manually prepared shift plan, the model-generated plan reduced the total squared error between required and assigned representatives by 55.3%, indicating a substantial improvement in staffing efficiency. In terms of root mean squared error (RMSE), the model reduced the hourly error from 7.07 to 3.78 representatives, corresponding to an average improvement of approximately 3.29 representatives per hour. As a result, the system supports a more stable and responsive call center operation, especially during peak hours.

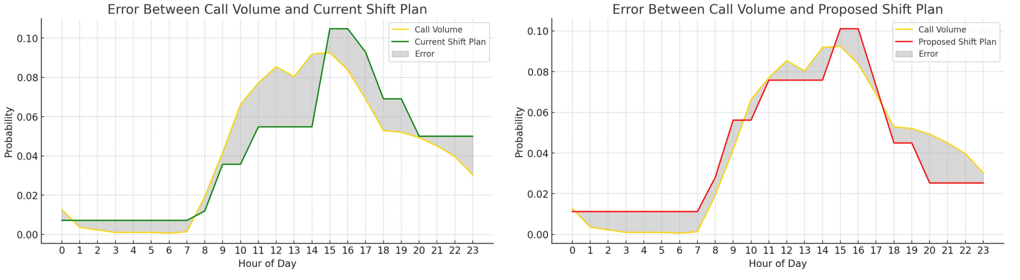


Figure 9.5: Error levels for the current (left) and proposed shift plans.

9.8 Conclusion

The proposed solution system has addressed the key challenges faced by Hayat Finans in its customer demand management processes. By introducing machine learning-based classification tools and optimization-driven shift scheduling models, the project has provided the company with decision support mechanisms that improved operational efficiency and reduced manual workload. Initial testing and validation efforts confirmed that the system meets the company's operational needs and expectations.

The programs have been fully integrated into the internal IT infrastructure, and the system is now actively operating. Observations during the deployment phase demonstrated that the algorithms adapt effectively to real-time inputs and operational dynamics, supporting continuous operational improvements.

Bibliography

Pinsky, M. A. and S. Karlin (2011). *An Introduction to Stochastic Modeling* (Fourth ed.). Academic Press (Elsevier).

Scikit-Learn Developers (2024a). Clustering. Accessed: 2024-10-25.

Scikit-Learn Developers (2024b). Ensemble methods, randomforest, scikit-learn documentation. Accessed: 2025-02-23.

Appendices

9.A M/M/s Queueing Model

Parameters

λ: Arrival rate.

μ: Service rate.

P_0: The probability that the system is empty.

P_{wait}: The probability that a customer waits in the queue.

L_q: Expected number of customers in the queue.

W_q: Expected waiting time in the queue.

$\overline{W_q}$: Maximum acceptable expected waiting time in the queue.

$\overline{P_{\text{wait}}}$: Maximum acceptable probability of waiting.

Decision Variable

s: Number of servers.

Model

$$
\begin{aligned}
\min \quad & s, && (9.1)\\
\text{s.t.} \quad & && \\
& P_0 = \left[\sum_{n=0}^{s-1} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^s}{s!} \cdot \frac{1}{1-\frac{\lambda}{s\mu}}\right]^{-1}, && (9.2)\\
& L_q = \frac{P_0 \cdot (\lambda/\mu)^s \cdot \frac{\lambda}{s\mu}}{s! \cdot \left(1-\frac{\lambda}{s\mu}\right)^2}, && (9.3)\\
& W_q = \frac{P_0 \cdot (\lambda/\mu)^s \cdot \frac{1}{s\mu}}{s! \cdot \left(1-\frac{\lambda}{s\mu}\right)^2}, && (9.4)\\
& P_{\text{wait}} = \frac{(\lambda/\mu)^s}{s!} \cdot P_0, && (9.5)\\
& W_q \le \overline{W_q}, && (9.6)\\
& P_{\text{wait}} \le \overline{P_{\text{wait}}}, && (9.7)\\
& s \ge 0. && (9.8)
\end{aligned}
$$

This model calculates the minimum number of customer representatives required for each hour by modeling the call center as an M/M/s queueing system. Constraints (9.6) and (9.7) ensure that both the expected waiting time and the probability of waiting in the queue stay within the predefined limits. A heuristic algorithm incrementally increases the number of servers until the service level constraints are satisfied.

9.B Shift Scheduling Model

Parameters

a_i: Requirement of hour i.

R_{ij}: $\begin{cases} 1, & \text{if shift } j \text{ covers hour } i \\ 0, & \text{otherwise} \end{cases}$

H: Hours, $\{0, 1, \ldots, 23\}$.

S: Shift blocks, $\{1, 2, \ldots, 5\}$.

Decision Variables

x_j: Number of representatives assigned to shift j.

y_i: Total representatives working in hour i, where $y_i = \sum_{j \in S} R_{ij}\, x_j$.

Model

$$\min \quad \sum_{j \in S} x_j \tag{9.9}$$

$$\text{s.t.} \quad \sum_{j \in S} R_{ij}\, x_j \geq a_i \quad \forall i \in H \tag{9.10}$$

$$x_j \in \mathbb{Z}_+ \quad \forall j \in S \tag{9.11}$$

This model assigns representatives to predefined shift blocks to fully meet the hourly staffing requirements determined by the queueing model. It aims to minimize the total number of representatives needed while constraint (9.10) ensures that staffing levels in each hour are sufficient.

9.C Bounded Shift Scheduling Model

Parameters

a_i: Requirement of hour i.

R_{ij}: $\begin{cases} 1, & \text{if shift } j \text{ covers hour } i \\ 0, & \text{otherwise} \end{cases}$

H: Hours, $\{0, 1, \ldots, 23\}$.

S: Shift blocks, $\{1, 2, \ldots, 5\}$.

M: Maximum total number of customer representatives available.

Decision Variables

x_j: Number of representatives assigned to shift j.

y_i: Total representatives working in hour i, where $y_i = \sum_{j \in S} R_{ij}\, x_j$.

Model

$$\min \quad \sum_{i \in H} \left(a_i - \sum_{j \in S} R_{ij}\, x_j \right)^2 \tag{9.12}$$

$$\text{s.t.} \quad \sum_{j \in S} x_j \leq M \tag{9.13}$$

$$\sum_{j \in S} R_{ij}\, x_j \geq 1 \quad \forall i \in H \tag{9.14}$$

$$x_j \in \mathbb{Z}_+ \quad \forall j \in S \tag{9.15}$$

This model generates a feasible shift schedule when the number of available representatives is limited. It relaxes the strict requirement coverage constraint and minimizes the total squared deviation between staffing needs and actual shift assignments. Constraint (9.13) ensures that the total number of assigned representatives does not exceed the limit ands constraint (9.14) ensures there is at least one representative is assigned for each hour.

10 Özel Emeklilik Sisteminde Katılımcı Risk Profillerine Uygun Fon Seçkisi Oluşturulmasına Yönelik Derecelendirme Sistemi

Emeklilik Gözetim Merkezi

Proje Ekibi

Diyar Kağanarslan, Efe Deniz Karaaslan, Yiğit Işık Köymen,
Yener Doğa Öncel, Osama Tafish, Tolga Yılmaz, Ezgi Zeybek

Şirket Danışmanı
Hicran Aktaş Coşar
Genel Müdür Yardımcısı

Akademik Danışman
Doç. Dr. Çağın Ararat
Endüstri Mühendisliği Bölümü

Özet

Bu projenin amacı, bireysel emeklilik sisteminde katılımcıların risk profiline özel bir fon derecelendirme sistemi geliştirmektir. Bireysel emeklilik sisteminin başarısı, katılımcıların doğru yatırım tercihleriyle emeklilikte tatmin edici bir gelire ulaşmasına bağlıdır. Mevcut sistemde katılımcıların fon seçimi konusunda yeterli destek alamadığı tespit edilmiştir. Mevcut derecelendirme kurumlarının risk profiline özgü bir sistem sunmaması nedeniyle, TOPSIS yöntemi kullanılarak kişiselleştirilmiş bir fon öneri modeli geliştirilmiştir. Modeli doğrulamak için önde gelen derecelendirme kuruluşlarından biri tarafından yapılan fon derecelendirme sonuçları ile kıyaslama yapılmıştır. Modelin doğrulanmasına yönelik çalışmalara, EGM nezdinde devam edilecektir. Ayrıca, kullanıcıların erişimini kolaylaştırmak amacıyla mobil uyumlu bir tasarım hazırlanmıştır.

Anahtar Sözcükler: Emeklilik Gözetim Merkezi, Bireysel Emeklilik Sistemi, Otomatik Katılım Sistemi, Finansal Ürün Analizi, Emeklilik Tasarruf Yönetimi

Rating System for Creating a Selection of Funds Suitable for Participant Risk Profiles in Private Pension System

Abstract

The aim of this project is to develop a fund rating system tailored to participants' risk profiles within the individual pension system. The success of the pension system depends on participants making the right investment choices to achieve a satisfactory retirement income. It has been identified that participants currently receive insufficient support in selecting appropriate funds. Since existing rating agencies do not offer a system specific to individual risk preferences, a personalized fund recommendation model was developed using the TOPSIS method. To validate the model, a comparison was made with the fund rating results of a leading rating agency. Validation efforts will continue under the supervision of EGM. Additionally, a mobile-friendly design has been created to facilitate user access.

Keywords: Pension Monitoring Center, Private Pension System, Automatic Enrollment System, Financial Product Analysis, Retirement Savings Management

10.1 Company Information

Emeklilik Gözetim Merkezi (EGM), established in 2003, is responsible for ensuring the secure and effective operation of Türkiye's private pension (BES) and automatic enrollment (OKS) systems. As of October 15, 2024, BES and OKS have approximately 9.3 million and 7.6 million participants, respectively. EGM operates as a private company with the Ministry of Treasury and Finance and 16 pension providers as shareholders. As it mentioned in Emeklilik Gözetim Merkezi (2024), its main revenue (90%) comes from Monitoring Service Fees, with the rest from licensing exam fees for agents.

10.2 System Analysis and the Problem

10.2.1 System Analysis

EGM provides central monitoring service to both 17 million users and 15 companies with more than 400 funds and pension plans. EGM's primary goals are to ensure the secure and effective operation of the pension systems and to protect participant rights. Key operations include monitoring pension companies, managing state contributions, rating fund performance, handling complaints, and enabling system-wide data analysis. EGM collects and consolidates data from pension providers, Portfolio managers, Central

Securities Depository and Trade Repository of the Turkish Capital Markets,Takasbank, Reuters, and other data enablers to improve its oversight and services.

10.2.2 Problem Definition

In the current system, there are 17 million users. It is hard to expect every user in the system to have financial literacy. Furthermore, it is hard to keep track of all 400 pension funds, and categorize and rank them for personal preferences individually. EGM desires to create a supportive ranking system that will facilitate the decision system for the users' benefit. For this purpose, the performance measures considered are fund return rates, participant satisfaction, fund-switching frequency, and complaint volume. The deliverable is a data-driven decision support tool that improves fund selection for users, increases overall system transparency, and enhances customer satisfaction and at the end the overall success of the system.

10.3 Model and Proposed System

10.3.1 Conceptual Model

In this project, we aim to suggest to the users the best Pension Company and best Pension Funds according to user's expectations. For this purpose, we create a rating system that will support each user's decision-making process in choosing the best company and fund according to their best interests and preferences. We propose two different methods, offering two different evaluation and ranking solutions for the different needs of users: Company Rating System and Fund Ranking System. In addition to our user interface design, we create a new efficient flow for users. This flow is shown in Figure 10.1.

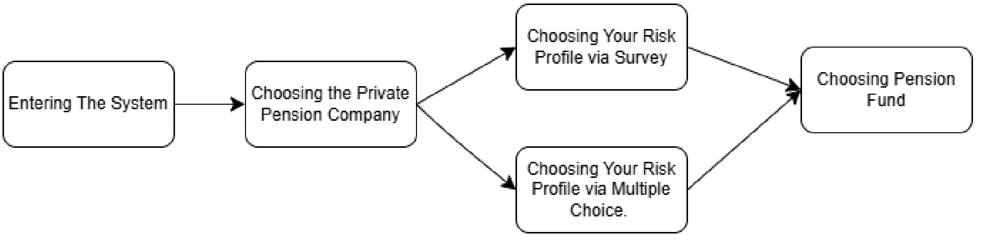


Figure 10.1: Information Flow

10.3.2 Company Rating System

There are fifteen Pension Companies in Turkey. To objectively rate these companies, we decided on several criteria. Some of these criterias are about the financial health of companies, and other criterias are about service quality. To calculate the financial health of the companies, we use financial ratios. These financial ratios, determined based on the suggestions we received from the company, are profitability, return on equity, economic profitability, operating profit margin, current ratio, and debt-to-equity ratio. In addition, we assign weights for each ratio with the expert opinion of EGM. These weights are shown in Figure 10.2.

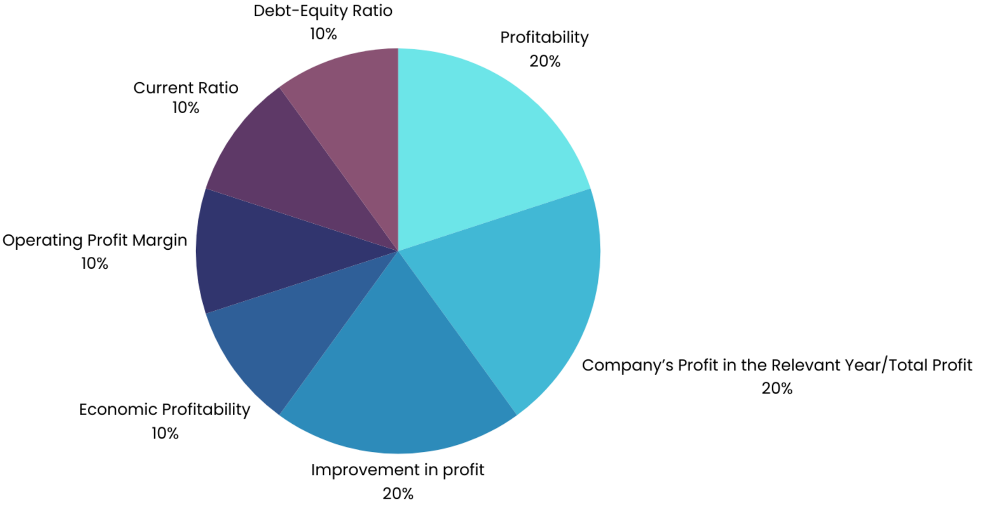


Figure 10.2: Weights of Ratios

In addition to the financial evaluation, we developed a second score to measure customer satisfaction for each company. This customer satisfaction score was designed based on a set of criteria mutually agreed upon with the company. The criteria include both service quality and operational efficiency indicators. However, as this collaboration is still ongoing, the final version of the customer satisfaction score will be incorporated into the project in the future.

Rather than combining the financial health score and the customer satisfaction score into a single index, we chose to present both scores separately to the users. This way, users will be able to view and evaluate both aspects independently when making their fund selection decisions.

10.3.3 Determining User's Risk Level

To determine users' risk profiles, we developed a survey based on research conducted by Ludens for the Pension Monitoring Center (Sarıoğlu and Baş, 2022). According to the scores obtained from the survey, users are categorized into different risk profiles. Based on these risk profiles, specific weights are assigned to each criterion in the Fund Rating System. In the survey, the first seven questions assess risk capacity, while the Financial Literacy

Checking Question measures risk perception. The weights assigned to each criterion for each risk profile are presented in Table 10.1.

Risk Profile	Sharpe Ratio (%)	Value at Risk (%)	Expected Shortfall (%)	Gain-Loss Ratio (%)
Low Risk	15	35	40	10
Medium Risk	25	30	30	15
High Risk	35	25	25	15
Very High Risk	40	20	20	20

Table 10.1: Weight Distribution for Risk Profiles and Ratios

10.3.4 Fund Rating System

The personalized fund rating system was created according to the results of the survey. Four main criteria were identified to evaluate the performance of the funds: Sharpe Ratio, Value at Risk, Expected Shortfall, and Gain/Loss Ratio. Additionally, from the work of Cheridito et al. (2006) the chosen ratios satisfy all the properties of Monotonicity. These criteria are as following: Each criterion's weight is based on the survey, where the risk capacity and risk perception of the user are assessed individually. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was employed to objectively rank the funds. TOPSIS is a multi-criteria decision-making method that ranks alternatives based on their distance to an ideal best and an ideal worst solution. Furthermore, it was proven by us that the TOPSIS method satisfies Pareto optimality; specifically, if alternative B performs better than alternative A in at least one criterion and is no worse in others, TOPSIS will rank B higher than A. In addition, we use exponential averaging because monthly ratios were calculated for each fund, but an aggregated ratio was required to apply the TOPSIS algorithm (Carhart, 1997).

10.3.5 TOPSIS Method Formulation

Definitions

- x_{ij}: Score of alternative (fund) i under criterion j.
- r_{ij}: Normalized value of x_{ij}.
- w_j: Weight of criterion j.
- f_{ij}: The weighted score for alternative i under criterion j.
- f_j^+: The best (most desirable) value for criterion j among alternatives.
- f_j^-: The worst (least desirable) value for criterion j among alternatives.

- D_i^+: Distance of alternative i from the positive ideal solution f_j^+.
- D_i^-: Distance of alternative i from the negative ideal solution f_j^-.
- C_i: Final TOPSIS score.
- k_n: Weight of time interval (month) for exponential weighting, where n represents the given date.
- t_n: The number of months between a given date n and the current date.
- λ: Constant that controls the rate at which weights decay. Larger values of λ lead to a steeper decline, making older data points less significant.
- x_{ijn}: Metric value of alternative i on criterion j for the given date n.

Equations

- **Normalization:**

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{10.1}$$

- **Weighted Score:**

$$f_{ij} = r_{ij} \times w_j \tag{10.2}$$

- **Distance from Positive Ideal Solution:**

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (f_{ij} - f_j^+)^2} \tag{10.3}$$

- **Distance from Negative Ideal Solution:**

$$D_i^- = \sqrt{\sum_{j=1}^{n} (f_{ij} - f_j^-)^2} \tag{10.4}$$

- **TOPSIS Score:**

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{10.5}$$

- **Formulation of Exponential Weighting:**

$$k_n = \exp\left(-\lambda \times (t_n + 1)\right) \tag{10.6}$$

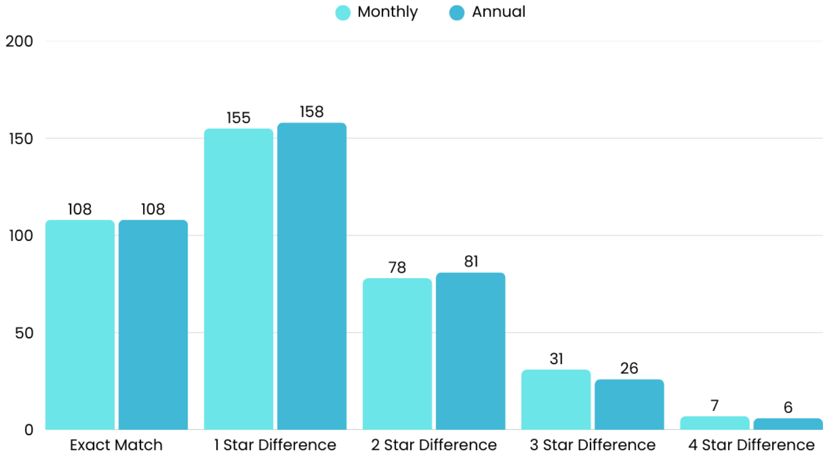


Figure 10.3: Comparison of Monthly and Yearly Results by Star Difference

- **Normalization of Weights:**

$$\bar{k}_n = \frac{k_n}{\sum_n k_n} \tag{10.7}$$

- **Final Weighted Average:**

$$\sum_n \bar{k}_n \times x_{ijn} \tag{10.8}$$

10.4 Validation

To validate our model, we have chosen one of the best known rating company. This company provides transparency by publishing the criteria used in their fund ratings on their official website, and their results are accessible through multiple platforms. Funds are evaluated according to these criteria and ranked from highest to lowest. Based on this ranking, the top 10% of funds are awarded 5 stars, the next 22.5% receive 4 stars, the following 35% receive 3 stars, the subsequent 22.5% receive 2 stars, and the bottom 10% are assigned 1 star.

For validation purposes, we adopted the same grading technique and applied equal weights to each of our selected criteria. By doing so, we ensured a fair and consistent comparison between our model's results and those of the independent agency. Following this approach, we conducted a sensitivity analysis and obtained the results presented in Figure 10.3.

The matching results are summarized in the table below. As shown, the percentage of funds with a perfect match (same star rating) is 28.6% for both monthly and yearly analyses. Additionally, small deviations (1-star and 2-star differences) cover a significant proportion of the funds, reflecting a strong alignment between our model and the independent ratings.

Percentage Table	Monthly	Yearly
Exact Match	28.6%	28.6%
1-Star Difference	40.9%	41.6%
2-Star Difference	20.6%	21.4%
3-Star Difference	8.1%	6.9%
4-Star Difference	1.8%	1.5%

Table 10.2: Monthly and Yearly Percentage Distribution

10.5 Integration and Implementation

EGM aims to build an integrated system that provides users with performance data, past results, and rating scores for all currently active pension funds. The goal of EGM is to offer customers access to a variety of statistics and scores for all funds. Results gathered from our personalized rating system, which utilizes the TOPSIS method, will be displayed within this integrated environment, alongside more conventional rating methods such as the Sharpe Ratio, Alpha value, and ratings provided by a reliable fund rating agency.

Furthermore, we have designed a user interface, as shown in Figure 10.4, for an application that will run independently and will be developed by professionals within EGM, implementing the TOPSIS-based system we have developed. In this application, users will be able to take a survey to determine their risk profiles or select a profile from four predefined options. After completing the survey or selecting a profile, users will be able to view the company rating scores and the fund ratings personalized according to their risk profiles. Users can search through the available funds and view detailed information about each fund by navigating to the respective fund's page.

On these fund pages, separate scores for each criterion—such as Sharpe Ratio, Value at Risk, Expected Shortfall, and Gain/Loss Ratio—can be viewed. Additionally, the application will include features that enable users to compare different funds and review the historical performance of each fund. The dynamic rating system algorithm we have developed will be embedded in the application, meaning that the ratings will be automatically updated whenever EGM inputs the latest available data for the funds.

10.6 Benefits to the Company

This project has several possible contributions to the company. EGM aims to provide guidance to all the participants and don't want to use one exclusive method. It wants to include different model and be as inclusive as

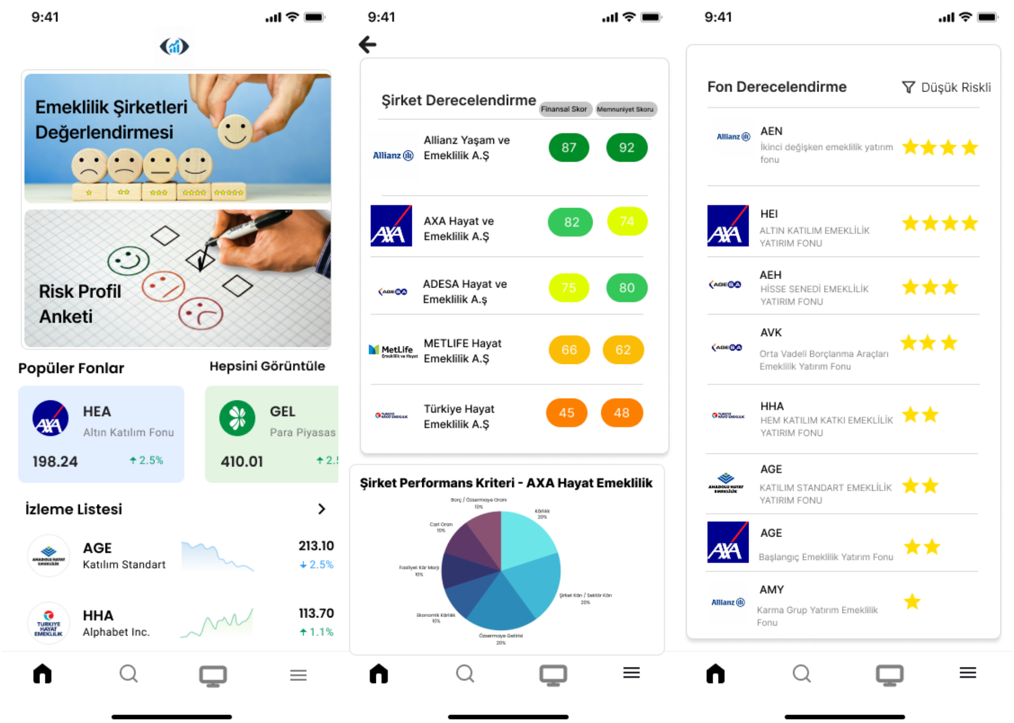


Figure 10.4: User Interface

possible. Therefore, the company will benefit from our rating system since the system consists of different criteria weighted according to the users' risk profiles, merging these criteria, that would normally be difficult for the general audience to understand and in- terpret, into a simple final score that is understandable for almost everyone

Executives of EGM are satisfied with the results of our project, since the validation and verification steps yielded successful results. Comparison of the results of our rating system with relevant indexes for each risk profile (BIST KYD DIBS for low risk, BIST100 RC10 for medium risk, BIST100 RC30 for high risk, and BIST100 for very-high risk) turned out high percentages of success. The top 10 suggestions resulted by our decision support system for four different risk profiles all had a 100% success rate, meaning that our system's top 10 suggestions had outperformed the top 10 results of the relevant indexes in all four risk profiles. Also, the top 10 suggestions yielded by our rating system were all different for the four different risk profiles. This shows that our project has indeed resulted in a personalized rating system, which was desired by EGM from the beginning. The performance of our decision support mechanism satisfied the company's expectations in terms of both accuracy and personalization.

10.7 Conclusions

In this project, we developed a personalized rating system for EGM to evaluate pension funds based on users' risk profiles. By using the TOPSIS method and applying different weights according to the risk levels, we created a system that gives simple and understandable scores for all users. Additionally, project includes company rating measuring financial performance of pension companies.

The results showed that our system worked successfully by outperforming the benchmark indexes for all risk profiles. With this system, EGM can now manage and update both fund and company ratings independently, making it more flexible and less dependent on external agencies. Overall, the project achieved its goals and provided EGM with a strong tool for improving their services.

Bibliography

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance 52*(1), 57–82.

Cheridito, P., F. Delbaen, and M. Yor (2006). Reward-risk ratios. *Journal of Risk*.

Emeklilik Gözetim Merkezi (2024, August). Emeklilik gözetim merkezi. Accessed on 6 November 2024.

Sarıoğlu, S. E. and N. K. Baş (2022, July). EGM Risk Profili Anketi Puanlama Metodolojisi Raporu. Technical report, Prepared for Emeklilik Gözetim Merkezi (EGM) BEFAS Bilgilendirme Platformu.

11 | Palet Ayak İzi ve Araç İçi Doluluğunun Eniyilenmesi

Nestlé Türkiye

Proje Ekibi
Aslı Baytar, Ada Çalışkan, Berkay Hoşafçı,
Zeynep Kaynak, Alpaslan Kızıltaş, Ece Şenoğlu, Alperen Yıldız

Şirket Danışmanları
Selami Çakmak, Kıdemli Ulaşım Yöneticisi
Nazlı Çetin Berber, Ulaşım Yöneticisi
Elçin Kocaman, BT İnovasyon Yöneticisi

Akademik Danışman
Doç. Dr. A. Selin Kocaman
Endüstri Mühendisliği Bölümü

Özet

Çevreye duyarlılık ve sürdürülebilirlik ilkelerine odaklanan Nestlé, araç içi doluluğunu artırarak sevkiyatlarındaki karbon emisyonlarını ve maliyetleri azaltmayı hedeflemektedir. Proje kapsamında Karacabey Fabrikası'ndan dağıtım merkezlerine yapılan sevkiyatlarda kullanılan tır sayısının en aza indirilmesi amaçlanmıştır. Bu doğrultuda, Kutu Yerleştirme Problemi temelli bir matematiksel model içeren sezgisel bir yaklaşım ve Açgözlü Arama tabanlı bir sezgisel yaklaşım geliştirilmiştir. Bu yaklaşımlar kullanıcı dostu bir karar destek sistemine entegre edilmiştir. Geliştirilen bu sistem sayesinde, yıllık ortalama 163 tırın daha az kullanılmasıyla $144.260 değerinde maliyet tasarrufu sağlanmış ve 33.385 kg karbon emisyonu azaltılarak 1.590 ağacın kurtarılmasına olanak tanıyan bir yük planlayıcısı ortaya konulmuştur.

Anahtar Sözcükler: Araç içi doluluk, Kutu Yerleştirme Problemi, sevkiyat, karbon emisyonu.

Optimizing Pallet Footprint and Vehicle Loading

Abstract

Nestlé, focused on environmental sustainability and eco-conscious principles, aims to reduce carbon emissions in its shipments by increasing vehicle capacity utilization. The project aims to minimize the number of trucks used for shipments from the Karacabey Factory to distribution centers. To achieve this, a Bin Packing Problem-based matheuristic and a Greedy Search-based heuristic approach have been developed. These approaches are integrated into a user-friendly decision support system. Through the developed system, an annual reduction of about 163 trucks has been achieved, saving $144,260 in costs and cutting 33,385 kg of carbon emissions, which is equivalent to saving 1,590 trees.

Keywords: Vehicle capacity utilization, Bin-Packing Problem, shipment, carbon emission.

11.1 Company and System Analysis

This section discusses Nestlé's brief history and description in Turkey, as well as how the current system operates.

11.1.1 Company description

Nestlé, the world's largest food and beverage company, operates nearly 500 factories worldwide. Nestlé's first sales office in Turkey opened in 1909 and its first chocolate factory in 1927. Today, the company offers 800 products in seven categories in Turkey, with shipments distributed through four centers: Bursa, Gebze, Ankara, Osmaniye (Nestlé S.A., 2024; Nestlé Türkiye, 2024).

Committed to environmental sustainability, Nestlé launched the Net Zero 2050 project to reduce CO_2e emissions to zero by 2050. In 2018, logistics-related emissions were 7.5 million tons, projected to reach 10 million tons by 2030. By improving vehicle load efficiency, 0.4 million tons of emissions could potentially be reduced (Nestlé S.A., 2023).

11.1.2 Current system analysis

Nestlé Karacabey Factory operates a large-scale distribution network involving stock transfers of finished goods. There are three different types of stock keeping units (SKUs): short-light, short-heavy, and long. Long and short-heavy SKUs cannot be carried on top of any SKU. On the other hand, short-light SKUs can be carried on short-heavy and short-light SKUs.

Two types of trucks are utilized for shipments of these SKUs: tente (nontemperature controlled), and frigo (temperature controlled) trucks. SKUs shipped in a tente truck can also be shipped in a frigo truck if necessary. For every truck, 33 euro pallets fit on both of these trucks' bases and if the pallets' height and weight are suitable, an additional floor can also be arranged on top of the first floor. The logistics operation runs 24 hours a day, with the factory preparing the pallets starting at midnight. The factory has limited storage space; therefore, SKUs need to be shipped as soon as possible. While the number of trucks shipped per day is 20-24 in regular periods, this number may increase to 66 trucks per day due to the significant increase in demand or extreme cases in the production plan. These types of cases require careful scheduling to avoid delays and capacity issues.

11.2 Problem Definition

In accordance with the project scope, Nestlé's domestic supply chain focuses on maximizing vehicle capacity utilization (VCU) and reducing CO_2e emissions for shipments from the Bursa Karacabey Factory to the distribution centers in Bursa, Gebze, Ankara, and Osmaniye.

Shipment operations follow a weekly cycle. One week before production begins, the production plan is finalized. At the end of the week, the weekly shipment plan for the following week is prepared. The shipment plan must be finalized within 22 hours of its receipt. Consequently, the total runtime of the proposed solution approach does not exceed 22 hours.

The current human-dependent loading process lacks an automated load planner to optimize pallet patterns, resulting in operational inefficiencies. VCU experienced a year-on-year decline, dropping from 72.7% in 2023 to 71.6% in 2024. Therefore, the project aims to restore and improve those utilization rates. Nestlé conducts an annual operation that involves approximately 70,000 to 75,000 pallets in total. This substantial amount of pallet movement demonstrates the significant demand and operational scale needed to fulfill Nestlé's distribution goals across different regions. Effectively managing the pallet pattern is crucial for logistics operations to ensure product safety and transportation efficiency. The goal is to achieve an improvement in VCU by optimizing shipping processes to reduce CO_2e emissions, which is crucial for supporting Nestlé's sustainability goals.

11.3 Proposed Solution Methodology

This section describes the critical assumptions, major constraints, objectives, solution approach, conceptual model, and mathematical model used to solve the problem.

11.3.1 Critical assumptions

SKU heights are assumed to be fixed, and truck shipment times are assumed to be deterministic. Reliance on third-party logistics providers removes any daily limit on truck availability. Furthermore, the loaded SKUs have the same base dimensions as the base area of the pallets (80 cm x 120 cm), ensuring complete coverage without overflow or unused space. SKUs rarely fail quality control. Therefore, these cases are assumed not to occur. Finally, since there are no rush orders, no emergency shipment occurs.

11.3.2 Major constraints

The solution approach incorporates several constraints that reflect real-life regulations and operational restrictions. Certain SKUs can be stacked on top of each other, while others cannot due to varying weight-bearing capacities. This information is used as a parameter based on company data. For the solution approach, the bases of the trucks are divided into 33 equal slots. In cases where the height and weight restrictions are met, an additional imaginary second floor inside the truck with 33 new slots is created and the maximum number of slots that could be placed for both trucks increases to 66. Each SKU is assigned to a single slot. For SKUs on the second floor, if an SKU is carried on another SKU, it gets the $(i+33)^{\text{th}}$ slot on the second floor that is on top of the i^{th} slot on the first floor.

11.3.3 Objectives

The aim of the project is to reduce carbon footprint and transportation costs by decreasing the total truck usage while ensuring on-time delivery. A solution approach with the objective of minimizing the number of trucks used in shipments is developed. This approach increases the VCU rate and reduces carbon emissions.

11.3.4 Solution approach

Given the extensive shipment history at Nestlé's Karacabey Factory, we analyzed historical data on VCU values, SKU dimensions, and truck specifications. Using tools such as Excel, R, and Python, potential correlations in the data are examined. A mathematical model based on the Bin Packing Problem (BPP)was customized and implemented using integer programming with the Gurobi solver in Python, which was later converted to the open-source HiGHS solver. As found in the literature review, BPP is NP-Hard, meaning model runtime increases exponentially with the number of SKUs. In extreme cases where the mathematical model could not provide results within the required time frame, a Greedy Search Heuristic was developed as an alternative solution method.

Although the model produced results within the time threshold, its runtime was still impractical for frequent use. Two key improvements are proposed to enhance performance. Initially, the stackability matrix used by the model was highly complex. The stackability rules were revised to simplify complexity by adopting category-based definitions (short-heavy, short-light, long) instead of SKU-ID-specific stacking rules. Secondly, to reduce the feasible region, the assignment of long SKUs to trucks early in the process was prioritized. It is ensured that the total long SKU weights did not exceed truck capacity, and stackability was preserved as long SKUs could not be stacked on or under other SKUs. These significantly reduced the complexity of the compatibility matrix and improved model performance.

During the pilot study, the Nestlé team introduced swapping flexibility that allows changing the shipment destination of SKUs across different days while keeping the shipment day fixed. In this approach, the total number of each SKU sent to a specific destination must remain constant over the week. However, the specific day they are sent to a particular destination can vary. This is only permitted if the SKUs being swapped have the same SKU ID, ensuring SKU consistency. This swapping was not considered in the initial phase of the solution approach. To adopt this valuable opportunity for optimization, the model was first updated to incorporate swapping. However, the expanded feasible region made it impossible to obtain results within the required time frame. As a solution, a swapping heuristic algorithm was developed that takes the model's output as input and identifies beneficial day swaps to reduce total truck usage. Since the final result is derived through both mathematical modeling and heuristic adjustments, this approach is classified as a matheuristic method. After observing promising results, the swapping algorithm was also integrated into the Greedy Search Heuristic.

As a result, the solution approach in the decision support system consists of construction and improvement steps. The construction step starts with the mathematical model or the Greedy Search Heuristic. After the construction step finishes, the swapping algorithm tries to improve the solution as part of the improvement step.

While the Matheuristic generally produces better results, it requires more computation time. Therefore, the system runs both approaches in parallel. Since there is a trade-off between solution quality and runtime, the decision support system leaves the final decision to the user to make it more convenient.

11.3.5 Conceptual model

The load planning system requires two input types: fixed and variable. Fixed information is provided to the model in advance. This information

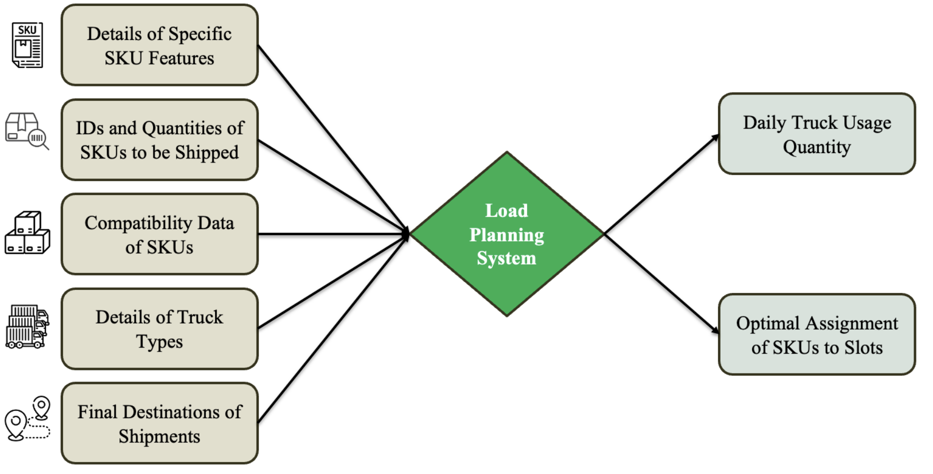


Figure 11.1: Schematic Representation

includes details of SKUs, compatibilities of SKUs, and truck type details. These parameters are consistent across shipments, allowing them to be reused for each run. However, when the company runs the system, two variable inputs are required: SKU IDs with weekly shipment quantities and their final destinations. These parameters need to be updated and taken as input for each run.

Once all inputs are entered, the load planning system executes the solution approach and outputs the number of trucks needed along with the placement of each SKU within the truck. The representation of the entire system can be seen in Figure 11.1.

11.3.6 Mathematical model

The mathematical model is in the appendix with explanations of the sets and parameters, decision variables, objective function, and constraints.

As previously stated, the objective function is to minimize the number of trucks used for weekly shipments. In addition, it incorporates a penalty cost for loading SKUs into frigo trucks when they could instead be loaded into tente trucks. This penalty discourages the overuse of frigo trucks, given their higher costs and greater carbon emissions.

Constraint (11.1) ensures that each SKU is assigned exactly once to one of the slots. Constraint (11.2) prevents long and short-heavy SKUs from being placed in the upper floor slots. Constraint (11.3) implies that no SKU can be put on long SKUs. Constraint (11.4) guarantees that there is sufficient support for the SKUs placed on the upper floor in a truck. Constraint (11.5) prevents overlapping or double assignment in a single slot. Constraint (11.6) ensures that if an SKU is placed in a truck, that truck is marked as used. Constraint (11.7) guarantees that the truck's load does not exceed its limit. Constraint (11.8) ensures that each used truck is assigned exactly one truck type. Constraint (11.9) ensures that SKUs that need temperature protection can only be placed in frigo trucks, while other SKUs can be placed in both frigo and tente trucks. Constraints (11.10), (11.11), and (11.12) indicate that variables are binary.

11.3.7 Heuristic algorithm

The Greedy Search Heuristic begins by sorting SKUs in descending order of height. It then prioritizes loading the long SKUs into the trucks in groups of 33. After the maximum number of trucks are fully loaded with 33 long SKUs, firstly the remaining long SKUs and then the short-heavy SKUs are placed onto the first floor of the trucks. If there is remaining space on this first floor, short-light SKUs are also loaded. Subsequently, the heuristic checks whether these short-light SKUs can be stacked on top of other SKUs in accordance with the stacking rules. If stacking is feasible, the heuristic places them accordingly. This process continues, assigning SKUs to the truck until its capacity is reached. Once a truck is fully loaded, the algorithm moves to the next truck, repeating this process until all SKUs are allocated.

11.4 Validation

Validation of the matheuristic and the heuristic are carried out to check the credibility of our solution approaches and to see whether they could work in a real-life system. The validation is carried out using Nestlé's demand and supply planning data of February and March 2025. This data provides detailed information on the SKU shipment, including the quantity dispatched, the designated distribution center, and the corresponding shipment date. Industrial Advisors (IAs) carefully reviewed how inputs are handled, the type of outputs generated, and the overall structure of the matheuristic and heuristic. After assessing these aspects, they confirmed its validity, acknowledging that it accurately reflects the real-world dynamics of the problem being addressed. This confirmation reinforces the reliability of the approach and its applicability. The matheuristic and heuristic outputs were compared to the historical data provided. The heuristic results were very similar to the historical data, especially since the number of trucks used in shipments was the same. However, the matheuristic's results were better than those observed in the current system. This finding suggests that a theoretical improvement is achievable by the solution approach. For example, based on the validation for February and March 2025, the average results in Table 11.1 are obtained, showing a direct improvement in the number of trucks used and the VCU rate.

Table 11.1: Validation summary

	# of Trucks	VCU	Carbon Footprint
Current Plan (Nestlé)	110	71.6%	29,919.06 kg
Load Planner	97	73.04%	29,277.04 kg
Improvement	2.73%	2.01%	2.15%

11.5 Implementation and Pilot Study

Site visits were conducted at Nestlé's Karacabey Factory and Bursa Distribution Center to adapt the decision support system under real operating conditions. The decision support system, developed as a Python-based application with an HTML front-end, had previously been tested and confirmed to operate smoothly on Nestlé's servers, meeting security and access requirements. Feedback from the Transportation, Innovation, and Technology teams was incorporated, and the finalized decision support system was delivered for trial use, which was highly appreciated and deemed useful by the IAs. The pilot study began on April 18, coinciding with the company's shipment planning day. Testing with shipment data from Weeks 16 and 17 of 2025 showed that the system provided a more efficient pallet pattern than the current system, meeting expectations according to IAs and the transportation team.

11.6 Benchmarking and Benefits

A comparative analysis is conducted between the current system and the outcomes generated by the proposed load planner, utilizing historical shipment data provided by Nestlé. One of the key performance indicators (KPIs) considered in this analysis is the number of trucks used, as it directly reflects potential reductions in transportation costs and carbon emissions per truck.

Table 11.2 summarizes the yearly impact of the project by projecting weekly reductions over one year. Each KPI is calculated from the aver-

Table 11.2: Yearly Average Impact of the Project

KPI	Value	Anticipated Value
Number of trucks reduced	163	1,649
Carbon footprint reduced	33,384.71 kg	337,846.27 kg
Cost saved	$144,260	$1,459,906
Trees saved	1,590	16,091

age weekly savings observed after implementation, then multiplied by 52 to estimate the annual contribution. Initially limited to pilot tests at distribution centers, the project will soon expand to cover all Nestlé Türkiye shipments, from factories to distribution centers and customers nationwide. Based on company data, the projected yearly impact of full implementation, indicated as the anticipated value, shows substantial benefits for both the company and the environment. This approach clarifies the long-term economic and environmental benefits, highlighting the importance of continuous operational optimization for broader sustainability goals.

The project aims to reduce costs and carbon emissions while ensuring on-time delivery within a 22-hour weekly time frame. To achieve this, a load planner is developed for Nestlé to generate weekly load plans, featuring an HTML-based decision support system designed for easy web deployment. It allows users to upload shipment data, SKU info, and truck type data via Excel files, which the heuristic and matheuristic use to generate efficient load plans. The main page of the load planner can be seen in Figure 11.2.

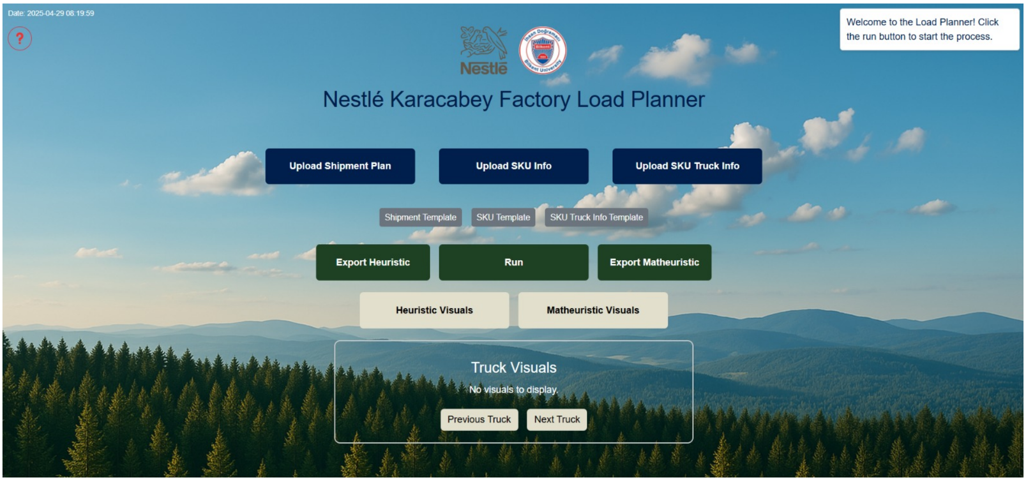


Figure 11.2: Decision Support System Main Page

To improve user experience, a user manual is provided, accessible through a red question mark icon at the top left corner of the page, offering a comprehensive step-by-step guide for using the load planner. After the user uploads the Excel files and clicks the “Run” button, both the matheuristic and the heuristic algorithm are executed simultaneously. The decision support system delivers the complete weekly load plan in a significantly shorter time compared to the current operational time frame. Once the process is complete, users can separately export the weekly load plans generated by the matheuristic and the heuristic as Excel files using the export buttons. Additionally, visual representations are provided to show how the pallets are arranged inside the truck according to the generated loading plan. The results are displayed as in Figures 11.3 and 11.4.

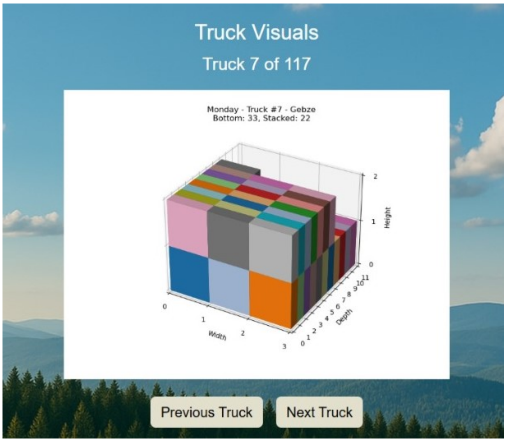


Figure 11.3: Truck Visual 1

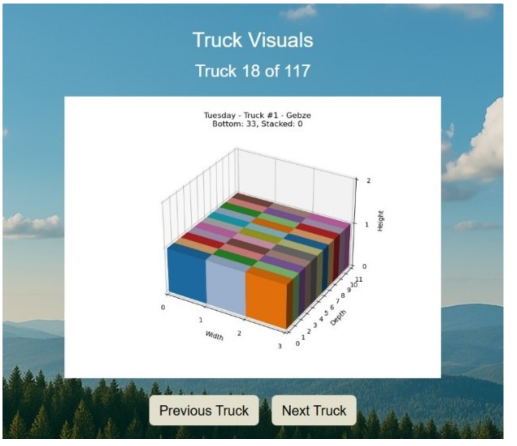


Figure 11.4: Truck Visual 2

11.7 Conclusion

The project provides the Nestlé Transportation team with a significant opportunity to optimize vehicle utilization. By considering SKU types and shipment quantities, the decision support system leverages a Bin Packing Problem-based matheuristic alongside a Greedy Search Heuristic to allocate SKUs within vehicles optimally. This system reduces human errors and process inefficiencies. As a consequence, VCU is increased while the number of trucks is reduced, thereby lowering both transportation costs and the emitted carbon footprint.

At the end of this project, the annual reduction of 163 trucks has led to a 33,384.71 kg decrease in carbon emissions, aligning with Nestlé's environmental goals. These improvements also generate $144,260 in savings, equivalent to saving 1,590 trees each year. VCU improved from 71.6% to 73.04%. In conclusion, the project not only boosts Nestlé's financial performance but also plays a crucial role in advancing its sustainability goals.

Bibliography

Nestlé S.A. (2023). Creating Shared Value and Sustainability Report 2023.

Nestlé S.A. (2024). Nestlé Company History. https://www.nestle.com/about/history/nestle-company-history [Online; accessed 24-October-2024].

Nestlé Türkiye (2024). Nestlé Hakkında. https://www.nestle.com.tr/hakkimizda [Online; accessed 24-October-2024].

Appendix: Mathematical Model

Table 11.3: Sets and parameters

Symbol	Description
$\mathcal{I}$	Set of SKUs
$\mathcal{B}$	Set of available trucks
$\mathcal{L}$	Lower slots: $\{1, 2, \ldots, 33\}$
$\mathcal{U}$	Upper slots: $\{34, 35, \ldots, 66\}$
$\mathcal{S}$	Set of all slots: $\mathcal{L} \cup \mathcal{U}$
$\mathcal{T}$	Set of truck types: {frigo, tente}
w_i	Weight of SKU i
c_i	Category of SKU i; $c_i \in \{\mathrm{L}, \mathrm{SH}, \mathrm{SL}\}$
δ_i	1 if SKU i requires tente truck, 0 otherwise
C_{f}	Capacity of frigo truck
C_{t}	Capacity of tente truck
λ	Penalty parameter for frigo truck usage

Table 11.4: Decision variables

Symbol	Description
$z_{i,s,b} \in \{0, 1\}$	Binary variable indicating whether SKU i is placed in slot s in truck b, where $i \in \mathcal{I}$, $s \in \mathcal{S}$, $b \in \mathcal{B}$
$y_b \in \{0, 1\}$	Binary variable indicating whether truck b is used, where $b \in \mathcal{B}$
$u_{b,t} \in \{0, 1\}$	Binary variable indicating whether truck type t is used for truck b, where $b \in \mathcal{B}$ and $t \in \mathcal{T}$

Objective Function

$$\min \quad \sum_{b \in \mathcal{B}} y_b + \lambda \sum_{b \in \mathcal{B}} u_{b,\mathrm{frigo}}$$

Constraints

$$\sum_{b \in \mathcal{B}} \sum_{s \in \mathcal{S}} z_{i,s,b} = 1, \qquad \forall i \in \mathcal{I} \tag{11.1}$$

$$z_{i,s,b} = 0, \qquad \forall i \in \mathcal{I},\ c_i \in \{\mathrm{L}, \mathrm{SH}\},\ \forall b \in \mathcal{B},\ \forall s \in \mathcal{U} \tag{11.2}$$

$$\sum_{i:\, c_i \in \{\mathrm{L}\}} z_{i,s,b} + \sum_{j \in \mathcal{I}} z_{j,s+33,b} \leq 1, \qquad \forall b \in \mathcal{B},\ \forall s \in \mathcal{L} \tag{11.3}$$

$$\sum_{i:\, c_i \in \{\mathrm{SL}\}} \sum_{s \in \mathcal{U}} z_{i,s,b} \leq \sum_{i:\, c_i \in \{\mathrm{SL},\mathrm{SH}\}} \sum_{s \in \mathcal{L}} z_{i,s,b}, \qquad \forall b \in \mathcal{B} \tag{11.4}$$

$$\sum_{i \in \mathcal{I}} z_{i,s,b} \leq 1, \qquad \forall b \in \mathcal{B},\ \forall s \in \mathcal{S} \tag{11.5}$$

$$z_{i,s,b} \leq y_b, \qquad \forall b \in \mathcal{B},\ \forall i \in \mathcal{I},\ \forall s \in \mathcal{L} \tag{11.6}$$

$$\sum_{i \in \mathcal{I}} \sum_{s \in \mathcal{S}} w_i \cdot z_{i,s,b} \leq C_{\mathrm{f}} \cdot u_{b,\mathrm{frigo}} + C_{\mathrm{t}} \cdot u_{b,\mathrm{tente}}, \qquad \forall b \in \mathcal{B} \tag{11.7}$$

$$\sum_{t \in \mathcal{T}} u_{b,t} = y_b, \qquad \forall b \in \mathcal{B} \tag{11.8}$$

$$\sum_{s \in \mathcal{S}} z_{i,s,b} \leq u_{b,\mathrm{frigo}} + \delta_i \cdot u_{b,\mathrm{tente}}, \qquad \forall i \in \mathcal{I},\ \forall b \in \mathcal{B} \tag{11.9}$$

$$z_{i,s,b} \in \{0,1\}, \qquad \forall i \in \mathcal{I}, \forall s \in \mathcal{S}, \forall b \in \mathcal{B} \tag{11.10}$$

$$y_b \in \{0,1\}, \qquad \forall b \in \mathcal{B} \tag{11.11}$$

$$u_{b,t} \in \{0,1\}, \qquad \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \tag{11.12}$$

12 | Personel Servisleri Durak Düzenlenmesi ve Rota Eniyilemesi

Beko Pişirici Cihazlar İşletmesi

Proje Ekibi

Ece Aysoy, Yunus Emre Burca, Yaren Nehir Çoban
Amine Berra İşler, Mehmet Kerem Kaya, Atakan Öktem, Berfin Özbek

Şirket Danışmanı
Ufuk Çetek
Sosyal ve İdari İşler Uzmanı

Akademik Danışman
Dr. Emre Uzun
Endüstri Mühendisliği Bölümü

Özet

Bu projede, Beko Bolu Pişirici Cihazlar Fabrikası'nın personel servis sistemi için bir eniyileme çözümü sunulmaktadır. Çalışan sayısının vardiyalara ve dönemsel istihdama bağlı olarak değişkenlik göstermesi, mevcut sistemdeki servis rotalarının verimsizliğine yol açmaktadır. Beko Bolu Pişirici Cihazlar Fabrikası'nda durakların konumunu yeniden belirleyerek ve rota yapılarını sezgisel algoritmalarla eniyileyerek, araç sayısında %32,69, toplam günlük maliyette ise %23,37 oranında iyileştirme sağlanabilmektedir.

Anahtar Sözcükler: Rotalama, durak yerleşimi, heterojen araç rotalama problem (HVRP), personel taşımacılığı, sürdürülebilirlik.

Stop Rearrangement and Routing Optimization of Employee Transportation

Abstract

This project presents an optimization solution for the personnel transportation system of the Beko Bolu Cooking Appliances Factory. Variations in the number of employees due to shift schedules and seasonal employment lead to inefficiencies in the current service routes. By redefining the locations of the bus stops and optimizing the route structures using heuristic algorithms, it is possible to achieve a 32.69% reduction in the number of vehicles and a 23.37% improvement in the total daily cost at the Beko Bolu Cooking Appliances Factory.

Keywords: Routing, heterogeneous vehicle routing problem, dynamic routing, employee transportation, sustainability

12.1 Problem Definition

Bolu Cooking Appliances Factory provides employee transportation through 52 routes operated by two different contracted companies, dividing the city into two service regions (Sezer Proje, 2024). The system currently utilizes a heterogeneous fleet composed of 25 buses with a 35-passenger capacity, 20 midibuses with a 27-passenger capacity, and 7 minibuses with a 16-passenger capacity, serving a total of 181 designated stops. The factory operates on a three-shift schedule: Shift A (00:00–08:00) with 240 employees, Shift B (08:00–16:00) with 1,200 employees, Shift C (16:00–00:00) with 800 employees, an additional standard shift (08:00–17:30) with 250 employees. The transportation planning primarily focuses on Shift B, during which the majority of employees require transportation. Currently, transportation planning is conducted weekly following the production plan, which dictates assembly line schedules and employee allocation per shift. Based on this information, vehicle assignments are manually adjusted by considering the determined shift schedules, employee amounts and the vehicle occupancy rates of the previous week. However, due to irregular and dynamic employee behavior including variable attendance, changing shifts, and seasonal hiring, demand fluctuates significantly. This creates challenges in maintaining efficient transportation operations and results in underutilization of vehicle capacities. Moreover, planning based solely on historical patterns is insufficient to respond to these variations. These inefficiencies lead to increased operational costs, unnecessary fuel consumption, and higher carbon emissions. In addition, current stop configurations are also based on historical patterns and not optimized to the current workforce, 72.93% of stops have another stop located within a 500-meter radius, which is the maximum walkable distance accepted by the company. The proximity of stops results in overlapping service areas, increasing total travel distance and reducing overall route efficiency.

12.2 Proposed Solution Strategy

To address the problem defined in Section 12.1, the solution strategy proposes the restructuring of employee transportation through a mathematical model that assigns stops and routes to vehicles of different types. Our initial priority was to develop and run a mathematical model using the data provided by the company to generate an optimal routing plan. However, due to the computational complexity and prolonged solution times, especially under high-demand scenarios, heuristic methods were also employed. Critical assumptions were defined, and major constraints were incorporated throughout the model development process.

12.2.1 Critical Assumptions

There are five critical assumptions considered during the development of the mathematical model. Firstly, the routes serving rural areas are treated as fixed due to limited infrastructure and the lack of alternative paths and thus are excluded from the optimization process. Secondly, the travel time and distance required for vehicle drivers to reach the first or last stop from their homes are assumed to be out of the scope of the project. Thirdly, once a vehicle departs from its first stop, it cannot return to pick up any employee who missed the vehicle. In addition, the stopping time spent at each stop is considered to be uniform, regardless of location or demand. Lastly, it is assumed that weekly transportation demand remains stable, with no significant fluctuations occurring throughout the week.

12.2.2 Major Constraints

The model incorporates several real-world operational constraints while generating feasible transportation plans. Each employee must be assigned to a stop within a 500-meter walking distance from their residence, in accordance with company policy. The total duration of any vehicle's route is restricted to a maximum of 20 minutes to ensure timely arrival before shift start times. Vehicle occupancy should not exceed a company-defined threshold to accommodate potential fluctuations in demand. Furthermore, the total number of available vehicles is limited to 52, which reflects the current operational fleet size. Finally, each stop has a capacity limit based on the company's specifications.

12.2.3 Objectives

The primary objective of this project is to minimize total employee transportation costs, which consist of fixed rental fees for each vehicle and variable costs calculated based on the distance traveled and the cost per kilometer. The aim is to generate a weekly transportation plan that enhances vehicle utilization through effective stop and route assignments.

12.2.4 Solution Approach

The project explores two distinct solution approaches: existing stops and rearranged stops. Both approaches aim to support adaptability to changes, such as seasonal workforce fluctuations, focusing on creating a more cost effective routing solution through a Vehicle Routing Problem (VRP) model (Toth and Vigo, 2014)

Existing Stops Approach retains the current set of stops with the flexibility to eliminate redundant ones but without introducing new stops.

Rearranged Stops Approach offers flexibility by dynamically determining stop locations based on employee addresses provided by the company. This method is applied to the urban area of Bolu, defined within a polygonal boundary, while rural routes remain fixed due to limited alternatives. A 500-meter radius, representing the company's maximum allowable walking distance, is used to generate a grid of candidate stop locations based on street intersections and nodes obtained using the OpenStreetMap API. The stop selection algorithm begins from the polygon edges and iteratively adds stops to maximize area coverage with minimal overlap. Initially, 69 stops were identified to ensure 100% coverage. A refinement step was then applied to remove stops located within 500 meters of each other, reducing the final number of stops to 65 while maintaining a near-full coverage ratio of 99.96%. In the current system, there are approximately 100 stops within this area. Rearrangement process resulted in a 35% improvement over the current system.

To utilize these two approaches, according to the objective defined in Section 12.2.3, a mathematical model aiming to minimize total employee transportation costs is developed. Mathematical model provides the most efficient routing arrangement for a given demand distribution of the stops complying with travel time limitations, maximum walking distance, and the capacity of each vehicle. In the next step, a Tabu Search heuristic algorithm is developed to produce similar outputs in a near-optimal manner. For verification and validation, real datasets provided by the Beko team were utilized to evaluate the performance and applicability of the proposed methods.

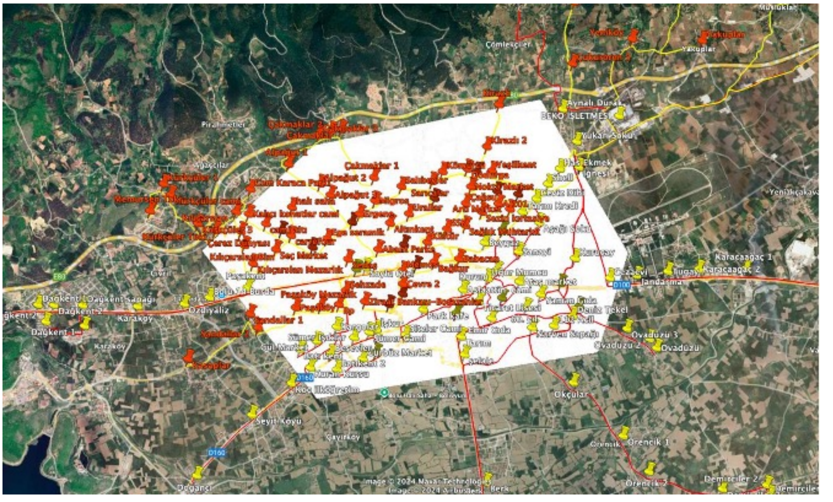


Figure 12.1: Current stops in the urban area covered by the polygon

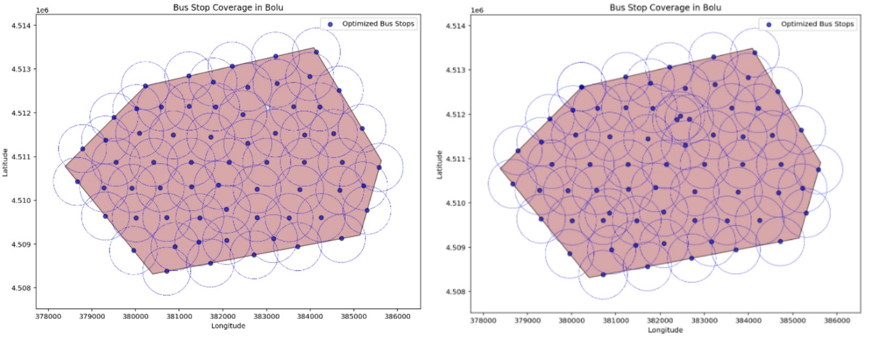


Figure 12.2: Rearranged stops in the urban area with 99.96% and 100% coverage ratio respectively

Mathematical Model

We developed an extension of the Open Heterogeneous Fleet Vehicle Routing Problem to address the specific operational requirements of Beko (Sariklis and Powell, 2000).

Index Set

- $k \in K$: Index set for all vehicles.
- $k \in \{1, 2, \ldots, M\}$: Vehicles of type m.
- $k \in \{M+1, M+2, \ldots, N\}$: Vehicles of type n.
- $k \in \{N+1, N+2, \ldots, K\}$: Vehicles of type l.
- $i, j \in V$: V is the set of all stops, including starting stop 0.

Parameters

- c_m: Cost per kilometer for vehicles of type m.
- c_n: Cost per kilometer for vehicles of type n.
- c_l: Cost per kilometer for vehicles of type l.
- d_{ij}: Distance between stop i and stop j.
- f_m: Fixed cost of renting a single vehicle of type m.
- f_n: Fixed cost of renting a single vehicle of type n.
- f_l: Fixed cost of renting a single vehicle of type l.
- Q_k: Capacity of vehicle of type k.
- e_i: Number of employees at stop i.
- S: Average speed of vehicles.
- T: Maximum allowable time for routes.

Decision Variables

$$x_{ij}^k = \begin{cases} 1, & \text{if vehicle } k \text{ travels from stop } i \text{ to stop } j, \\ 0, & \text{otherwise.} \end{cases}$$

$$y_i^k = \text{Load of vehicle } k \text{ upon departing stop } i.$$

Model

$$\begin{aligned} \min \quad & \Big(f_m \sum_{k=1}^{M} \sum_{j \neq 0} x_{0j}^k + f_n \sum_{k=M+1}^{N} \sum_{j \neq 0} x_{0j}^k + f_l \sum_{k=N+1}^{K} \sum_{j \neq 0} x_{0j}^k \\ & + \sum_{k=1}^{M} \sum_{i \neq 0} \sum_{j \neq 0} c_m (d_{ij} x_{ij}^k) + \sum_{k=M+1}^{N} \sum_{i \neq 0} \sum_{j \neq 0} c_n (d_{ij} x_{ij}^k) \\ & + \sum_{k=N+1}^{K} \sum_{i \neq 0} \sum_{j \neq 0} c_l (d_{ij} x_{ij}^k)\Big), \end{aligned} \tag{12.1}$$

s.t.

$$\sum_{k \in K} \sum_{i \neq j} x_{ij}^k = 1, \quad \forall j \in V \setminus \{0\}, \tag{12.2}$$

$$\sum_{k \in K} \sum_{j \neq i} x_{ij}^k \leq 1, \quad \forall i \in V \setminus \{0\}, \tag{12.3}$$

$$\sum_{i \neq j} x_{ij}^k - \sum_{i \neq j} x_{ji}^k \geq 0, \quad \forall j \in V, \ k \in K, \tag{12.4}$$

$$\sum_{i\neq j} x_{ij}^k - \sum_{i\neq j} x_{ji}^k \leq 1, \quad \forall j \in V\setminus\{0\}, \quad \forall k \in K, \tag{12.5}$$

$$\sum_{j\in V\setminus\{0\}} x_{0j}^k = 1, \quad \forall k \in K, \tag{12.6}$$

$$\sum_{i\in V\setminus\{0\}} x_{i0}^k = 0, \quad \forall k \in K, \tag{12.7}$$

$$\sum_{k\in K}\sum_{j\neq i} x_{0j}^k = K, \tag{12.8}$$

$$y_0^k = 0, \quad \forall k \in K, \tag{12.9}$$

$$y_j^k \geq y_i^k + (x_{ij}^k e_j) - ((1 - x_{ij}^k)Q_1), \quad \forall i,j \in V,\ i \neq j,\ k \in K, \tag{12.10}$$

$$y_j^k \geq \sum_{i\neq j} x_{ij}^k e_i, \quad \forall j \in V\setminus\{0\},\ k \in K, \tag{12.11}$$

$$y_i^k \leq Q_k, \quad \forall i \in V\setminus\{0\},\ k \in K, \tag{12.12}$$

$$\sum_{i,j\in V\setminus\{0\}} d_{ij}x_{ij}^k \leq TS, \quad \forall k \in K, \tag{12.13}$$

$$x_{ij}^k \in \{0,1\}, \quad y_i^k \geq 0, \quad \forall i,j \in V,\ k \in K. \tag{12.14}$$

The objective function (12.1) accounts for both the fixed and variable costs associated with the operation of vehicles. The fixed costs consist of the rental expenses for each vehicle type, while the variable costs represent the operating expenses per km for each vehicle type. Constraint (12.2) ensures that each stop is visited. Constraints (12.3), (12.4), and (12.5) demonstrates that when a vehicle arrives at a stop it can either depart from that stop or terminate at the stop since the model allocates its terminal stops dynamically. Constraint (12.6) demonstrates that each route must start at the depot. Constraint (12.7) ensures that there is no returning to the depot. Constraint (12.8) ensures that K vehicles departs the depot. Constraint (12.9) ensures that each vehicle start at the depot with no load. Constraints (12.10), (12.11), and (12.12) ensures that each vehicle's load remains within capacity as it depart from a stop while also preventing the formation of sub-tours. Constraint (12.13) demonstrate that total travel distance for any route must not exceed the maximum allowable time. Constraint (12.14) defines the domain of the decision variables.

Tabu Search Heuristic

A Tabu Search Heuristic algorithm is developed utilizing Python. The heuristic begins by constructing an initial solution using a greedy method that assigns stops to routes based on proximity, vehicle capacity, and time constraints (F.Glover and Laguna, 1997). Each route is associated with a specific vehicle type from a predefined fleet, with different capacities and cost structures. In each iteration, the algorithm explores the neighborhood of the current solution by applying a set of moves aiming to improve the current solution by balancing loads, reducing travel costs, and consolidating or splitting routes where appropriate (Ceschia et al., 2011). Each move generates a candidate neighbor, which is evaluated using an objective function that considers fixed vehicle costs, variable travel costs, penalties for underutilization, unvisited demands, and excessive vehicle usage. The algorithm maintains a tabu list to prevent cycling back to recently visited solutions (Misevicius and Valickis, 2004). A tabu move can be accepted if it leads to a better solution than the current best solution. In the neighborhood evaluation phase, the algorithm selects the best non-tabu neighbor to replace the current solution. The resulting implementations of Tabu Search Heuristic, using two approaches, can be seen in Figure 12.3 with OpenStreetMap routes between nodes.

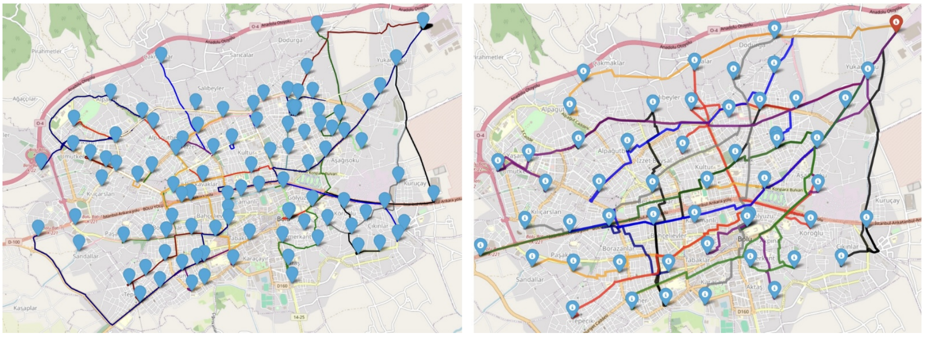


Figure 12.3: Tabu Search Routes for Existing Stops and Rearranged Stops Approaches

Verification and Validation of Mathematical Model and the Tabu Search Heuristic

After developing the mathematical model, it was implemented in Python using the Gurobi Optimizer to observe initial outputs and better understand the model's behavior. For the verification process, initial tests with simplified data verified expected vehicle allocation patterns based on cost efficiency. Further scenarios validated the model's feasibility under different capacity and time constraints. A pre-processing step was introduced to handle cases where demand at a single stop exceeded vehicle capacity. Lastly, the model was tested on actual demand distributions provided by the company. The outputs met all criteria, including route feasibility, coverage, and cost minimization. After verifying the model using the Gurobi

Optimizer, we tested its performance on open-source solvers for potential company use. However, none of the solvers yielded feasible solutions within acceptable time limits, leading us to proceed with the Tabu Search based heuristic algorithm. The heuristic algorithm was initially tested on small-sized datasets representing extreme scenarios to verify its accuracy and ensure proper model behavior. After verification, it was applied to multiple real datasets to evaluate the practicality of assumptions and the quality of the results. The validation process involved comparing the algorithm's outcomes against real demand data and the existing routing plan provided by the company. Our objective was to generate a routing plan that satisfies demand using fewer vehicles by improving vehicle utilization and reducing the number of stops. Both the methodology and the results were reviewed and validated along with our academic and industrial advisors.

12.2.5 Implementation and Pilot Study

A Decision Support System (DSS) is delivered to Beko Cooking Appliances Factory to support dynamic vehicle routing planning. The system enables the company to generate and update employee transportation routes based on address changes. It is tailored for use by the HR team, allowing them to enter, update, or upload employee addresses. The address entry module includes an intelligent search bar powered by the Google Places API, which autocompletes address entries similarly to Google Maps. Once an address is selected, it is automatically geocoded using the Google Maps Geocoding API, and a static map image is displayed via the Google Maps Static Images API for visual confirmation. Each address is saved in the internal database, linked to the corresponding employee. In addition to that, we have added a bulk upload button to our user interface. When this button is clicked, the system prompts the user to select a file containing the company's employee addresses. Upon selection, the system processes the uploaded file and generates an updated version. The file is processed automatically: addresses are extracted, converted into geographic coordinates using the Geocoding API, and visualized with map images retrieved from the Static Maps API. Finally, the processed data, including the addresses, their corresponding coordinates, and the associated map images, is saved as a new Excel file and added to database. This functionality ensures that the most recent and accurately Geo-coded address data is stored in a structured format. Once the addresses are processed, they are assigned to the nearest bus stops using a built-in allocation algorithm. Each employee is matched to the closest available stop based on proximity, which ensures routing accuracy and efficiency.

The system also supports scenario management by enabling users to revisit and visualize previously generated transportation plans. Each vehicle's route is recorded and stored, providing detailed tracking and allowing comparisons over time. Route optimization can be conducted for different companies, offering flexibility. Users can define planning parameters, such as maximum route duration, before initiating the algorithm. Additionally, the integrated budget planning feature allows for the estimation of total transportation costs based on selected scenarios. The feature also enables incremental demand updates by distributing new employee allocations proportionally to previous employee distributions. As part of this process, the system performs a cost analysis, reporting both absolute and percentage-based increases in overall transportation expenses resulting from the anticipated rise in demand. DSS can be found in Appendix 12.2.7.

Following the system development, we conducted a demonstration with the industrial advisor and received feedback to further improve the usability of the user interface before the pilot study. The pilot study was carried out in April 2025, utilizing a single vehicle on a designated route assigned by the DSS. Performance metrics were then analyzed and evaluated.

12.2.6 Benchmark and Benefits

The benchmarking strategy evaluates the system's impact by performing scenario analyses and comparing key performance metrics with existing data provided by the company. Five key metrics are used to compare Beko's current system with the DSS: transportation cost per employee, transportation cost per kilometer, vehicle utilization rate, average travel times per route and carbon emissions per trip. Improvement rates on average can be seen in Table 12.1.

Current system utilizes 52 vehicles, routes span 369.21 kilometers, and costs 19,535.29 TL per day. Running Tabu Search Heuristic on current stops results in 40 vehicles, spans 336.82 kilometers and yields 17,213.43 TL daily cost. Rearranging stops and then running Tabu Search Heuristic results in 35 vehicles, spans 295.6 kilometers, and yields 14,971.1 TL daily cost, achieving a 11.88% and 23.37% cost reduction, respectively. These improvement in operational efficiency is a direct result of the new routes and resource allocation, leading to smoother and more reliable workflows across the company.

12.2.7 Conclusion

This project aims to develop a decision support system that will provide a weekly transportation plan for Beko Bolu Cooking Appliances Factory. The DSS uses employee addresses, stop locations, vehicle capacities, and travel time limits as inputs and runs a routing model supported by a Tabu

Table 12.1: Improvement Rates

	Existing Stops	Rearranged Stops
Decrease in Number of Vehicles	23.08%	32.69%
Decrease in Transportation Cost per Employee	8.86%	20.66%
Decrease in Transportation Cost per Kilometer	2.23%	3.03%
Increase in Average Vehicle Utilization Rate	14.42%	25.85%
Decrease in Total Travel Time	7.36%	18.12%
Decrease in Carbon Emissions	7.47%	19.52%

Search Heuristic to generate cost-efficient transportation routes. The system features a user-friendly interface, which allows individual or bulk address entry and automatically assigns each employee to the nearest stop. The system processes the address data using Google APIs to obtain geographic coordinates and map visuals, and stores the results in a structured format for route planning. The DSS evaluates two approaches: using existing stops and rearranged stops. For both approaches, the heuristic model determines vehicle assignments and routing solutions while satisfying constraints such as vehicle capacity, maximum travel time, and stop coverage.

As a result, the DSS is expected to deliver weekly transportation plans that reduce operational costs, decrease the number of vehicles, and improve vehicle utilization. It provides a scalable and sustainable tool that supports dynamic workforce changes and contributes to Beko's operational efficiency and environmental goals.

Bibliography

Ceschia, S., A. Schaerf, and T. Stützle (2011). Local search techniques for scheduling problems: Classical methods and their extensions. *Springer Optimization and Its Applications 47*, 34–36.

F.Glover and M. Laguna (1997). Tabu Search. *Springer 36*(14), 123–170.

Misevicius, A. and V. Valickis (2004). Iterated tabu search for the vehicle routing problem. *Informatica 15*, 521–538.

Sariklis, D. and S. Powell (2000). A heuristic method for the open vehicle routing problem. *Journal of the Operational Research Society 51*, 564–573.

Sezer Proje (2024). Arçelik – Bolu. https://sezerproje.com/projeler/arcelik-bolu/ [Online; accessed 22-October-2024].

Toth, P. and D. Vigo (2014). *Vehicle Routing: Problems Methods and Applications*. SIAM.

Appendix: Decision Support System

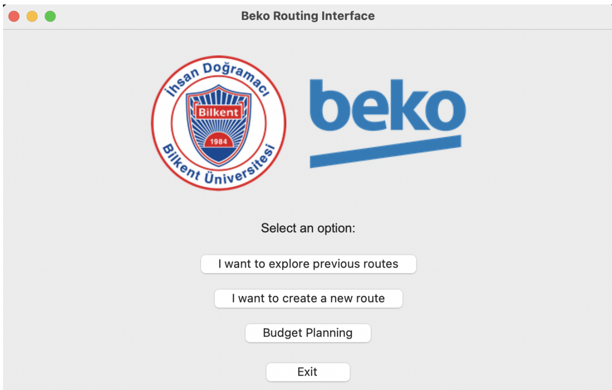


Figure 12.4: Main Page of DSS

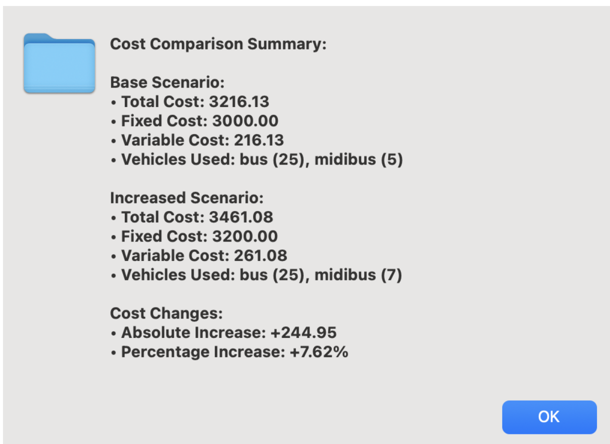


Figure 12.5: Budget Planning Page Notification of An Example Routing

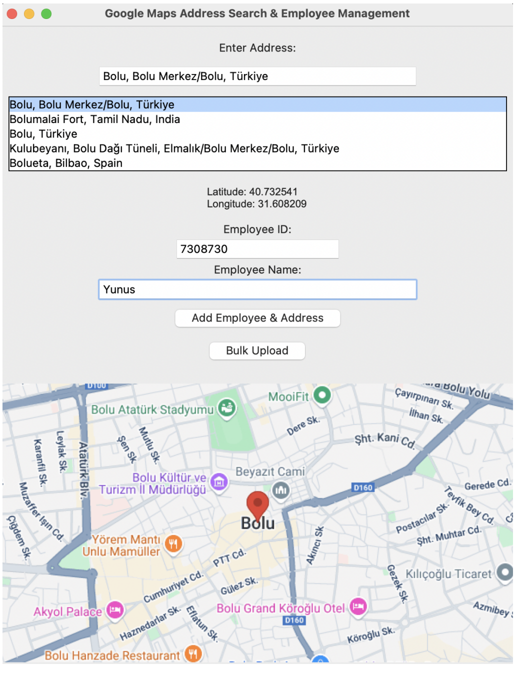


Figure 12.6: Adding Address Page for the Word 'Bolu'

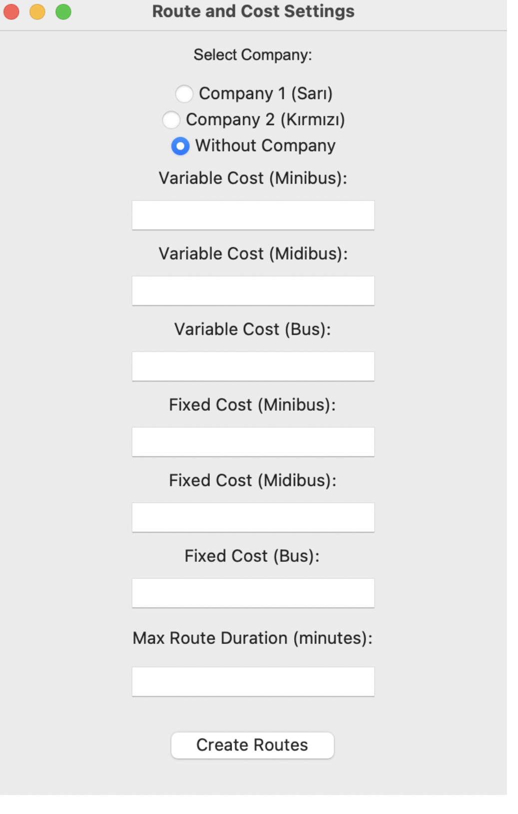


Figure 12.7: Company and Parameter Selection

Personel Taşıma Sistemi Eniyilemesi | 13

Enerjisa

Proje Ekibi
Emre Batın Arslan, F. Bilge Aygün, Utku Büyükbayraktar,
Zeynep Köse, Şükran Kurses, Nima Najafi, Yunus Berk Tektaş,

Şirket Danışmanları
Volkan Umar ve Sibel Kesgin

Akademik Danışman
Doç. Dr. Firdevs Ulus
Endüstri Mühendisliği Bölümü

Özet

Hibrit çalışma sistemine sahip Enerjisa'nın personel taşıma sistemi, araç doluluk oranlarındaki değişkenlik gibi nedenlerle çeşitli verimlilik sorunlarıyla karşı karşıya kalmıştır. Bu proje, toplam seyahat mesafesinin azaltılması, kullanılan araç sayısının düşürülmesi, maksimum yürüme mesafelerinin sınırlandırılması ve güzergâh dengesi sağlanarak adil ve çalışan memnuniyetini artıran bir yapı oluşturulmasını hedeflemektedir. Bu amaçla, Karma Tamsayılı Doğrusal Programlama (MILP), kapasiteli kümeleme ve sezgisel iyileştirme yaklaşımlarını bir araya getiren bir çözüm yöntemi geliştirilmiştir. Oluşturulan model, operasyonel kısıtlarla uyumlu, esnek ve etkili güzergâh planlaması sağlayan kullanıcı dostu bir Karar Destek Sistemi'ne entegre edilmiştir.

Anahtar Sözcükler: Personel taşımacılığı, güzergah optimizasyonu, ARP, sezgisel yöntem, matematiksel modelleme.

Optimization of Personnel Transportation System

Abstract

Hybrid working model led to various inefficiencies in Enerjisa's personnel transportation system, mainly due to fluctuating vehicle occupancy rates. This project aims to reduce total travel distance, minimize the number of vehicles used, limit maximum walking distances, and ensure route balance to promote fairness and enhance employee satisfaction. To achieve these goals, a solution approach combining Mixed Integer Linear Programming (MILP), capacitated clustering, and improvement heuristics was utilized. The resulting model was integrated into a user-friendly Decision Support System that enables flexible and effective route planning in compliance with operational constraints.

Keywords: Personnel transportation, route optimization, VRP, improvement heuristics, mathematical modelling.

13.1 Company Information

Enerjisa, established in 1996, is Turkey's leading electricity company, specializing in distribution, retail sales, and customer solutions. It serves around 10.7 million customers across 14 provinces and three distribution regions, reaching approximately 22 million people. With over 11,000 employees, Enerjisa focuses on delivering innovative, tech-driven, and sustainable solutions such as energy efficiency services, solar installations and EV charging stations (Enerjisa, 2024).

13.2 System Analysis

The current transportation system has 27 vehicles, each with a capacity of 15 passengers, serving approximately 480 registered employees commuting to Enerjisa headquarters in Ataşehir, Istanbul. The vehicle routes cover Europe and Asia sides as well as Izmit, however, since not all the employees commute to work everyday due to hybrid schedules, the vehicle capacities were being underutilized and resulted in an average daily occupancy rate of 38.6%. The company currently utilizes Google Maps to assess employee walking distances to the vehicle stops. Company considers a walking distance radius of 500 meters is acceptable while it can be extended up to 750 meters in some cases where the route layout poses challenges in terms of accessibility.

13.3 Problem Definition

The inefficiencies in the employee transportation system originates from not fully utilizing the vehicle capacities due to the hybrid work model while still dealing with the associated costs of operating these partially full vehicles. To obtain resource efficiency and cost effectiveness while handling daily fluctuating occupancy, the company requires some adjustments on route and transportation stop planning.

While calculating the associated cost of traveling, whenever an adjustment is done in the existing routes, the cost is regarded proportional to the changes in kilometers. However, if a new route is needed, it is affected by numerous variables, including the endpoint of the route and the passageways involved. There is no fixed cost formula for this calculation which adds complexity to route planning, especially when addressing new route demands or modifications.

Some additional constraints of the problem are as follows. The employee vehicles avoid side streets and prefer specific main stops, they refrain from stopping on the E80 motorway and use only bus stops on the D100. The company also has a rule against picking up or dropping off employees on the highway for safety reasons. Such restrictions lengthen some routes and increase walking distances to stops, which can impact employee satisfaction. Moreover, individual travel times are not tracked, and only the total travel time of each route is prioritized. As a result, the goal is to increase vehicle utilization by reducing walking distances to stops and minimizing total travel times, thus ensuring the system operates efficiently even under fluctuating vehicle occupancy.

13.4 Proposed Solution Strategy

13.4.1 Critical Assumptions

- Shuttles begin their travel from and end their travel at the main office building in Ataşehir (node 0).
- Every employee is assumed to use the shuttle service on a daily basis and every employee is assigned to exactly one bus stop.
- In the event of an employee's absence on a predetermined route, the driver can adjust the route based on their prior knowledge and experience.
- There are no stops on the E80 highway, and on the D100.
- Time deviations are outside the scope of the project model.

- Travel costs are directly proportional to the distance of routes. Therefore, instead of considering a budget constraint, we focus on minimizing travel distance which minimizes related travel costs.
- Different vehicles can visit the same bus stop.
- Maximum allowable walking distance is assumed to be 750 meters.

13.4.2 Major Constraints

According to company regulations and restrictions, the following constraints need to be considered:

1. The number of shuttle buses is currently 27. Hence, we are allowed to use a maximum of 27 shuttle buses.
2. Every employee should be assigned to exactly one bus stop.
3. Shuttle buses are required to start and end their routes in Ataşehir.
4. The shuttle bus capacity cannot exceed the passenger seat number of the shuttle bus, ensuring no employee is permitted to travel standing.
5. Each bus currently has a capacity of 15, but this was increased to 25 to improve occupancy rates. Based on personnel data (mean $\mu = 17.4$, standard deviation $\sigma = 7.4$), and using the formula $\mu + z \cdot \sigma$ with a 95% confidence level ($z \approx 1.96$), the estimated capacity is approximately 30, which serves as an upper bound. However, after discussions with the company and considering the new occupancy rate of $\sim 60\%$, the maximum number of passengers per bus has been set to 25 to ensure seating for all employees.

13.4.3 Objectives

The project's objective is to minimize the total travel distance of vehicles to ensure more efficient routes, reducing overall costs as well as employee commute times. This objective also offers fairness among employees by ensuring more balanced commute times. Our desire extends to improve employee satisfaction by providing a comfortable and timely transportation experience, reducing difficult routes. Data-driven decisions supports flexible and precise determinations of routes, stops, and capacities through in-depth data analysis.

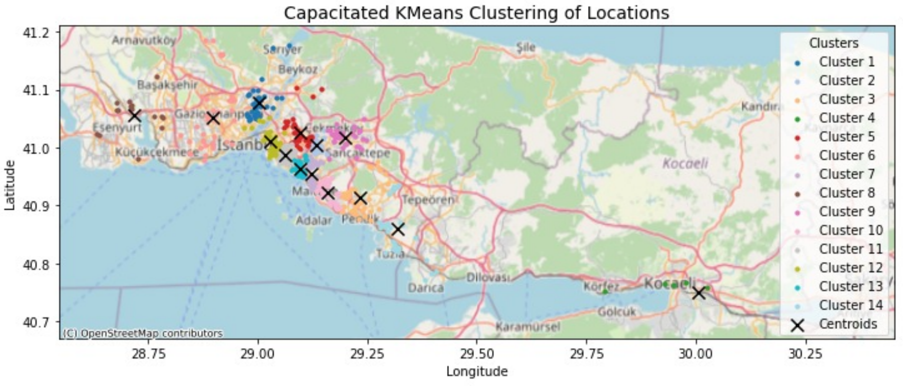


Figure 13.1: Capacitated K-Means Clustering Locations

13.4.4 Solution Approach and Conceptual Model

The conceptual model provides an abstraction of the solution approach for optimizing Enerjisa's personnel transportation system. The first phase is identifying the potential vehicle stops. Initially, we started with 14,912 IETT bus stops, which is a large number to solve VRP when fed into the MILP model. To address this issue, we developed a stop elimination algorithm which eliminates a large chunk of the IETT stops based on the set of employees. Our approach was to first set a 500 meter radius around each employee address. Then, among the IETT stops left in the radii, we first eliminated the stops serving a single employee, as they would be inefficient. We then merged the stops that serve either the same or similar sets of employees into one, which left us with 312 stops at the end. Finally, we have combined this with the addresses of each of the 481 personnel and the Ataşehir office to get a final stop list of 793.

After determining the potential bus stops, the second phase is utilizing capacitated K-means clustering, which limits each cluster to a maximum of 40 employees. In this approach, the personnel addresses would be divided into a minimum number of clusters to be solved by running the VRP model which is the third phase of the problem with the goal of reaching a better runtime result. The potential set stops from the algorithm also get clustered, and fed into the VRP along with the employee clusters as inputs.

13.4.5 Mathematical Model

Table 13.1: Sets

Sets	**Description**
$S = \{0, 1, \ldots, s_{max}\}$	Set of potential stops where index 0 represents office building in Ataşehir

$E = \{1, \ldots, e_{max}\}$	Set of employees
$V = \{1, \ldots, v_{max}\}$	Set of vehicles

Table 13.2: Parameters

Parameters	**Description**
d_{ij}	Distance between stop i and stop j
w_{ie}	Walking distance between stop i and employee e
$C = 25$	Capacity of each vehicle
$\alpha = 750$ m	Maximum allowed walking distance for employees to a stop

Table 13.3: Decision Variables

Decision Variable	**Description**
$x_{iv} = \begin{cases} 1 & \text{if stop } i \text{ is used by vehicle } v \\ 0 & \text{otherwise} \end{cases}$	Binary variable indicating if stop i is used by vehicle v
$y_{ijv} = \begin{cases} 1 & \text{if vehicle } v \text{ travels from stop } i \\ & \text{to stop } j \\ 0 & \text{otherwise} \end{cases}$	Binary variable indicating if vehicle v travels from stop i to j
$T_{iev} = \begin{cases} 1 & \text{if employee } e \text{ is assigned to stop } i \\ & \text{by vehicle } v \\ 0 & \text{otherwise} \end{cases}$	Binary variable indicating if employee e is assigned to stop i by vehicle v
$z_v = \begin{cases} 1 & \text{if vehicle } v \text{ is used} \\ 0 & \text{otherwise} \end{cases}$	Binary variable indicating if vehicle v is used in the solution
u_{iv}	Occupied capacity of vehicle v after leaving stop i

$$\min \sum_{i \in S} \sum_{j \in S} \sum_{v \in V} d_{ij} y_{ijv} \tag{13.1}$$

$$
\begin{aligned}
\text{s.t.}\quad & \sum_{v \in V} x_{0v} = \sum_{v \in V} z_v && && (13.2)\\
& \sum_{i \in S} y_{ikv} = x_{kv} && \forall k \in S,\ v \in V && (13.3)\\
& \sum_{j \in S} y_{kjv} = x_{kv} && \forall k \in S,\ v \in V && (13.4)\\
& y_{iiv} = 0 && \forall i \in S, \forall v \in V && (13.5)\\
& T_{iev} \leq x_{iv} && \forall i \in S, \forall v \in V, \forall e \in E && (13.6)\\
& \sum_{j \in S \setminus \{0\}} y_{ijv} \geq \frac{1}{C} \sum_{e \in E} T_{iev} && \forall i \in S \setminus \{0\},\ v \in V && (13.7)\\
& y_{ijv} \leq x_{iv} && \forall i, j \in S, \forall v \in V && (13.8)\\
& x_{iv} \leq z_v && \forall i \in S, \forall v \in V && (13.9)\\
& \sum_{i \in S} \sum_{v \in V} T_{iev} = 1 && \forall e \in E && (13.10)\\
& \sum_{i \in S} \sum_{e \in E} T_{iev} \leq C && \forall v \in V && (13.11)\\
& \sum_{v \in V} z_v \leq 27 && && (13.12)\\
& T_{0ev} = 0 && \forall e \in E,\ v \in V && (13.13)\\
& u_{jv} - u_{iv} \geq \sum_{e \in E} T_{jev} - C(1 - y_{ijv}) && \forall i, j \in S \setminus \{0\}, i \neq j,\ v \in V && (13.14)\\
& \sum_{e \in E} T_{jev} \leq u_{jv} && \forall j \in S \setminus \{0\},\ v \in V && (13.15)\\
& u_{jv} \leq C && \forall j \in S \setminus \{0\},\ v \in V && (13.16)\\
& w_{ie} T_{iev} \leq \alpha && \forall i \in S, e \in E, \forall v \in V && (13.17)\\
& x_{iv}, y_{ijv}, T_{iev}, z_v \in \{0, 1\} && \forall i, j \in S, \forall v \in V && (13.18)\\
& u_{iv} \geq 0 \text{ and integer} && \forall i \in S, \forall v \in V && (13.19)
\end{aligned}
$$

To further improve the model performance, three heuristics (Large Neighborhood Search (LNS), cross-exchange, and single node relocation) were applied sequentially. While cross-exchange and relocation did not yield improvements in this specific case, they showed significant gains in many other trials and are expected to perform well when the company utilizes the DSS. Since these post-LNS heuristics add virtually no computational burden, we chose to keep them in.

13.4.6 Runtime Analysis and Improvement Heuristics

A preliminary runtime analysis was conducted to evaluate the MILP model's efficiency under different problem sizes. As the number of stops and em-

Objective	LNS	Cross-Exchange	Relocation	Final Total Objective	Overall Improvement (%)
Solution Found	817.63 km	817.63 km	817.63 km	817.63 km	12.32%
Iteration	3597	1	1	-	-
Improvement Found?	Yes	No	No	-	-

Table 13.4: Optimization Process Results

ployees increased, the runtime increased significantly. To ensure feasibility, a 30-minute time limit per cluster was selected as an effective trade-off between runtime and solution quality. Following the initial optimization, improvement heuristics were utilized in the solution to improve the initial results obtained from the VRP model, as the runtime limitations of VRP only allowed us to progress only up to a certain point. Therefore, we have decided to utilize post-improvement heuristics so as to refine the solution and achieve better results in terms of total travel distances.

13.5 Validation

To ensure the credibility and practical applicability of the model, a comprehensive validation process was conducted by comparing the outcomes of the optimized system with Enerjisa's current transportation framework under similar conditions. In this validation, the model was run by using the company's existing stop and route structures. The walking distance constraint was relaxed, and it was assumed that each employee would walk to nearest available stop.

Running the model under these conditions, the total travel distance ended up being 715.5 kilometers. This is highly comparable to the company's current total route distance of approximately 712 kilometers. It should be noted that the latter figure is calculated by Google Maps distances, whereas the model utilizes OSRM based on OpenStreetMap data which is also the reason why the two numbers are not the same. These

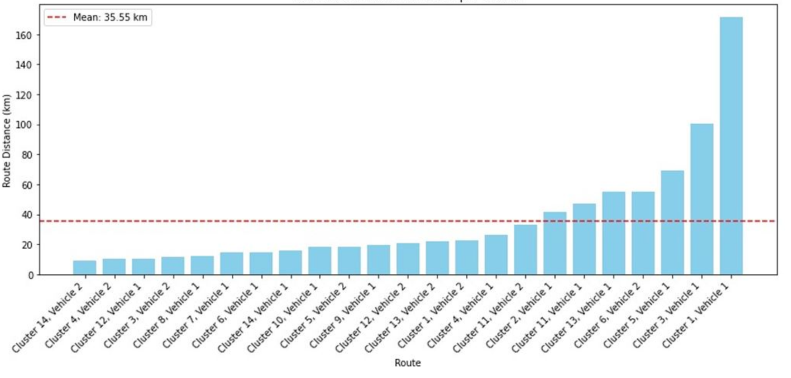


Figure 13.2: Route Lengths

results demonstrate that the model is capable of replicating the company's current solution and confirm that the company solution is in fact a subset of all the solutions the model can produce, which provides a solid foundation for further optimization efforts.

13.6 Results and Benefits to the Company

The primary benefit is the reduction in travelled distance that helps to save costs in terms of fuel and other operational costs. The project tries to assist the employees by reducing their traveling times and walking distances along with increasing fairness in the system. Second, it enhances the overall resource efficiency by avoiding under-utilization of vehicles. Another very important benefit would be the realignment of the transportation system toward the sustainability goals of Enerjisa through fuel consumption and reduced carbon emissions. The solution framework and model developed under this project might form a very strong basis for scaling up and adapting similar optimization efforts in other operational areas of Enerjisa. These models are integrated into the developed DSS and offer a user-friendly route management platform to Enerjisa. It also enables proper decision-making regarding resource allocation and ensures smooth adaptation in case of fluctuation in workforce attendance.

13.7 Benchmarking

Unlike the current company system, proposed system serves all 481 employees using four fewer vehicles, reducing the number of vehicles from 27 to 23, and ensuring that no employee walks more than 750 meters. In contrast, up to 265 employees in the current company system walk more than this distance. The average walking distance has been reduced to approximately 360 meters, route lengths have been balanced, and a fairer system has been offered in terms of employee satisfaction. Supported by heuristics such as LNS, Cross-Exchange, and Relocation, the model contributes to Enerjisa's goals of operational efficiency and sustainability, while empowering decision-making through a user-friendly DSS.

13.8 Decision Support System

The DSS, implemented in Python, features three main functionalities: reroute optimization and adding/deleting a single employee. In reroute optimization, the input Excel file with employee locations is used to solve VRP from scratch. The company can adjust key parameters like vehicle capacity, number of vehicles, and walking distance before optimization. The add employee button, if the bus capacity and walking distance criteria are met,

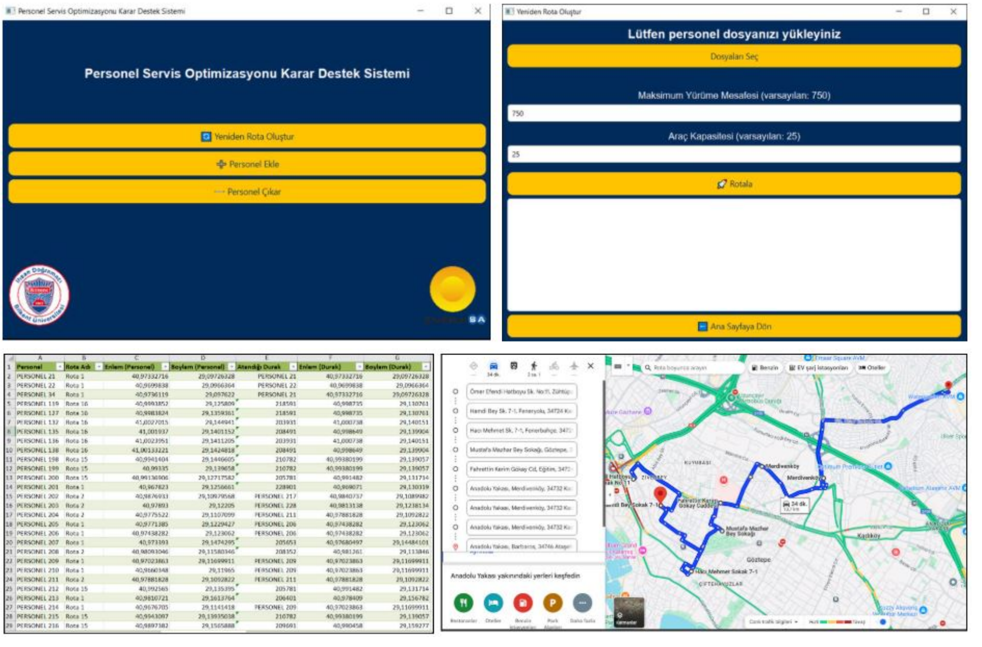


Figure 13.3: Home Screen (top) and Outputs of UI

uses a heuristic to assign an employee to the nearest route. Similarly, the delete employee button takes out an employee by a heuristic. The output is provided in Excel format, with detailed assignments and route information.

13.9 Conclusion

The project optimizes Enerjisa's personnel transportation system, reducing travel distances, operational costs, and improving resource utilization. By applying mathematical models and heuristics, the solution reduces walking distances and enhances employee satisfaction. The user-friendly decision support system offers real-time route management and flexibility, ensuring efficiency even with fluctuating workforce attendance. This framework can be scaled for other Enerjisa regions.

Bibliography

Enerjisa (2024). Enerjisa Enerji Official Website. https://www.enerjisa.com.tr [Online; accessed 29-October-2024].

Sports International Müşteri Sadakati Arttırma Stratejileri

14

Sports International

Proje Ekibi
Aziz Can Adıgüzel, Göksun Ural Çamurdan, Ömer Erdoğan, Elif Hamurculu, Eren Özyiğit, Ilgın Sulu, Sine Vural

Şirket Danışmanları
Hakan Öztürk, Genel Müdür
Kenan Ayduğan, Bilgi Teknolojileri Müdürü
Kübra Bircan Aygün, Bütçe ve Raporlama Uzmanı

Akademik Danışman
Prof. Dr. Savaş Dayanık
Endüstri Mühendisliği Bölümü

Özet

Proje, Sports International'a ait geçmiş ve mevcut müşteri verilerini analiz ederek, üyelik sözleşmelerinin yenilenme olasılığını etkileyen kalıpları ve faktörleri belirlemeyi amaçlar. Üye davranışları ve kullanım metriklerinden elde edilen önemli içgörüler ile bir Makine Öğrenme algoritması, Lojistik Regresyon kullanılarak, sözleşme yenileme oranını anlamlı şekilde artırabilecek stratejiler önerilmektedir. Elde edilen bulgular, müşteri sadakatini ve elde tutma oranını artırmaya yönelik hedef odaklı pazarlama çalışmaları geliştirilmesine katkı sağlayacaktır.

Anahtar Sözcükler: Veri Analizi, Müşteri Sadakati, Müşteri Kaybı Tahmini, Pazarlama Stratejileri, Sistem İyileştirme, Spor Kompleksi, Sözleşme Yenileme, Üye Davranışları, Veri Modeli

Sports International Customer Retention Strategies

Abstract

This project focuses on analyzing the past and current customer data of Sports International to identify patterns and factors that influence the likelihood of renewing contracts. By leveraging key insights from member behavior and usage metrics and the utilization of the Machine Learning Algorithm, Logistic Regression, we propose a model to enhance the strategy-making system that can significantly increase the renewal rate. The findings will help to create targeted marketing efforts to improve customer retention and loyalty.

Keywords: Data Analysis, Customer Loyalty, Customer Churn Prediction, Marketing Strategies, System Improvement, Sports Complex, Contract Renewal, Member Behaviors, Data Model

14.1 Company Information

Sports International is a leading fitness and wellness club chain in Türkiye, established in 1994 and operated by Bilkent Holding. It has 9 modern clubs located in major cities including Ankara, İstanbul, İzmir, and Mersin. The company provides a wide range of services such as gym and cardio areas, swimming pools, tennis and squash courts, group fitness classes (like yoga, pilates, spinning, and Zumba), personal training, and spa facilities. Its service system focuses on combining high-quality infrastructure with professional staff to promote a healthy lifestyle for all age groups, including tailored programs for children.

14.2 Current System Analysis

In Sports International's current system, the Sales Department's tasks include calling current members for feedback regarding facilities, reaching out to possible members through customer references, data collected at company's events, etc., and reaching out to ex-members to see if they would be interested in rejoining (Özdemir, 2024). The current system involves manual and unsystematic outreach to both existing members and potential customers. The Sales Team does not have a data-backed prioritization method. Calls to current and potential members are carried out without clear prioritization or insights, leading to excessive and inefficient outreach. This inefficiency results in wasted time and resources on low-priority leads and missed opportunities with high-potential ones. The database is not fully utilized to assess customer behavior and since the company does not perform data analysis, no enhancement in the system is made through the years.

Sports International is seeking a system improvement and enhancement. The membership retention and acquisition processes can be enhanced by adopting a systematic, data-driven approach. The goal is to implement a robust system for prioritizing outreach efforts based on insights derived from structured data analysis, ultimately improving member retention and new member acquisition. This goal is accessible through an extensive data analysis process focusing on churn prediction.

14.3 Data Analysis Methodology

Effective data analysis enhances decision-making and customer retention by uncovering patterns in customer behavior (de Medeiros et al., 2020). Exploratory Data Analysis (EDA) is a critical first step, involving data cleaning, visualization, and correlation analysis to guide model selection and feature engineering (Sabbeh, 2018). Logistic Regression remains a popular and interpretable model for binary classification tasks such as churn prediction. (Sabbeh, 2018) used Logistic Regressionalongside other machine learning models on customer data enriched with usage patterns and membership details, achieving 86% accuracy. The study emphasized preprocessing steps such as binary transformation, feature selection, and imputation techniques like Random Forest Imputation and SIM&HAMM (Subasi et al., 2011). Although ensemble models outperformed Logistic Regression in accuracy, Logistic Regression offered a strong baseline and interpretability, making it a valuable tool in business-focused predictive analytics as stated in Sabbeh (2018).

14.3.1 Exploratory Data Analysis

Initially, we were given 5 files of raw data containing:

- Customer Demographic information,
- Cancellation information,
- Membership Contract Information
- Facility Entry Logs containing information on facility entrance and exit times of customers,
- Membership Activity Records containing the dates, durations and context of the communication between the customers and the Sales Team.

The dataset provided by the company contained several issues and required preprocessing to extract valuable insights. Some of these problems were already indicated by the company, while others were identified through Exploratory Data Analysis (EDA) techniques, such as statistical summaries and data visualization methods. The following procedures were applied to prepare the dataset for predictive modeling (in this process Python codes and Excel were used):

- Customers whose marital status appeared as 'unspecified' ("Belirtilmemiş") were cross-checked against family membership details and primary contract holders to accurately determine their actual marital status.

- Incorrect customer exit times, notably entries recorded as 23:59, were corrected by assigning the average duration derived from historical activity data of all customers.

- The total number of visits made by customers during their contract period and the overall time spent at the facility were calculated. Using these values, the facility utilization rates, both overall and specifically for the last 30 days, were derived.

- Customers' average visit durations and typical visiting intervals throughout the day were computed and incorporated into the analysis.

- The number of times each customer was contacted by the sales team within the contract duration was calculated and integrated into the dataset.

- Membership prices were standardized by adjusting them to reflect their real value as of October 2024, based on inflation rates obtained from TÜİK's Consumer Price Index. For family memberships, the total price was distributed evenly among family members, and subsequently, a daily unit price was calculated per contract duration.

The datasets were merged based on unique contract codes to align customer information accurately, as the analysis was contract-oriented due to differing renewal behaviors across membership types. The binary dependent variable, renewal status, indicating renewals (1) or non-renewals (0), was defined and used to train predictive models.

A chi-square test was employed to statistically examine the relationship between the selected customer features (Membership Type, Gender, Age, Marital Status, Contract Type, Overall Facility Usage Percentage, Last 30

Days Utilization, Average Visit Interval, Outreach Amount, Unit Membership Price, Renewal Percentage, and Average Visit Duration) and the renewal outcome. Based on these results, these variables were confirmed for inclusion in subsequent predictive modeling analyses.

A chi-square test was employed to statistically examine the relationship between the selected customer features (Membership Type, Gender, Age, Marital Status, Contract Type, Overall Facility Usage Percentage, Last 30 Days Utilization, Average Visit Interval, Outreach Amount, Unit Membership Price, Renewal Percentage, and Average Visit Duration) and the renewal outcome. Based on these results, these variables were confirmed for inclusion in subsequent predictive modeling analyses.

14.3.2 Model Development

The Machine Learning algorithms of AdaBoost, XGBoost, Random Forest and Logistic Regression has been performed in terms of Predictive Modeling. Logistic Regression has yielded the highest accuracy. Therefore data analysis was performed using the Logistic Regression Model.

Logistic Regression is an algorithm used for binary classification problems, where the goal is to predict one of two possible outcomes, which in our case is whether a customer will renew their contract or not. Logistic Regression calculates coefficients showing the significance of features for the renewal.

These coefficients show the correlation between the features and the customer's renewal probability. It calculates a weighted sum of the input features (Membership type, age, etc.) and then applies the sigmoid function to estimate the probability of renewal based on the coefficients of the features that the customer belongs to. Based on this probability and a predefined threshold (which we determined as 0.5), the model classifies the data into one of the two categories (Hastie et al., 2017).

We initially performed Logistic Regression with numerical data which yielded 78.6% accuracy. However, we then observed that the data divided into ranges and categorized yielded a higher accuracy of 89.15%. Therefore, we have transformed some of the numerical features into intervals. The intervals are determined so that each interval contains an equal number of data. Numeric features have been turned into ranges that create categorical features, representing the underlying category of a certain feature that is associated with a customer.

Then it was questioned whether the COVID-19 period can skew the data. Thus, we eliminated the data from COVID-19 and performed a new Logistic Regression which yielded 76.83% accuracy. The decrease in accuracy could occur due to the fact that a great amount of data gets lost when eliminating data from COVID-19. Therefore, we have not eliminated any time period of the data.

Then in order to assess and increase the accuracy of our model, we tried different threshold values of 0.1, 0.2 to 0.5. The threshold value indicates: above which value would the customer be expected to renew based on their calculated probability of renewal. Based on the Logistic Regression model accuracies observed with different threshold values, the optimal value for the probability threshold was determined to be 0.5.

The final accuracy of our Logistic Regression model is 89.15% after improvements. Logistic Regression metrics are included in Table 14.1.

Table 14.1: Logistic Regression Metric Table

Metric	**Precision**	**Recall**	**F1score**	**Support**
Class 0	0.89	0.96	0.92	1111
Class 1	0.89	0.74	0.81	494
Accuracy			0.89	1605
Macro Avg	0.89	0.85	0.87	1605
Weighted Avg	0.89	0.89	0.89	1605

Confusion Matrix

	Predicted 0	**Predicted 1**	
Actual 0	1064	47	Metric: Accuracy
Actual 1	127	367	Value: 0.8915

14.3.3 Goodness of Fit Testing

In order to assess the fit of the Logistic Regression model to Sports International's dataset, goodness of fit testing was performed.

The Hosmer-Lemeshow test is a statistical test used to evaluate the goodness of fit for Logistic Regression models. It checks whether the predicted probabilities from the Logistic Regression model align well with the observed outcomes. The implemented Hosmer-Lemeshow test result shows that the Logistic Regression Model fits the data well. The Hosmer-Lemeshow metrics and results are included in Tables 14.2 and 14.3.

Table 14.2: Hosmer-Lemeshow Metrics

Observed 1	**Expected 1**	**Observed 0**	**Expected 0**	**Chi2**
7	6.4889	314	314.5110	0.0411
14	15.0682	307	305.9318	0.0795

Table 14.3: Hosmer-Lemeshow Results

Value	Chi2	p-value	Goodness of fit
Value	1.822	0.6100	Good

Observed 1	Expected 1	Observed 0	Expected 0	Chi2
38	32.2928	283	288.7072	1.1215
127	132.0975	194	188.9026	0.3343
308	306.1307	13	14.8693	0.2464

14.4 Validation

In order to validate the model, we collaborated with the company to obtain updated membership data for contracts expiring after October 14th. Using the coefficients derived from the Logistic Regression model, renewal scores were computed for customers whose memberships were set to terminate between October 14th and November 14th, effectively simulating the real-life decision-making process of the sales department. The model projected that 30 customers would renew their memberships, while 164 would not. The real outcomes indicated that 15 would renew while 179 would not. Upon comparing these predictions with actual renewal outcomes, 15 of the 30 predicted customers ultimately renewed their memberships. Additionally, cross-validation has been performed by dividing the data sets into folds and utilizing them one by one to train and test the data. The cross-validation results are in Table 14.4.

14.5 Integration and Implementation

14.5.1 Decision Support System - SIMS

A decision support system integrated as user interface (UI) is designed for the Sales team to utilize. The tool has a straightforward interface designed for usability. Upload Raw Data Folder part is where users input raw data. Once uploaded, the system automatically runs the analysis and generates outputs, including: Logistic Regression coefficients and feature lists that highlight important predictors. These outputs are used within the system

Table 14.4: Cross-Validation

Folds	Mean Accuracy	Min Accuracy	Max Accuracy
10	0.894	0.872	0.920

to rank the customers based on their likeliness to renew. The sales team will call the customers in this ranked list to achieve a high-efficiency call operation. When the testdb.xlsx file is uploaded to the Upload testdb part, the system processes it in under 10 seconds. Users can immediately: Review the prediction results from the "excel" window that appears after the data is processed. The system allows the end user to compare each customer's profile with the base customer found through the analysis by clicking on the specific features. This makes it fast and easy for the Sales team to act on the data and tailor their strategies in real time. The frontend design of the UI can be seen in Figures 14.1-14.3. In conclusion, the deliverables of this project are the ranked call list of customers, the Churner Profiles window that allows the end user to analyze false positive customer profiles, and the feature that allows the end user to compare customer profiles with the base customer for marketing purposes.

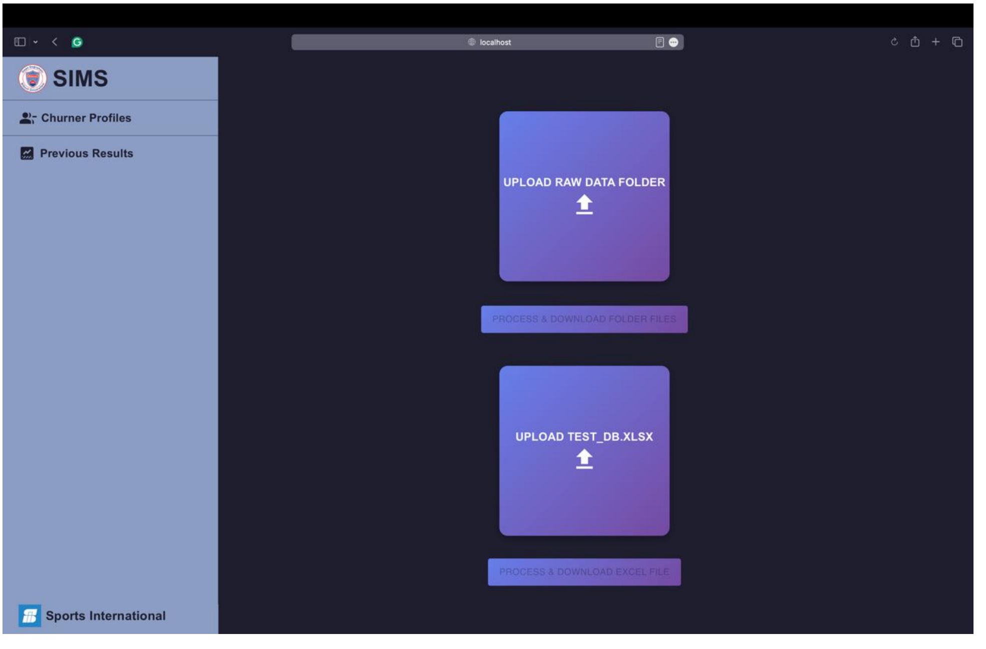


Figure 14.1: User Interface Main Page

14.5.2 Pilot Study

The pilot study and integration process started in 10th of April. Sports International's Bilkent Facility has been visited for implementation. The company uses the LAPIS system, which is a common platform across all of its locations. We set up a compatible computer environment and installed the Python packages needed for the user interface and model operations. Following setup, we used actual customer data from the previous three years

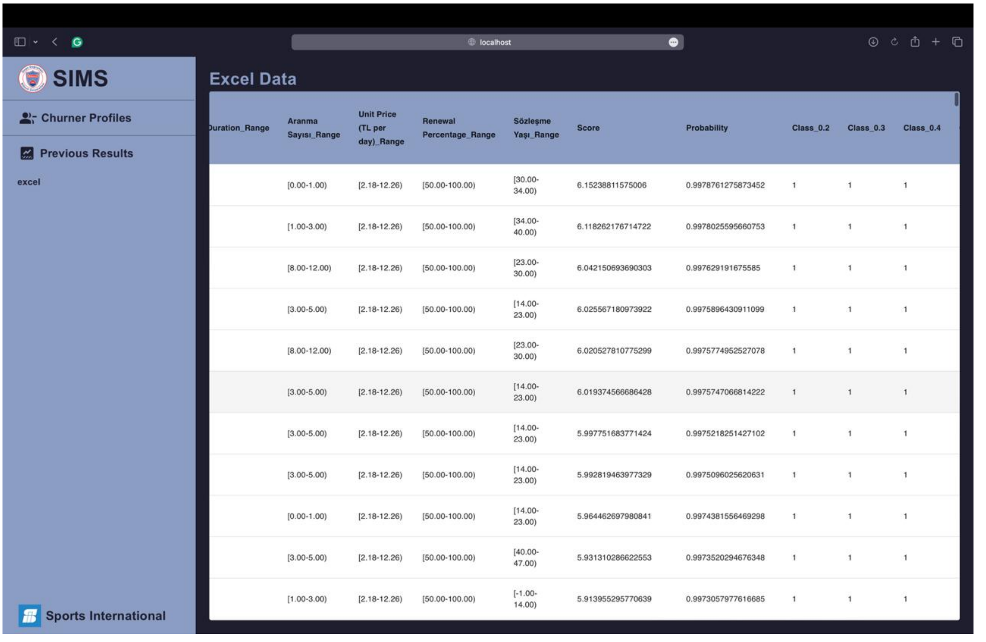


Figure 14.2: Probability of Customers

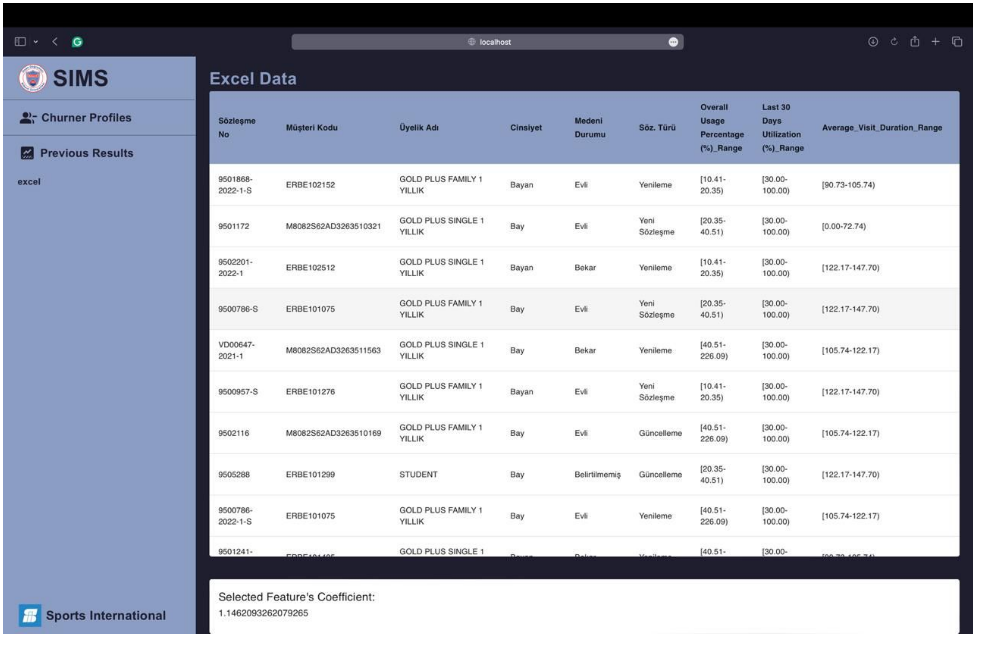


Figure 14.3: Feature Coefficient

to test the model and user interface. Beyond uploading the raw data files, end users did not need to make any manual changes in the code because the model was built to handle the missing values and inconsistencies common in the LAPIS database.

During the implementation phase, the model was tested for its robustness and adaptability. Instead of using the Kuzu Effects data, the model is trained with the Bilkent facility data to check its adaptability. The Bilkent data includes more entries and required higher computational power, yet the model was able to handle it. With Kuzu Effect's 5 years of data the model was able to give outputs in approximately 15 minutes, while the Bilkent 5 years of data was able to terminate in 35 minutes.

The pilot study showed that the model's predictions for renewals and real customer behavior were highly aligned where 65% of renewals, and 92% of non-renewals were captured by the model predictions giving a total of 84% accuracy. After the successful tests, the system was given to the Sales Team for practical use. There, it started to support their operations by offering precise, data-driven customer prioritization, laying the groundwork for longer term deployment and additional optimization based on the input.

14.6 Benefits to the Company

This project delivers two main benefits to the company:

- **Smarter Workforce Allocation:** Since customers are prioritized based on their likelihood to renew, sales consultants can focus their efforts where they're most needed leading to more efficient use of time and resources.

- **Customer-Centric Marketing Strategies:** By analyzing customer profiles, the company can design tailored strategies for retention. Understanding which types of customers are less likely to renew allows us to shape data-driven company policies that directly aim to improve customer retention.

In the bigger picture, all of these efforts support better budget and resource planning, workforce efficiency, and marketing strategy development. Ultimately, this drives both financial performance and customer satisfaction. Proposed application of the model can be seen in Figure 14.4.

Bibliography

de Medeiros, M. M., N. Hoppen, and A. C. G. Maçada (2020). Data science for business: benefits, challenges and opportunities. *The Bottom Line 33*(2), 149–163.

Hastie, T., R. Tibshirani, and J. Friedman (2017). The elements of statistical learning: data mining, inference, and prediction.

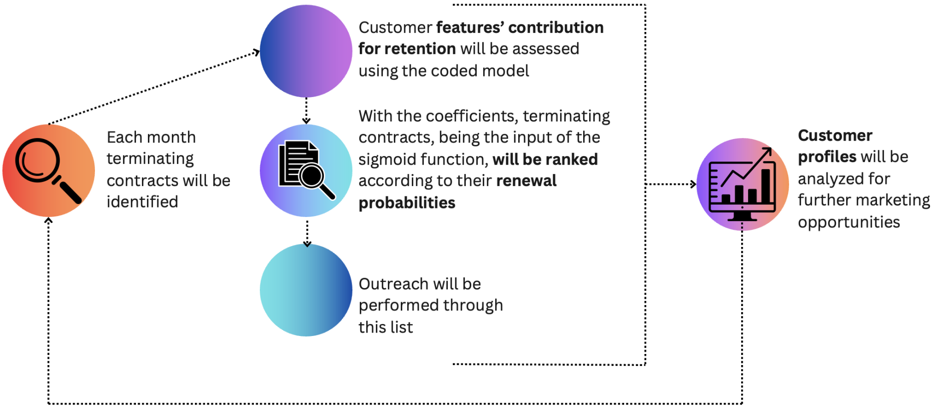


Figure 14.4: Model's Application Flowchart

Sabbeh, S. F. (2018). Machine-learning techniques for customer retention: A comparative study. *International Journal of Advanced Computer Science and Applications (IJACSA) 9*(2).

Subasi, M. M., E. Subasi, M. Anthony, and P. L. Hammer (2011). A new imputation method for incomplete binary data. *Discrete Applied Mathematics 159*(10).

Özdemir, H. (2024). Personal communication. Interview on October 10, 2024.

15 Stok Yönetimi ve Tedarikçi Değerlendirmesi için Karar Destek Sistemi

Tepe Home

Proje Ekibi
Ceren İlhan, Zeynep Karakaş, Eren Özdilkural, Bahar Özkırlı, Osman Eren Sargın, Elif Üstündağ, Muhammed Emin Yılmaz

Şirket Danışmanı
Ceren Evcimen
Pazarlama ve İhracat Müdürü

Akademik Danışman
Prof. Dr. Bahar Yetiş Kara
Endüstri Mühendisliği Bölümü

Özet

Bu proje kapsamında, Tepe Home'un e-ticaret operasyonlarındaki teslimat sürelerinin iyileştirilmesine yönelik bir karar destek sistemi geliştirildi. Sistem, envanter yönetimi ve tedarikçi değerlendirme olmak üzere iki ana bileşenden oluştu. İlk aşamada, geçmiş satış verileri analiz edilerek ürünler ABC sınıflandırmasına tabi tutuldu ve kritik ürünler için bütçe kısıtları altında stok önerileri belirlendi. Tedarikçi değerlendirme modülünde ise ürün grubu ve tedarikçi bazında teslimat süreleri analiz edildi; maliyet ve kalite kriterleri de dikkate alınarak tedarikçiler puanlandı ve sıralandı. Geliştirilen sistemle stok yönetimi, sipariş planlaması ve tedarikçi seçimi süreçleri optimize edildi; geçmiş dönem verileriyle test edilerek teslimat sürelerinde anlamlı iyileşmeler gözlemlendi.

Anahtar Sözcükler: Envanter Yönetimi, Tedarikçi Değerlendirme, ABC Analizi, Teslimat Süresi, E-Ticaret, Sipariş Planlaması, Bütçe Hesaplama

Decision Support System for Stock Management and Supplier Evaluation

Abstract

In this project, a decision support system was developed to improve delivery times in Tepe Home's e-commerce operations. The system consisted of two main components: inventory management and supplier evaluation. In the first stage, historical sales data were analyzed, products were classified through ABC analysis, and stock recommendations for critical products were determined under budget constraints. In the supplier evaluation module, delivery times were analyzed on both product group and supplier bases; suppliers were scored and ranked by also considering cost and quality criteria. Through the developed system, inventory management, order planning, and supplier selection processes were optimized, and significant improvements in delivery times were observed after testing with historical data.

Keywords: Inventory Management, Supplier Evaluation, ABC Analysis, Delivery Time, E-Commerce, Order Planning, Budgeting

15.1 Company and System Analysis

15.1.1 Company Description

Tepe Home, established in 1969, is one of Turkey's pioneering brands in the furniture and home decoration sector. The company offers a wide range of products including modular furniture, accessories, and seasonal items, appealing to diverse customer segments through both its physical retail network and expanding e-commerce operations. With its strong design and production capabilities, Tepe Home combines aesthetics and functionality, providing customers with customizable and trend-driven collections. The company operates multiple sales channels including brick-and-mortar stores, franchise operations, and an online platform. Its e-commerce infrastructure has gained increasing strategic importance in recent years, especially in meeting demand across a wider geographical reach. Focused on delivering a consistent customer experience and operational efficiency, Tepe Home continuously adapts its supply chain and technological capabilities to meet modern retail requirements. The company has positioned itself as a key player in the Turkish furniture market, with growing aspirations in digital transformation and omnichannel retailing.

15.1.2 Current System Analysis

Tepe Home's current e-commerce order management system is based on a make-to-order approach, where products are procured from suppliers only after the customer order is received. This process consists of multiple stages including procurement, quality control, packaging, and final delivery. The operational flow proceeds as follows: Once a customer places an order, Tepe Home forwards the request to the relevant supplier. The supplier then processes the procurement, and upon completion, the product is shipped to Tepe Home's facility. Here, quality control and packaging procedures are carried out, and the product is finally delivered to the customer. This structure enables low inventory costs and provides flexibility in operations. However, to effectively respond to fluctuating market demands, systematically monitor supplier performance and implement strategic stock planning, a more integrated and structured system infrastructure is required. Currently, order fulfillment is solely triggered by customer demand and all product groups are managed under a uniform procurement logic. Factors such as product criticality, supplier delivery history, or seasonal fluctuations are not explicitly incorporated into decision-making. Moreover, delivery lead times are not measured or analyzed within a formal framework. With the development of the proposed system, the goal is to enhance procurement and order management processes by introducing a more analytical, scalable and dynamic structure.

15.2 Problem Definition

Short and predictable delivery times have become one of the key indicators of operational efficiency in the e-commerce sector. Maintaining delivery performance at competitive levels is essential for companies to manage service quality in a consistent and scalable manner. At Tepe Home, the current order management process is based on procuring products from suppliers only after a customer places an order. While this reduces inventory holding costs, it causes delivery durations to exceed market averages when no preemptive planning is in place. Currently, the system lacks a forecasting-based planning infrastructure to respond proactively to demand fluctuations. All order decisions are made reactively, without anticipatory stock positioning or supplier coordination. In addition, there is no supplier evaluation mechanism in the existing system to monitor performance or guide procurement decisions. Supplier lead times or behavior across product groups are not systematically tracked, and no data-driven evaluation process is conducted. The core problem addressed in this project is that delivery durations remain above the market average, and the system lacks both a forecasting-driven planning model and a structured supplier evaluation mechanism to support improved operational responsiveness.

15.3 Proposed Solution and Methodology

The proposed solution features a decision support system where the user's can obtain the order quantity, estimated monthly and yearly budget and evaluation of the suppliers.

To address the inventory management problem for accessories, furniture, and Christmas decoration items a comprehensive solution was developed that integrates demand forecasting based on historical sales data, stock policy determination, and an optimization-based order quantity model. This mathematical model determines optimal stock levels and order quantities by considering forecasted demand and cost parameters. In addition, since the operational flow for Christmas product groups significantly differs, a separate approach based on the Newsvendor Model was formulated. This strategy ensures effective inventory control tailored to product characteristics while satisfying operational constraints and maintaining desired service levels.

15.3.1 Critical Assumptions

Critical Assumptions for Accessories and Furniture Model:

For each product type, a fixed order cost is considered. Orders are placed at the beginning of each month and are assumed to arrive within the same month to fulfill the demand for the following month. Given the uncertainty in the demand for accessories and furniture, a safety stock approach is adopted to reduce the risk of stock shortages. A common holding cost is calculated for accessories based on average volume, and a similar approach is used for furniture. Back-order penalty costs are evaluated as lost revenue, using outlet sales prices as a reference. The minimum and maximum order quantities for each product group are defined in the supplier agreements, and it is assumed that the company will provide initial inventory levels for each product group.

Critical Assumptions for Christmas Decoration Items Model:

For Christmas season products, only one bulk order is placed before the season, without the possibility of adjustment after observing the actual demand. Given the single-order nature of this process, the News-vendor model is applied to determine the optimal order quantity. Demand is assumed to follow a uniform distribution defined by historical minimum and maximum order quantities. Since unsold Christmas products are of no value in future seasons, it is critical to strike a balance between shortage and excess inventory costs. Warehouse capacity constraints are not considered for these items, as ample storage space is available in both retail stores and central warehouses.

By maintaining stock for high-selling product groups and placing monthly replenishment orders, the project aims to shorten delivery times, thus improving customer satisfaction and market responsiveness, and to reduce potential lost sales by ensuring consistent product availability.

15.3.2 Decision Support System

The solution combines forecasting and determination of stock policies to create a model that improves inventory management and streamlines the order fulfillment process, and was applied separately to accessories, furniture, and Christmas decoration items, with forecasting models and stock policies developed for each product category to address their specific operational dynamics. The overall decision support system consisted of two main modules: an inventory management module and a supplier evaluation module. In the inventory management module, an ABC analysis was conducted to prioritize products based on their importance levels. Forecasting methodologies were implemented to predict future demand, and a mathematical stock model was developed to define stock policies under estimated yearly budgets. These components were integrated to optimize stock levels while maintaining budgetary constraints and minimizing delivery lead times.

Inventory Management Module

ABC Analysis

An ABC analysis was implemented within the decision support system to classify products based on their revenue contribution and sales quantity. Products were divided into A, B, and C classes by analyzing cumulative sales quantities on the X-axis (80%, 95%, 100%) and cumulative revenue on the Y-axis. The classification of the Y-axis depends on the revenue concentration and determines the function type: if 10% of products generate over 80% of the total revenue, the function is considered *steep* with Y-axis thresholds (10%, 50%, 100%); if 20% of products generate more than 80% of revenue, it is considered *moderate* with thresholds (20%, 60%, 100%); and if 40% of products contribute over 80%, it is classified as *shallow* with thresholds (40%, 80%, 100%). For example, in the moderate case, 20% of the products are responsible for 80% of total revenue, indicating a balanced distribution. Based on the function type, Z-values are assigned as follows: $(z_a, z_b, z_c) = (1.282, 1.645, 2.326)$ in the moderate case. These Z-values are then used to calculate safety stock levels for each product using the formula

$SS = \sigma \cdot Z$, where σ represents the standard deviation of demand. This approach ensures that safety stock levels are aligned with the revenue impact of each product, enabling more effective inventory control (Bozarth and Handfield, 2013).

Forecast Methodology

To generate forecasted values, various time series and regression-based forecasting methods are applied. These methods include Single Exponential Smoothing, Double Exponential Smoothing, Triple Exponential Smoothing, ARIMA and SARIMA models, Poisson Regression, Negative Binomial Regression, and Random Forest algorithms. Each technique offers different strengths depending on the characteristics of the data, such as seasonality, trend, or count-based behaviors.

To calculate the Mean Squared Error (MSE), the historical dataset is split into two subsets: training and testing. 80% of the data is used to train the model, and the remaining 20% is used for validation. Each forecasting method is fitted on the training data and generates predictions for the test period. The predicted values are then compared with the actual test data, and the MSE scores are computed. The method with the lowest MSE is selected and presented on the user interface. In the final step, the system forecasts the next 12 periods using the entire historical dataset and the best-performing model.

Model: Inventory Management for Accessories and Furnitures

The mathematical model can be seen in the appendix with the parameters, decision variables, objective function and the constraints. The objective function of the mathematical model aims to minimize the total inventory-related costs, which include inventory holding costs, shortage penalty costs, and fixed ordering costs for both accessories and furniture. The cost minimization is performed separately for each product category across all time periods. The mathematical model incorporates several key operational constraints to ensure practical feasibility. Inventory balance constraints maintain logical stock flow by updating inventory levels across all time periods based on initial stock, incoming orders, and forecasted demand. Warehouse capacity constraints ensure that total inventory levels do not exceed storage limits defined for accessories and furniture, reflecting space availability. Supplier order constraints enforce the contractual minimum and maximum order quantities for each supplier, allowing orders only when the associated binary decision variable is active. Together, these constraints ensure that the procurement plan is practically applicable and responsive to real-time conditions

Safety Stock as an External Parameter

The safety stock levels, determined through the ABC analysis, are incorporated into the model externally by adjusting the first-month order quantities. This adjustment is made based on the comparison between the available initial inventory and the cumulative demand of the first two months. If the initial inventory is insufficient, the model increases the first-month order quantity by adding the required safety stock. In cases where the shortage is less than the predefined safety level, the safety stock is partially added by accounting for the existing gap. If the available inventory already exceeds the safety threshold, no adjustment is made. This rule-based approach ensures that demand fluctuations are buffered without embedding safety stock directly into the optimization constraints.

Estimated Budget

To support financial planning, an estimated yearly budget is calculated using order quantities determined by the mathematical model. This includes the cost of the first month's adjusted orders and the projected costs for the remaining months. If the total exceeds the company's budget, the system proportionally reduces order quantities to remain within limits. Moreover, the model calculates the upcoming month's budget based on the order quantities determined by the mathematical model, and in cases where this budget is exceeded, it recalculates the order quantities proportionally and presents the updated values to the user. This feature enables effective and trackable budget planning throughout the year.

Newsvendor Model for Christmas Decoration Items

The optimal order quantity in the Newsvendor model is determined by the critical fractile formula that can be seen in appendix. Since New Year's products are ordered in bulk for a single season and cannot be stored or resold afterward, a Newsvendor model was used to determine the optimal order quantity. Historical sales data by product category were analyzed to construct a uniform demand distribution, with bounds adjusted annually based on recent sales trends. If the latest year's sales volume exceeds that of the previous year and all prior years, the upper bound is increased proportionally; if the latest year marks the lowest sales, the lower bound is decreased. The growth rate between the last two years is used to scale these bounds accordingly. To capture the cost implications of misaligned ordering, underage costs were calculated as the lost profit due to stockouts, while overage costs reflect unsellable excess inventory. These costs were defined separately for each product category. By integrating historical trends, growth rates, and cost factors into a data-driven framework, the model en-

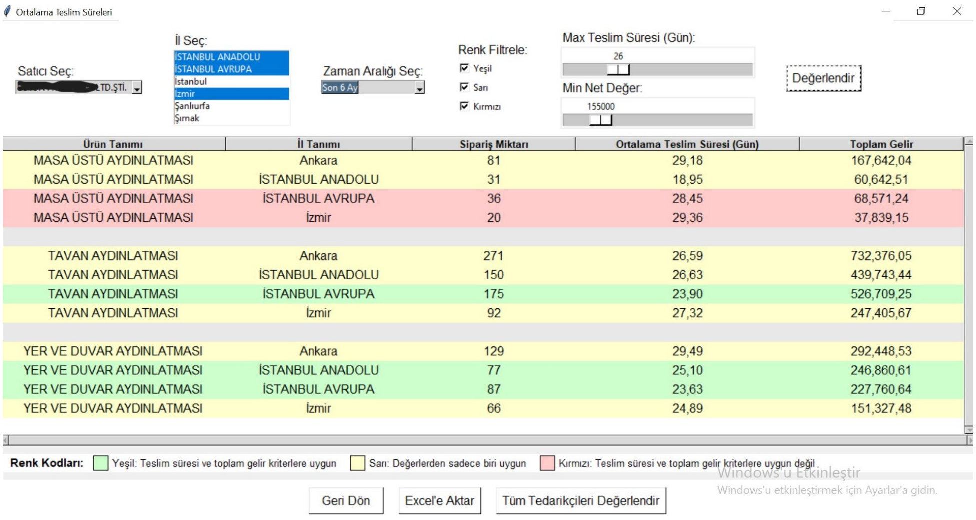


Figure 15.1: Supplier Performance Evaluation by Suppliers Module

sures both cost minimization and effective demand fulfillment for seasonal product planning.

Supplier Performance Evaluation System

In addition to its core features, the developed decision support system includes a dynamic Supplier Performance Evaluation module. This module enables users to assess supplier performance across key categories such as average lead time by order location, by supplier, and by product definition, as well as periodic lead time analysis and the revenue contribution of each supplier's products. As illustrated, the system allows users to set custom threshold values for each performance metric. Based on these thresholds, suppliers are automatically color-coded to highlight performance levels, making it easy to interpret results at a glance. This flexible, user-driven structure ensures that the evaluation adapts to changing business needs and priorities. Furthermore, the system supports exporting performance evaluation results directly to Excel, enabling seamless integration into reporting workflows and strategic decision-making. The ability to adjust thresholds and receive instant visual feedback empowers users with a highly interactive and actionable evaluation tool.

15.4 Validation

To ensure the reliability and practical applicability of our system, it was essential that the model produce results closely aligned with real-world outcomes. To validate this, we compared the forecasted values used by our mathematical model with the actual realized order quantities. Since the model determines order quantities based on demand forecasts for upcoming months, it was critical that these forecasts reflect real demand patterns. However, due to the lack of sufficient historical data for Tepe Home's e-commerce accessory sales, the validation process was carried out using past in-store sales data. Thanks to the flexible file structure of the developed decision support system, the model can seamlessly operate not only for e-commerce product categories but also for physical store orders. The validation results confirmed that the forecasted values were well aligned with actual sales data from physical stores, demonstrating both the accuracy of the forecasting module and the system's adaptability across different sales channels.

15.5 Implementation and Pilot Study

We finalized the decision support system for the project based on valuable feedback from our Industrial Advisors. As a result, we developed a user-friendly system that enables the company to effectively implement our proposed solution. The final version of the decision support system was presented to the Industrial Advisors, who responded positively, indicating that the system would be highly beneficial to the company.

The system was developed entirely in Python using open-source tools and libraries, making it cost-effective and accessible. To simplify deployment and eliminate the complexity of installation, the decision support system was converted into a standalone executable application and installed accordingly at the company.

Following the implementation, our Industrial Advisors confirmed that the supplier and product groups identified through the ABC analysis were highly accurate. They also noted that the demand forecasting module produced reasonable and consistent results. Moreover, they highlighted that, by maintaining stock for selected ABC-prioritized supplier-product groups, the average lead time could be reduced substantially providing significant operational efficiency.

15.6 Benefits to the Company

The decision support system we developed provides several significant benefits to the company. First and foremost, under the existing system, orders were placed without holding stock, resulting in delivery times that were well above market averages. By introducing a data-driven inventory management model, our system enables the company to hold stock for high-impact product groups based on demand forecasts. This has led to a substantial reduction in average delivery times—up to 90% on average—offering a strong competitive advantage in the market.

Also, in the absence of a forecasting system, decisions were made based on intuition, resulting in order quantities that exceeded actual demand. By incorporating demand forecasting, order quantities are now determined in a way that closely reflects real demand. As a result, the system prevents unnecessary expenditure of the budget.

In addition, the integration of a dynamic budgeting module within the system addresses a key limitation in the current process. Previously, the company lacked visibility into whether its procurement exceeded planned budgets. Our solution now allows for continuous budget monitoring and early detection of overruns. This functionality is especially critical for seasonal product groups such as New Year's items, where orders are placed once a year. The company can now allocate budgets more effectively and manage spending with greater control.

Lastly, the existing system lacked a tool to evaluate supplier performance. The supplier performance evaluation module we introduced allows the company to monitor performance metrics in real time and benchmark suppliers against one another. This feature not only enhances transparency but also supports more informed and strategic supplier management decisions. Overall, the system delivers measurable operational efficiency, financial oversight, and supply chain visibility—empowering the company with a comprehensive, decision-oriented platform.

15.7 Conclusion and Recommendations

In this project, a decision support system was developed to reduce delivery times and improve procurement processes for accessories, furniture, and Christmas products. In the current system, since no stock is held, delivery times often exceed market standards. The new system incorporates demand forecasting based on historical sales, optimization of order quantities to minimize costs, and a supplier performance evaluation module. Forecasts are generated using multiple models, with the best-performing one selected automatically, and are used in a cost-minimization model considering holding, ordering and shortage costs. For seasonal Christmas products, a Newsvendor model is applied. Validation results showed that the model aligns closely with actual sales data, and a pilot demonstrated up to an 90% reduction in lead times. The system also enables continuous budget monitoring and real-time supplier performance evaluation, improving delivery speed, budget control and supply chain visibility. It offers a practical, scalable and user-friendly tool that supports smarter, data-driven decision-making. Future recommendations include expanding the system to all product categories and using supplier performance metrics to strengthen sourcing strategies.

Acknowledgment

This project was supported by TÜBİTAK BİDEB 2209/B Program under Grant 1139B412409517.

Bibliography

Bozarth, C. C. and R. B. Handfield (2013). *Introduction to Operations and Supply Chain Management*. Pearson.

Appendix: Mathematical Models

15.A Furniture and Accessories

Table 15.1: Decision variables

Notation	**Description**
$Q_{a,j,t}$	Order quantity for accessories ($j \in J_a$) in month t
$Q_{f,j,t}$	Order quantity for furniture ($j \in J_f$) in month t
$I^+_{a,j,t}$	Inventory level of accessories at the end of month t
$I^-_{a,j,t}$	Lost accessory sales at the end of month t
$I^+_{f,j,t}$	Inventory level of furniture at the end of month t
$I^-_{f,j,t}$	Lost furniture sales at the end of month t
$O_{a,j,t}$	Binary, 1 if accessory order is placed in month t
$O_{f,j,t}$	Binary, 1 if furniture order is placed in month t

Table 15.2: Parameters

Notation	**Description**
h_a, h_f	Unit holding cost for accessories/furniture
p_a, p_f	Shortage cost for accessories/furniture
f_a, f_f	Fixed ordering cost for accessories/furniture
c_a, c_f	Warehouse capacity for accessories/ furniture
$D_{a,j,t}, D_{f,j,t}$	Demand in month t
$I^{\text{init}}_{a,j}, I^{\text{init}}_{f,j}$	Initial inventory levels
$\text{MinQ}_a, \text{MinQ}_f$	Minimum order quantity per product
$\text{MaxQ}_a, \text{MaxQ}_f$	Maximum order quantity per product

Objective Function

$$
\begin{aligned}
\min \sum_{j \in J_a} \sum_{t \in T} \left(h_a \cdot \frac{I^+_{a,j,t} + I^+_{a,j,t+1}}{2} + p_a \cdot I^-_{a,j,t} + f_a \cdot O_{a,j,t} \right) \\
+ \sum_{j \in J_f} \sum_{t \in T} \left(h_f \cdot \frac{I^+_{f,j,t} + I^+_{f,j,t+1}}{2} + p_f \cdot I^-_{f,j,t} + f_f \cdot O_{f,j,t} \right)
\end{aligned} \tag{A.1}
$$

Constraints

$$I^+_{a,j,1} - I^-_{a,j,1} = I^{\text{init}}_{a,j} - D_{a,j,1} \tag{A.2}$$

$$I^+_{f,j,1} - I^-_{f,j,1} = I^{\text{init}}_{f,j} - D_{f,j,1} \tag{A.3}$$

$$I^+_{a,j,t} - I^-_{a,j,t} = I^+_{a,j,t-1} + Q_{a,j,t-1} - D_{a,j,t}, \quad \forall t > 1 \tag{A.4}$$

$$I^+_{f,j,t} - I^-_{f,j,t} = I^+_{f,j,t-1} + Q_{f,j,t-1} - D_{f,j,t}, \quad \forall t > 1 \tag{A.5}$$

$$\mathrm{MinQ}_a \cdot O_{a,j,t} \leq Q_{a,j,t} \leq \mathrm{MaxQ}_a \cdot O_{a,j,t} \tag{A.6}$$

$$\mathrm{MinQ}_f \cdot O_{f,j,t} \leq Q_{f,j,t} \leq \mathrm{MaxQ}_f \cdot O_{f,j,t} \tag{A.7}$$

$$\sum_{j \in J_a} (Q_{a,j,t} + I^+_{a,j,t}) \leq c_a, \quad \forall t \in T \tag{A.8}$$

$$\sum_{j \in J_f} (Q_{f,j,t} + I^+_{f,j,t}) \leq c_f, \quad \forall t \in T \tag{A.9}$$

$$Q_{a,j,t}, Q_{f,j,t}, I^+_{a,j,t}, I^-_{a,j,t}, I^+_{f,j,t}, I^-_{f,j,t} \geq 0 \tag{A.10}$$

$$O_{a,j,t}, O_{f,j,t} \in \{0, 1\} \tag{A.11}$$

15.B Safety Stock Integration for Furniture and Accessories

Table 15.3: Additional Decision Variable

Notation	**Description**
$\mathrm{adjQ}_{a,j,1}$	Adjusted order quantity including safety stock in month 1

Table 15.4: Parameters

Notation	Description
$Q_{a,j,1}$	Order quantity for accessories in month 1
SS_a	Safety stock level for accessories
$I_{a,j}^{\text{init}}$	Initial inventory level for accessories
$D_{a,j,1}$	Demand for accessories in month 1
$D_{a,j,2}$	Demand for accessories in month 2

Inventory Difference Calculation

$$\text{inventory\_diff} = I_{a,j}^{\text{init}} - (D_{a,j,1} + D_{a,j,2}) \tag{A.12}$$

Adjusted Order Quantity

$$\text{adjQ}_{a,j,1} = \begin{cases} Q_{a,j,1} + SS_{a,j} & \text{if } Q_{a,j,1} > 0 \\ Q_{a,j,1} + SS_{a,j} & \text{if inventory\_diff} < 0 \\ Q_{a,j,1} + SS_{a,j} - \text{inventory\_diff} & \text{if } 0 \leq \text{inventory\_diff} < SS_{a,j} \\ Q_{a,j,1} & \text{if inventory\_diff} \geq SS_{a,j} \end{cases} \tag{A.13}$$

15.C Budget-Based Adjustment Model for Order Quantities

Table 15.5: Budget notation

Notation	Description
$cost_{a,j}$	Unit cost of an accessory in category j
$adjQ_{a,j,1}$	Adjusted order quantity for initialization month
$Q_{a,j,t}$	Order quantity of an accessory in category j at time t
T	Total number of time periods considered
B_{Tepe}	Tepe Home's Current Month Ordering Budget

Yearly Estimated Budget

$$\text{Yearly Budget} = \sum_{j} \left(adjQ_{a,j,1} \cdot cost_{a,j} + \sum_{t=2}^{T=12} Q_{a,j,t} \cdot cost_{a,j} \right) \tag{A.14}$$

Budget Needed for Initializing Month

$$\sum_j adjQ_{a,j,1} \cdot cost_{a,j} = B \tag{A.15}$$

Alternative Budget Expression

$$\sum_j adjQ_{a,j,1} \cdot cost_{a,j} \tag{A.16}$$

Budget-Based Order Quantity Adjustment

$$Q_{j,\text{new}} = \begin{cases} adjQ_j \times \left(\frac{B_{\text{Tepe}}}{B}\right) & \text{if } B_{\text{Tepe}} < B \\ adjQ_j & \text{otherwise} \end{cases} \tag{A.17}$$

15.D Newsvendor Model

$$Q^* = F^{-1}\left(\frac{c_u}{c_u + c_o}\right) \tag{A.18}$$

Table 15.6: Notation

Symbol	Description
Q^*	Optimal order quantity
c_u	Underage cost
c_o	Overage cost
F^{-1}	Inverse cumulative distribution function (CDF) of demand, which depends on the probability distribution (e.g., uniform)

16 | Talep Yönetimi ve Üretim Planlama

Nesco Gıda

Proje Ekibi
Mert Efe Aydın, Tan Durucan, Ege Hamdi Özcan, Emre Sarıbay, Ömer Mert Şahin, Ömer Tekinsiz, Fatma Nur Uslu

Şirket Danışmanı
Nazlı Esen Ummansu
Kurucu/CEO

Akademik Danışman
Doç. Dr. Emre Nadar
Endüstri Mühendisliği Bölümü

Özet

Bubble tea'de kullanılan patlayan boba incilerini üreten Nesco Gıda, özellikle Nisan-Eylül ayları arasındaki yoğun dönemlerde, üretim kapasitesi kısıtları nedeniyle müşteri talebini karşılamakta zorluk yaşamaktadır. Bu proje, Nesco Gıda'nın mevcut kapasitesini daha verimli yönetmesine ve müşteri taleplerini daha etkin karşılamasına yardımcı olacak bir karar destek sistemi geliştirmeyi amaçlamıştır. Doğrusal programlama (LP) yaklaşımı kullanılarak geliştirilen karar destek sistemi, hangi müşterilere, ne zaman ve ne kadar ürün tedarik edileceğini belirlemektedir. Ayrıca, yeni müşterilere yapılan sevkiyatların geciktirilmesinin kârlılığını değerlendirmek amacıyla bir gölge fiyat analizi gerçekleştirilmiştir. Bu yaklaşım, ceza maliyetlerinde ve birikmiş sipariş sayısında yaklaşık olarak %3,5 oranında bir azalma sağlamıştır.

Anahtar Sözcükler: Boba, Müşteri Önceliklendirmesi, Maksimum Kârlılık, Karar Destek Sistemi, Gölge Fiyat

Demand Management and Production Planning

Abstract

Nesco Company, a producer of popping boba pearls used in bubble tea, faces production capacity constraints that limit its ability to meet customer demand during peak months, particularly from April through September. This project aimed to develop a decision support system to help Nesco Gıda manage its limited capacity more efficiently and better meet customer demand. Using a linear programming approach, the system determines which customers to serve, when to serve them, and how much to supply. A shadow price analysis was conducted to evaluate the profitability of delaying shipments to new customers. This approach resulted in a 3.5% reduction in the number of backlogged orders.

Keywords: Boba, Customer Allocation, Maximum Profitability, Decision Support System, Shadow Price

16.1 Description of the System in Nesco

16.1.1 Company Description

Founded in 2016, Nesco is an innovative beverage company that specializes in premium craft tea bags and boba tea. Its key brands include TeaCo. and BobaCo., which are known for high-quality products that meet international standards such as ISO9001, ISO22000, and FDA certifications. Nesco exports to nearly 30 countries and supplies over 3,500 businesses—including cafes, hotels, and markets—within Türkiye.

TeaCo. produces artisanal tea blends using tea leaves imported from eight different countries. With a production capacity of 125 tons per year, it is the leading tea importer in Türkiye. TeaCo. prioritizes sustainability and consumer health by using hand-packed, 100% cotton, plastic-free tea bags (Fortune Türkiye, 2024). Their blends cater to both local and global preferences.

BobaCo., on the other hand, produces flavored boba pearls for bubble tea, a beverage that has seen significant growth in popularity in recent years. The production process involves cooking a base mixture, cooling it, shaping it into spheres using a chemical setting technique, and then preserving and packaging the final product. BobaCo. serves a wide customer base, including international food chains, national coffee shops, and local cafés.

As the only major boba manufacturer in the country, Nesco is facing an overwhelming surge in demand—estimated to be 12 times higher than current capacity. This has led to the need for a system that can intelligently allocate limited supply to maximize strategic and financial returns.

16.1.2 System Analysis

The team conducted a detailed analysis of Nesco's boba production process, particularly focusing on the factory operations. The process begins with a 65-minute cooking phase for 250 kg batches, followed by a 25-minute cooling step. Afterward, shaping machines drop the mixture into a chemical solution to create the iconic spherical boba shape. The product is then placed into buckets with a preservative, pasteurized for 60 minutes, cooled for 11 minutes, and finally labeled and packaged.

The shaping machines were identified as the main bottleneck, being slower than all other stages and limiting the overall output. Given this fixed capacity and the assumption of continuous full operation, the team excluded production line modifications and flavor changeovers from the project scope. Instead, the focus is on demand-side optimization.

16.1.3 Problem Definition

With the booming popularity of bubble tea in Türkiye—especially in summer—demand for boba has rapidly outpaced Nesco's production capabilities. The company expects 2025 demand to be multiple times higher than what it can currently supply, but expanding production is not immediately possible due to the constraints in the shaping stage.

This creates the need for a prioritization system that can intelligently allocate the existing production to the most valuable customers. The project aims to develop a decision-support system that incorporates multiple factors such as customer willingness to pay, order size, delivery deadlines, and customer prestige.

Customers are categorized based on various factors, including brand prestige, order volume, and strategic value, to guide how production capacity is allocated. The system helps determine which customers to serve, when, and in what quantity—with the understanding that not all demand can be fulfilled.

The goal is to design a model that ensures the most efficient and profitable use of Nesco's limited capacity—allowing the company to continue leading the Turkish market for boba tea, even under severe supply constraints. Some customers will have their demands fully met, while others may receive only partial or no fulfillment on time based on their strategic importance.

Indices	Description
$c \in \{1, 2, 3, \ldots, n\}$	Customer ID
$w \in \{0, 1, 2, \ldots, 26\}$	Week number

Table 16.1: Table 1: Indices

16.2 Proposed Solution Strategy

The main goal of this project is to maximize profit while adhering to operational and strategic constraints. In addition to profitability, the model aims to fulfill as much customer demand as possible by efficiently allocating limited production capacity. The planning spans approximately six months, during which most customer orders are received in advance. This allows the company to plan proactively—deciding which orders to accept, propose a counter offer, or reject entirely.

The solution approach begins with the development of a linear programming model that generates an aggregate production plan over a six-month horizon.. Initially, previously accepted orders, cost data, and current inventory levels are incorporated. New incoming orders are evaluated based on factors such as price, quantity, delivery time, and customer importance (e.g., prioritizing large or strategic clients). We develop a demand management algorithm that evaluates the profitability of the following three scenarios: accept the order, reject the order, or propose a counter offer when appropriate based on a shadow price analysis. Once an offer is accepted, the corresponding shipment is added to the model, and the evaluation continues for subsequent orders.

16.2.1 Linear Programming Model

Objective Function:

$$\text{Maximize } \sum_{w} \sum_{c} \left((SP_c - UC) \cdot S_{c,w} - \text{Pen}_c \cdot B_{c,w} \right)$$

Decision Variables	Description
$S_{c,w}$	Sales quantity to customer c in week w.
$B_{c,w}$	Backlog for customer c at the end of week w.
I_w	Inventory level at the end of week w.
P_w	Production level at week w.

Table 2: Decision Variables

Constraints:

$$
\begin{aligned}
& I_w \leq I_{\max} && \forall w \\
& P_w - \sum_c S_{c,w} = I_w - I_{w-1} && \forall w \\
& \sum_w S_{c,w} = \sum_w D_{c,w} && \forall c \\
& \sum_c S_{c,w} - P_w \leq I_{w-1} && \forall w \\
& B_{c,w} + S_{c,w} - B_{c,w-1} = D_{c,w} && \forall c, w \\
& P_w \leq P_{max} && \forall w \\
& S_{c,w} \geq 0 && \forall c, w \\
& B_{c,w} \geq 0 && \forall c, w \\
& I_w \geq 0 && \forall w \\
& P_w \geq 0 && \forall w
\end{aligned}
$$

The objective function aims to maximize the profit generated from sales while accounting for possible penalty costs incurred due to backlogged orders. The constraints are constructed to reflect real-world limitations that must be considered. These constraints include: maximum inventory capacity, weekly inventory changes, sales and demand equality (every accepted demand is assumed to result in a sale and must be fulfilled by the end of the time horizon), total weekly sales constrained by inventory and production levels, backlog limitations, maximum production capacity, and non-negativity requirements.

16.2.2 Demand Management Algorithm

The algorithm optimizes demand allocation to maximize profitability while respecting system constraints and customer priorities. It begins by running

Parameters	**Description**
CP_c	Customer priority level of customer c.
$D_{c,w}$	Demand for customer c at week w.
SP_c	Base sales price per unit for customer c.
UC	Unit production cost.
Pen_c	Penalty cost for customer c.
P_{max}	Weekly maximum production quantity.
I_{max}	Total inventory capacity.

Table 3: Parameters

the model twice, first without the last customer, then with the last customer to establish baseline results. For each week where the last customer has demand, the algorithm evaluates the shadow price of the backlog constraint. If the shadow price is positive or zero, the demand is accepted for that week; if it is negative, the algorithm considers shifting the demand to a future week with a higher shadow price to improve profitability. Customers are assigned priority levels that determine how far their demand can be shifted: up to three weeks for highest-priority customers, four weeks for second-tier, and five weeks for the rest. The algorithm identifies the future week within the allowed range that has the greatest positive difference in shadow prices and shifts demand incrementally to that week. After each shift, the model is rerun, and infeasible shifts are excluded from future evaluations. Once a specific demand is allocated, it is not revisited. This iterative process continues until no further beneficial shifts are possible, ensuring that demand is reallocated only when it improves the objective value, while maintaining a balance between profitability, constraints, and customer flexibility. The full pseudocode for the algorithm can be found in the appendix.

16.3 Validation

A structured validation process was conducted to ensure the Decision Support System (DSS) aligns with Nesco Gıda's objectives and reflects real-world operational constraints. This process included three phases: conceptual validation, operational validation, and expert validation.

In the conceptual validation phase, model assumptions—such as limited inventory, fixed capacity, and customer prestige levels—were reviewed with the Academic Advisor. The model was tested under various simulated scenarios, consistently producing feasible results or correctly identifying infeasibility in extreme cases.

The operational validation phase used real company data from June–July 2024 to test the system's performance. Despite prestige levels being unavailable historically, they were reasonably inferred from order volumes. The model replicated past outcomes accurately, with all customer demands fulfilled within the nine-week time frame, matching historical performance.

In the expert validation phase, the model was reviewed via the developed user interface with the Academic Advisor, making result evaluation more efficient. Overall, the DSS proved reliable, adaptable, and effective—offering improved efficiency, reduced penalties, and stronger decision support compared to manual methods.

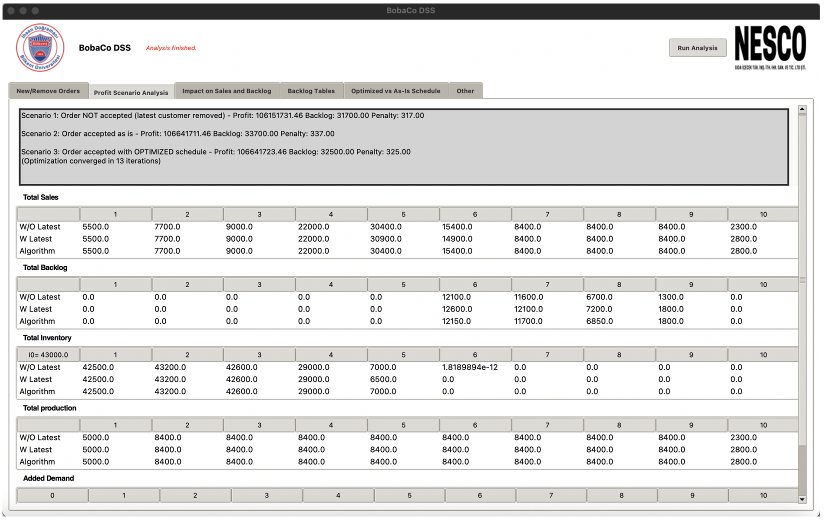


Figure 16.1: Profit Scenario Analysis Tab

16.4 Implementation and Pilot Study

The Decision Support System (DSS) was developed using PuLP, an open-source optimization library, and Tkinter, a built-in Python library for creating graphical user interfaces (GUIs). A user-friendly interface was created entirely in Python. To enhance usability, the system was integrated with Microsoft Excel, allowing users to update customer information, modify orders, and adjust demand directly—without switching between applications.

On April 18th, implementation was conducted at BobaCo.'s offices in İvedik with the support of the Industrial Advisor. We aimed to refine the system based on real-world feedback and ensure it aligned with the company's operational needs. During the session, the DSS was explained in detail to company officials, including how it operates and how it is linked to Microsoft Excel to enhance ease of use.

16.5 User Interface of the System

The graphical user interface (GUI) of the system operates through a structured process, which consists of three main steps, detailed as follows:

Step 1: Profit Scenario Analysis

In this step, the system provides an overview of the financial implications of the decision through three distinct scenarios:

- **Scenario 1: The order is not accepted.**
  - This scenario illustrates the profit the company would maintain if the order is declined.

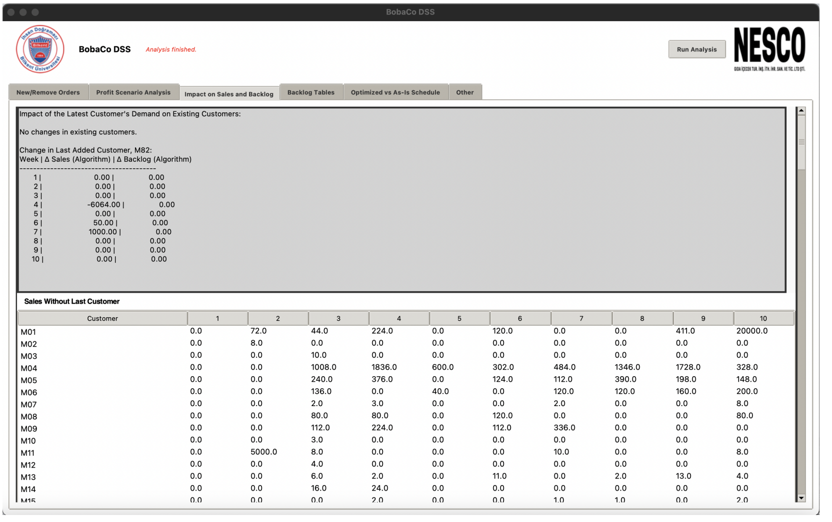


Figure 16.2: Impact on Sales Tab

- **Scenario 2: The order is accepted as is.**
  - The system shows the expected profit if the order is taken without any modifications to the delivery schedule.
- **Scenario 3: The order is accepted with an improved delivery schedule.**
  - This scenario presents the potential profit after applying an improved delivery schedule to maximize efficiency.

It is important to note that the system does not provide a definitive output, such as 'accept' or 'reject.' Instead, it presents these scenarios to assist the decision-maker in evaluating their options. The differences in optimal profit result from shifts in demand and the acceptance or rejection of the new customer.

Step 2: Impact on Sales and Backlog

The second step highlights the operational impacts of accepting the order. It identifies which companies' sales and backlog values will change, enabling the decision-maker to assess the broader implications of their decision.

Step 3: Delivery Schedule Overview

In the final step, the system presents detailed delivery schedules for each company. This includes specific timelines and allocations, providing users with a clear understanding of how the order will be fulfilled in practice.

16.6 Benefits to the Company

Currently, Nesco manages order selection and customer allocation through manual decision-making processes. While this approach has been sufficient under past conditions, demand in the upcoming season is projected to significantly exceed the company's current production capacity. In response to this challenge and recognizing the limitations of manual planning, the DSS has been developed to optimize production planning and customer prioritization through data-driven, analytical methods.

The DSS provides several key advantages. Most notably, it enables the company to improve profitability by prioritizing orders with the highest economic return while remaining within production constraints. This allows BobaCo to generate greater revenue, even when all customer orders cannot be fulfilled. Additionally, the system strategically prioritizes loyal and high-prestige customers, reinforcing long-term relationships and enhancing overall customer satisfaction.

Flexibility is another major strength of the system. It can adapt to various operational scenarios, including changes in production capacity, the introduction of new product lines, or shifts in demand patterns. When new input data such as a sudden influx of orders is introduced, the model can be quickly rerun to produce an updated production and allocation plan. This responsiveness is especially valuable in high-demand situations, supporting agile and informed decision-making.

To evaluate the model's performance, we tested it using three different simulated demand datasets: uniform demand, mid-heavy demand, and end-heavy demand scenarios. Across all tests, the system consistently produced feasible and profitable outcomes. The most significant improvement was observed in the mid-heavy demand scenario which aligns with the expected real-world demand pattern for the upcoming season. Overall, we observed a 3.5% reduction in total backlog and penalty costs, highlighting the tangible benefits of transitioning from manual processes to a data-driven approach.

In summary, adopting the DSS allows BobaCo to operate more efficiently and competitively. The system not only increases profitability but also improves, strategic customer management, and long-term planning by taking into account key operational factors such as profit, customer satisfaction, and contractual obligations.

16.7 Conclusion

In conclusion, this project successfully delivered a robust DSS tailored to Nesco Gıda's operational needs. By combining a linear programming model with real-world constraints, customer priorities, and an interactive interface, the system enables the company to improve production planning and customer allocation under high-demand scenarios. Validation using both simulated and real data confirmed the model's reliability, efficiency, and alignment with past performance. With its flexibility, scalability, and improved decision-making capabilities, the DSS offers a practical solution that supports Nesco's current operations and positions the company for future growth.

Bibliography

Fortune Türkiye (2024, August). Nesco, İhracatta emin adımlarla İlerliyor. *Fortune Turkey*. https://www.fortuneturkey.com/nesco-bubble-tea-ile-cirosunu-4e-katladi.

Appendix: Pseudocode of the Algorithm

Initialization:
    Set $f \leftarrow 1$.
    Set $run\_count \leftarrow 0$.
    Set w_set empty.
    Define the Model.
While $f = 1$ **do**
    Increment run_count.
    If $run\_count = 1$ **then**
        Run the model excluding the last customer demand.
    Else if $run\_count = 2$ **then**
        Run the model with the last customer demand.
    Else
        Calculate shadow prices for backlog constraint.
        For each demand week w of the last customer **do**
            If w in w_set **then** continue.
            Compute shadow price for backlog constraint.
            If shadow price ≥ 0 **then**
                Add week w to w_set.
                Continue.
            For each demand from week $w + 1$ to $w + flexibility[c]$
                Compute shadow price for backlog constraint.
                Calculate difference with shadow price of week w.
                Select maximum shadow price difference.
            If max shadow price difference > 0 **then**
                Shift n units of demand from week w to week
                with highest shadow price.
                Break.
            Else
                Add week w to w_set.
            End if.

End for.

End if.

If demands do not change in last two iterations **then**

Set $f \leftarrow 0$.

End while.

Output:

Delivery schedule without the last customer.

Delivery schedule with the last customer.

Delivery schedule with shifted demand.

Objective function value without the last customer.

Objective function value if the customer is accepted as requested.

Objective function value if the customer is accepted with shifted demand.

Tedarik Zinciri Verimliliğini Artırma Odaklı Talep Tahmini | 17

Nestlé Türkiye

Proje Ekibi
Kayra Kaan Akpınar, Aybüke Aldırmaz, Acar Karabıçak,
Bora Kol, Cengiz Menten, Ilgın Tekirdağ, Sera Tekkök

Şirket Danışmanları
Elçin Kocaman, Bilgi Teknolojileri İnovasyon Yöneticisi
Görkem Sayalı, Kıdemli Talep ve Tedarik Planlama Yöneticisi

Akademik Danışman
Doç. Dr. A. Selin Kocaman
Endüstri Mühendisliği Bölümü

Özet

Bu proje, Nestlé'nin talep tahmin hatalarından kaynaklanan iade veya satılamayan ürün sorununu çözmeyi hedeflemektedir. Perakende Satış Kanalı'na odaklanarak, veri odaklı bir talep tahmin sistemi ve matematiksel model ile stok, satış ve dağıtım yönetimi optimize edilmiştir. Mevcut manüel süreçler nedeniyle düşük olan talep planlama doğruluğu artırılmış, gerçek zamanlı verilerle üretim ve talep daha iyi dengelenmiştir. Böylece israf azaltılmış, maliyetler düşürülmüş ve sürdürülebilirlik hedeflerine katkı sağlanmıştır. Bunun için makine öğrenmesi modellerinden LightGBM ve optimizasyon için matematiksel modelleme birlikte kullanılmıştır. Geliştirilen karar destek sistemi, kötü ürün miktarını azaltırken tedarik zinciri verimliliğini artırmış ve Nestlé'nin operasyonel performansına sürdürülebilir bir katkı sağlamıştır.

Anahtar Sözcükler: Talep Tahmini, Envanter Optimizasyonu, Tedarik Zincirinde Veri Analizi, Kötü Ürün Azaltma

Demand Forecasting for Enhanced Supply Chain Efficiency

Abstract

This project aims to solve Nestlé's issue of returned or unsellable products caused by demand forecasting errors. Focusing on the Retail Sales Channel, it seeks to optimize inventory, sales, and distribution management through a data-driven demand forecasting system and mathematical model. Due to current manual processes, demand planning accuracy is low; the project improved this by using real-time data to better align production with demand. This helped reduce waste, lower costs, and support sustainability goals. For this purpose, machine learning model LightGBM and optimization tool PuLP are used in an integrated way.

Keywords: Demand Forecasting, Inventory Optimization, Data Analysis in Supply Chain, Bad Good Reduction

17.2 System Analysis and the Problem

Nestlé's current sales planning process is carried out through five structured weekly meetings involving various teams such as Category Development, Demand and Supply Planning (DSP), and Sales Operations. These meetings lead to the creation of an 18-month forecast and finalized production and distribution decisions. Additionally, a Vendor-Managed Inventory (VMI) system is used during Monthly Business Planning (MBP) to manage distributor-level inventory and replenishment. However, demand forecasting is still largely manual and based on simplistic methods, such as multiplying past sales figures by a fixed constant, without applying advanced mathematical models. This lack of data-driven forecasting has led to low Demand Planning Accuracy (DPA), currently below 50% in some channels. Consequently, Nestlé faces issues like overproduction, overstocking, and increased levels of bad goods which are products that expire before being sold. By September 2024, the cost of bad goods reached over $187 million, driven mainly by poor inventory planning and amplified by the bullwhip effect. This results in inefficiencies across the supply chain, including higher storage costs, reduced product freshness, and operational waste. The project aims to address these issues by implementing a more dynamic and data-driven demand forecasting system (Nestlé Global, 2024).

17.3 Proposed Solution Strategy

To address the problem defined in Section 17.2, our solution consists of two integrated models. The first is a demand forecasting model based on machine learning techniques and traditional forecast techniques, which utilizes historical sales and inventory data to generate accurate demand predictions. These predictions are then used as input for our second model—an optimization model designed to determine the ideal sales and distribution quantities. By combining these two models, we aim to reduce the volume of bad goods caused by overproduction and poor inventory alignment while keeping the unmet demand levels at a certain level. This two-step approach enables a data-driven and scalable solution that aligns production with actual market demand while minimizing waste.

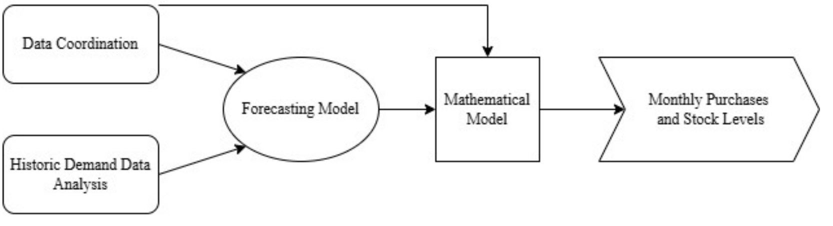


Figure 17.1: Flow Chart for the Conceptual Model

17.3.1 Critical Assumptions

To ensure a more reasonable and manageable model, several critical assumptions were made. Lead times are assumed to be negligible, as Nestlé provides frequent shipments and our model operates on a monthly basis. The focus is on the identified underperforming business groups: Coffee and Beverages, Chocolate and Confectionery, Infant Nutrition, and Children's Beverages, and their data is used for validation. It is assumed that production, inventory capacities, and supplier reliability are sufficient to meet forecasted demand, excluding uncertainties from these factors. Political disruptions, such as boycotts, are also excluded from the scope although it includes scenario-based planning for unexpected demand fluctuations. Lastly, all shipments are assumed to be at a constant freshness, disregarding any variation in product aging from Nestlé's warehouses.

17.3.2 Major Constraints

The primary constraints stem from the current VMI system, which calculates stock levels based on a fixed three-week demand coverage without considering cost factors, leading to heuristic and sometimes suboptimal decisions. This rigid approach also creates inefficiencies for products with longer shelf lives. Another major limitation is data availability as many product ID codes change annually at Nestlé, restricting the usable historical data to the years 2022–2024. This short data window may introduce bias and reduces the effectiveness of forecasting models, as compiling a longer, consistent dataset is not feasible under current system limitations.

17.3.3 Objectives

The main objective of this project is to reduce the quantity of bad goods, measured in kilograms, while balancing the trade-off with unmet demand using a weighted scenario approach, leaving the unmet demand threshold decision to Nestlé's planning team. Key sub-objectives include improving demand forecasting accuracy, particularly for retail distributors, where the lack of a robust forecasting system has led to significant mismatches between predicted and actual demand. Additionally, optimizing Nestlé's primary sales to distributors is crucial to avoid both overstocking, which increases bad goods, and understocking, which results in unmet demand, especially important given the current economic volatility. Ultimately, the goal is to enhance supply chain efficiency and generate substantial cost savings for Nestlé by reducing the rising trend of bad goods.

17.4 Solution Approach

17.4.1 Demand Forecasting Model

A hybrid demand-forecasting model was developed using the *Secondary Sales* dataset, which contains monthly demand columns for each month of 2022–2024, plus a *Grand Total* column summing all months. Distributor identities are stored in the *Customer Code L6* column, product categories in *BusinessCategoryTR*, subcategories in *FGroup*, and finer subgroups in *Local Attribute 5*. To forecast demand for a given month, all other month columns—as well as the encoded categorical fields—serve as input features.

During preprocessing, all categorical variables were label-encoded, demand values were scaled to [0, 1] to account for wide value ranges, and any rows with missing data were removed.Our comprehensive approach fits five forecasting methods: Moving Average, Exponential Smoothing, ARIMA, Neural Networks, and LightGBM for each product-distributor series. Each method's forecasts are evaluated on a hold-out set using RMSE, and the lowest-error model is automatically selected per series.

This dynamic strategy captures varying seasonalities, trends, and volatility across different series, resulting in a dramatic accuracy improvement: the overall RMSE dropped from around 150 kg under the LightGBM-only model to approximately 55 kg with the hybrid approach. Model performance is reported via R^2—indicating explained variance—and RMSE, which measures average prediction error.

17.4.2 Mathematical Programming Model

A two-stage stochastic optimization model is developed to minimize the quantity of bad goods. The parameters used only in the Python PuLP code are as such:

- μ: Mean forecast value for demand.
- σ: Standard deviation for demand.
- F_t: Forecasted demand for month t.
- α : Confidence level for scenario generation (related to quantiles).

μ and σ is used to calculate the maximum inventory capacity. F_t is used to calculate the demand. Finally, α is used for generating scenarios, with its value being 5% as expected. The two-stage stochastic optimization model is given below.

Sets

- $T = \{1, 2, \ldots, 24\}$ for months.
- $J = \{1, 2, \ldots, 24\}$ for shipment months.
- $K = \{1, 2, \ldots, n\}$ for scenarios.
- $\mathrm{EB}(t) = \{j \in J \mid j \leq t \text{ and } t - j < PL\}$ for shipment months whose products remain within their shelf life and are available for sale in month t.

Parameters

- $D_{k,t}$: Demand in month t for scenario k.
- M: Maximum inventory threshold.
- PL: Product life cycle in months.
- w_k: Weight for scenario k.
- ϵ: Maximum allowed expected unmet demand, controlling the trade-off between inventory costs and service levels.

Decision Variables

- P_t: Primary sales in month t.

- $S_{t,j,k}$: Sales from production month j in month t for scenario k.
- $BG_{t,k}$: Bad goods in month t for scenario k.
- $UD_{t,k}$: Unmet demand in month t for scenario k.
- $N_{t,j,k}$: Inventory at the end of month t for shipment month j and scenario k.
- EXt, j, k: Expired inventory in month t from shipment month j in scenario k.

Model

$$
\begin{aligned}
\min \quad & \sum_{k=1}^{K} w_k \sum_{t=1}^{T} BG_{t,k} && && (17.1)\\
\text{s.t.} \quad & \sum_{k=1}^{K} w_k \sum_{t=1}^{T} UD_{t,k} \leq \epsilon && && (17.2)\\
& N_{j,j,k} = P_j - S_{j,j,k}, && j \in T, k \in K && (17.3)\\
& N_{t,j,k} = N_{t-1,j,k} - S_{t,j,k}, && t \in T, j \in T, k \in K && (17.4)\\
& EX_{t,j,k} = N_{t-1,j,k}, && t \in T, j \in T, k \in K, t = j + PL && (17.5)\\
& BG_{t,k} = \sum_{j \in T} EX_{t,j,k}, && t \in T, k \in K && (17.6)\\
& S_{t,j,k} \leq D_{k,t-1}, && t \in T, j \in \mathrm{EB}(t), k \in K && (17.7)\\
& S_{t,j,k} \leq D_{k,t-1} - \sum_{i \in \mathrm{EB}(t), i<j} S_{t,i,k}, && t \in T, j \in \mathrm{EB}(t), k \in K && (17.8)\\
& \sum_{j \in \mathrm{EB}(t)} S_{t,j,k} + UD_{t,k} = D_{k,t-1}, && t \in T, k \in K && (17.9)\\
& N_{t,j,k} \leq M, && t \in T, j \in T, k \in K && (17.10)\\
& P_t, S_{t,j,k}, BG_{t,k}, UD_{t,k} \geq 0, && t \in T, j \in J, k \in K && (17.11)
\end{aligned}
$$

The objective function (1) minimizes the weighted bad goods and unmet demand across all scenarios. The epsilon constraint (2) transforms the biobjective problem into a single-objective formulation by bounding unmet demand within a user-defined threshold ϵ, allowing emphasis on minimizing bad goods. The third constraint (3) defines the initial inventory at the beginning of the planning horizon as the difference between primary sales and scenario-specific sales. The fourth constraint (4) updates inventory levels each month by reducing the previous month's inventory by the current month's sales, following the FIFO principle. The fifth constraint (5) identifies expired inventory as any stock that remains unused at the end of its expiration period. The sixth constraint (6) aggregates expired inventory across all months and scenarios to compute the total amount of bad goods. The seventh constraint (7) ensures sales from older batches are prioritized and do not exceed demand from earlier periods. The eighth constraint (8) restricts sales from newer batches to the leftover demand not satisfied by older batch sales. The ninth constraint (9) enforces that total sales and unmet demand together fulfill the demand in each period. The tenth constraint (10) ensures that inventory for each production month and scenario stays within the maximum allowable limit. Finally, the eleventh constraint (11) ensures that all decision variables—such as sales, bad goods, and unmet demand—are non-negative to reflect realistic conditions.

The two-stage stochastic optimization model was solved using Pyhton Gurobi. For validation, the model was adapted to PuLP, an open-source alternative. To generate preliminary results, the model was run for one distributor and one product. Historical data was used to determine inventory limits, guided by Nestlé's service level logic (Type 2), which assumes minimal unmet demand. Demand was modeled as Normally distributed, supported by statistical analysis, and a service level $\beta_2 = 99.9\%$ was applied to estimate maximum inventory. Demand was obtained using the dynamic forecast model. Although the model runs for 24 months, only the first 12 months are used to evaluate bad goods and unmet demand, as the objective is annual optimization with consideration of future dynamics.

To account for uncertainty, multiple demand scenarios were created by sampling from a Normal distribution with parameters derived from the forecast. The model was solved iteratively by expanding the scenario set until objective values stabilized under a predefined tolerance. Once stable, the final scenario set was fixed and used to generate a robust solution. Lastly, the epsilon constraint method was applied, which functions as a way of limiting the unmet demand, producing the Pareto frontier and scenario-objective plot using validated demand data.

17.5 Verification and Validation

Forecasting Model:

The forecasting model was verified through three tests: (1) *Continuity Testing* confirmed stability by scaling demand inputs and observing proportional RMSE changes; (2) *Degeneracy Testing* showed reliable predictions under extreme inputs; (3) *Consistency Testing* validated logical behavior across different model depths.

For validation, data cleaning removed irrelevant entries and applied PCA

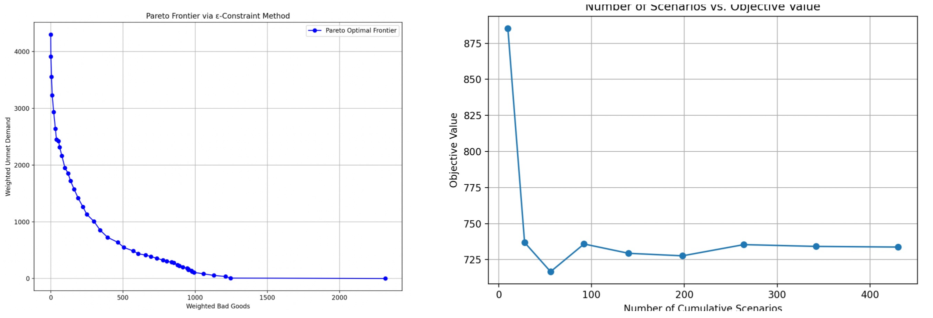


Figure 17.2: Pareto optimal frontier (left) and number of scenarios vs the objective

for dimensionality reduction. One-hot encoding and power transformation were used before splitting data 80/20. Monthly hyperparameter tuning with Optuna improved performance. The model achieved an RMSE of 55 and R^2 of 74.85%, though monthly scores were lower due to high variance in individual months.

Optimization Model: Verification included: (1) *Deterministic Comparison*, where the simplified model gave 0 bad goods/unmet demand; (2) *Continuity Testing*, which confirmed expected behavior under parameter changes; (3) *Degeneracy and Consistency Testing*, which validated model response to extreme and boundary cases.

Validation used historical data from October 2022 to 2024, taking the average ofmost sold 20 products, focusing on bad goods accumulation. Compared to historical data (301.90 kg):

- With secondary sales: 198.41 kg (34.28% improvement)
- With primary sales: 233.19 kg (22.76% improvement)

Scenario weights were derived from a 95% confidence interval assuming Normal distribution. A user interface is planned for flexibility, and the model is implemented in PuLP for compatibility with Nestlé's systems.

17.6 Implementation Plan and Pilot Study

To ensure successful adoption, a structured implementation plan has been developed in collaboration with the company. A key component is the development of a UI/UX interface to serve as both a demo and an explanatory tool, clarifying model inputs, outputs, and functionality. Technical reliability, code robustness, and security compliance will be addressed, including access control and authentication.

Initial integration includes a presentation on how local data feeds into the models and how the outputs support production optimization. Cross-

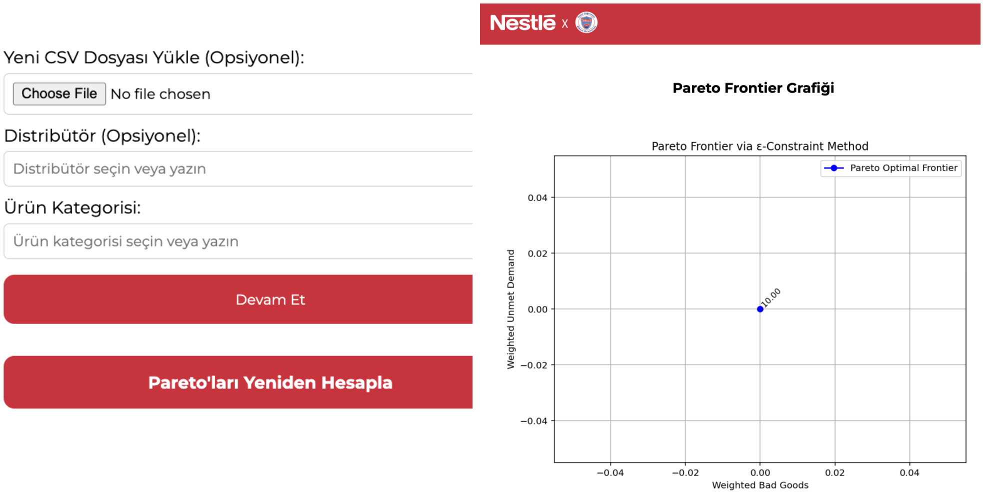


Figure 17.3: User Interface: Input Screen and Pareto Frontier Table

departmental involvement, especially from sales and marketing teams, helps align model use with business goals and gather feedback for future improvements. The aim is to embed the system into daily operations while maintaining scalability and adherence to internal software standards.

A pilot study was conducted using historical data from 2022–2023 to evaluate model effectiveness, since real-time validation isn't feasible due to long product shelf lives. The decision support system was applied to cleaned production and defect data, and its predictions were compared to actual bad goods reports.

The pilot measured potential reductions in bad goods, operational efficiency gains, and overall model reliability. Feedback from Nestlé's industrial advisors helped refine the model and documentation. Key milestones included system implementation by May 18th, evaluation by May 28th, and final presentation on June 11th. The pilot confirms the strategy's feasibility and offers a reliable foundation for full-scale deployment.

17.7 Benefits to the Company

The project addresses the issue of bad goods (BG), which affects multiple cost centers—production, logistics, storage, and disposal. By reducing BG, the company can lower operational costs while advancing sustainability and digitalization goals.

The LightGBM-based demand forecasting system improves demand accuracy at the city and market levels, helping prevent overproduction and unmet demand. This leads to more efficient distribution, reduced transportation, and optimized inventory management.

The mathematical model further enhances decision-making by analyzing key variables such as sales, inventory, and BG for each scenario. These insights will guide policy improvements and strengthen distributor coordination. Reducing BG also means less environmental waste, particularly from packaging and consumable materials.

Data outputs—both graphical and numerical—highlight trends by product, location, and distributor. This enables proactive actions like adjusting shelf life practices and improving storage conditions. Operational flexibility is also improved, allowing the company to better plan production, lead times, and safety stock.

While eliminating BG entirely may not be possible, the tools developed help minimize it and identify recurring problem areas. Ultimately, the integration of forecasting, optimization, and analytics supports a data-driven, scalable decision-making structure that aligns with the company's long-term transformation strategy.

17.8 Conclusion

This project addresses a critical challenge in Nestlé Türkiye's supply chain: the high volume of bad goods driven by inaccurate demand forecasting and misaligned inventory planning. By designing an integrated decision support system that combines a machine learning and traditional methods, a dynamic demand forecasting model, with a two-stage stochastic optimization framework, the project offers a scalable and data-driven solution to align production with actual demand. The forecasting model enables accurate monthly demand predictions by leveraging historical secondary sales data, while the optimization model minimizes bad goods and unmet demand across multiple scenarios.

Pilot results have shown significant improvements: a 34.28% reduction in bad goods for secondary sales and 22.76% for primary sales. Additionally, the development of a user interface supports future integration and usability within Nestlé's existing planning systems. By improving forecast accuracy and optimizing inventory decisions, this solution enhances supply chain efficiency, reduces waste, and supports Nestlé's sustainability and digitalization goals.

Acknowledgment

This project was supported by TÜBİTAK BİDEB 2209/B Program under Grant 1139B412408414.

Bibliography

Nestlé Global (2024, February). Nestlé annual review 2024. https://www.nestle.com/sites/default/files/2025-02/annual-review-2024-en.pdf. Accessed: 2025-04-25.

18 | Tedarikçi Karne Sistemi

Beko Küçük Ev Aletleri Direktörlüğü

Proje Ekibi
Cem Tuna Açıkgöz, Zeynep Naz Aldıkaçtı, Emre Erdoğan,
Ece Kuşdemir, Oğuz Kağan Özkan, Uğur Sorar, Egehan Uğraş

Şirket Danışmanı
Serdar Değirmenci
Pişiriciler ve İçecek Hazırlama
Kalite Yöneticisi

Akademik Danışman
Prof. Dr. Nesim K. Erkip
Endüstri Mühendisliği Bölümü

Özet

Beko Küçük Ev Aletleri Direktörlüğü ürün temini yaptığı tedarikçilerin performanslarının değerlendirilmesi için bir performans değerlendirme sistemi kullanmaktadır. Yapılan analizler doğrultusunda, kullanılan sistemin güvenilirliğinin ve sonuçlarının tutarlılığının test edilmediği, tedarikçilerin gelecek performansları ile alakalı ön bilgi edinilmediği ve literatürde olan bazı değerlendirme kriterlerinin sistemde olmadığı saptanmıştır. Tedarikçi performans sistemini iyileştirmek amacıyla performanslar farklı yöntemler ile sınanarak sistemin güvenilirliği ve tutarlılığı ölçülmüş, geliştirilen erken tespit mekanizması ile tedarikçilerin gelecek performansları hakkında öngörü elde edilmesi sağlanmıştır. Geliştirilen karar destek mekanizmaları, kullanılan sistemin sonuçlarına olan güvenilirliği arttırmakla beraber, tedarikçilerin gelecek performanslarını %60'a yakın oranda doğru tahmin ederek tedarikçi performansı kaynaklı kayıpların önüne geçilmesi ve yeni tedarikçi arayışı sürecinin hızlandırılmasına yardımcı olmaktadır.

Anahtar Sözcükler: Çok kriterli karar verme, duyarlılık analizi, korelasyon analizi, erken tespit sistemi, tedarikçi performansı değerlendirmesi.

Supplier Evaluation System

Abstract

The Directorate of Small Domestic Appliances of Beko uses a performance evaluation system to evaluate the performance of suppliers from which it supplies products. In line with the analyses conducted, it was determined that the reliability of the system used and the consistency of its results were not tested, preliminary information regarding the future performance of suppliers was not obtained, and some evaluation criteria in the literature were not included in the system. In order to improve the supplier performance system, the reliability and consistency of the system were measured by testing the performances with different methods, and the developed early detection mechanism provided foresight about the future performance of suppliers. The developed decision support mechanisms increase the reliability of the results of the system used, and by estimating the future performance of suppliers with a rate of approximately 60% accuracy, they help prevent losses due to supplier performance and accelerate the process of finding new suppliers.

Keywords: Multiple criteria decision analysis, sensitivity analysis, correlation analysis, early detection system, supplier performance evaluation.

18.1 General Information

Established in 1955, Beko is one of the leading white goods manufacturers in Türkiye and Europe, operating in over 100 countries under global brands such as Arçelik, Beko, and Grundig. The company employs over 40.000 people and focuses heavily on innovation through its 29 R&D centers worldwide. The Çayırova-based Small Domestic Appliances (SDA) Directorate is one of Beko's specialized facilities, responsible for compact domestic appliances such as coffee machines, kettles, and vacuum cleaners. (Beko, 2025) Most of these products are procured as finished goods from suppliers across Türkiye, China, and Europe.

18.1.1 Current System and Analysis

The supplier evaluation system currently in use creates an annual scorecard for each supplier based on five main performance categories. Each category is further broken down into sub-criteria, and responsible departments enter scores through SharePoint and later process them in Excel. The final scores are calculated using weighted averages, and each supplier is classified from A to D based on these scores. The system includes a ruleset to guide the company's response to underperformance, such as warnings or contract terminations for repeated C or D grades.

Historical data from 2015 to 2023 was analyzed to understand the distribution of scores, grade transitions, missing data patterns, and variance between categories. The results showed that while the system uses the full scoring scale, some sub-criteria suffer from significant missing data. Also, correlation analysis revealed statistical relationships between some criteria, possibly leading to biased results. There is no existing mechanism to test the system's robustness or detect declining supplier performance over time.

18.1.2 Problem Definition

The following problems were identified in the current system: Firstly, the robustness and consistency of supplier scores have not been validated from different perspectives, which may raise concerns about the reliability of the evaluation outcomes. Secondly, the system lacks an early detection mechanism to gain insights about suppliers' future performance and identify declining performance before it results in critical issues. This forces the company to manage supplier failures reactively, often with limited time to identify replacements. Lastly, the system has missing parts when the current trends in supplier evaluation are reviewed, especially in broader sustainabilitymetrics, which may align with the company vision.

18.2 Proposed Solution

Two critical assumptions have been established to guide this study's direction. The first assumption is that all departments using the evaluation system have adequate training and resources that ensure input accuracy. The second assumption asserts that inspections of delivered goods and quality control tests applied to these goods are suitable for quality performance measurement. These assumptions help us to ensure grades are accurate, and we aim to improve the logic and calculations behind the evaluation system.

Two major constraints have been highlighted to ensure a clear understanding of the limitations within this study. The first constraint indicates that, in some cases, only one supplier is available for a specific product, which limits alternatives and makes replacements difficult. The second constraint is that some suppliers provide multiple products, which complicates contract termination, as it may affect several items at once.

18.2.1 Objectives

This project aims to improve the supplier performance evaluation system in the current use of the Directorate of Small Domestic Appliances at Beko from the following perspectives: The robustness of the current system and consistency of the results are checked, and a decision support mechanism is developed to provide insights about the future performance of suppliers. Points that this project focuses on helping the Directorate to support strategic decision-making processes by establishing weights of criteria aligned with the company's priorities, ensuring consistency and robustness by alternative computation methods, and gaining insights about performances to prevent potential undesired situations in supplier performances. Decision support mechanisms in this project provide outcomes to the Directorate on their own and with top management meetings to see the current system's performance and make decisions about relationships with suppliers.

18.2.2 Solution Methods

Five different aspects were used in our project as solution approaches. The first, second, and third ones are used to ensure the robustness of the current system. The fourth one is developing an early detection mechanism to provide insights about future performances, and the fifth one is identifying missing parts in the criteria.

1. Alternative Computation Methods focus on the evaluation of the supplier evaluation system with two (MCDM) Multi-Criteria Decision-Making methodologies: TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and Ideal Point Distance with Squared Differences. It is beneficial to generate alternative rankings and identify discrepancies with the current system's rankings. (Thakkar, 2021) This method is used to see if the results of evaluations are dependent on the calculation method and if the results change significantly when we change the calculation method. Significant changes in the results show that the calculated performance of suppliers can change easily when we change the computation method. Comparing the results of the current system after evaluating supplier performances using two alternative computation methods helps us assess the consistency of the results of the current system. If we get significant changes among the three methods, this may show that classifying suppliers with just one calculation method may be a biased approach, and to classify them, all results could be considered, like classifying C and D for the suppliers who receive these grades in all computation methods. Results of these alternative methods and how similar to the current system can be seen in Table 18.1. Historical data were used for samples, and there are no significant differences between computation methods, and the current system is robust from this aspect.

Table 18.1: Similarity Ratio of Methods

Method	TOPSIS	Euclidean	Current System
TOPSIS	1	0.94	0.93
Euclidean	0.94	1	0.93
Current System	0.93	0.94	1

2. Sensitivity analysis approach examines how changes in the input parameters affect the optimal solution. Its main benefit is that it can be understood how much the current system is sensitive to the given weights (Pitchipoo et al., 2013). If the results exhibit that the system is very sensitive to weights, it could be a sign that calculations can change significantly based on weight changes. An LP model was designed for sensitivity analysis; this model shows how we can increase or decrease the weight of a criterion to see upper and lower bounds, while the sum of weights is kept as 1 and other weights are changed accordingly. If the range of weights for a criterion is too narrow, that could mean the given weight strictly determines the results; on the other hand, if the range is too wide, the criterion has less impact on results than thought. The percentage for relatively normal increases and decreases in the weights could change year by year according to company decisions and strategies, but $\pm$ 10% change in weights could be acceptable, and shows the system is not very sensitive for given weights.

   The mathematical model for sensitivity analysis is shown in Appendix 18.7 with the parameters, decision variables, objective function, and constraints.

   Explanation of objective function and constraints are as follows:

   - (1) Maximizes the sum of absolute weight changes across all criteria to reflect the overall adjustment impact.
   - (2) Ensures the new weights form a valid distribution by summing to 1.
   - (3) and (4) Define the absolute weight change for each criterion. These enforce that y_{criteria} is at least the positive difference between old and new weights.
   - (5) Computes each supplier's new total score using the updated weights and known performance scores.
   - (6) Ensures that the worst 10 suppliers (based on initial scores) remain below the performance threshold 60.

Table 18.2: Percentage of prediction match by Exponential Smoothing

Criterion	2020	2021	2022	2023
Quality	53.33%	45.56%	44.44%	45.46%
Logistics	56.67%	47.78%	45.56%	42.22%
Commercial	55.56%	50%	51.11%	56.67%
Project Management	50%	43.33%	36.67%	35.56%
Sustainability			100%	33.33%
Overall Grades	61.54%	67.03%	67.09%	68.13%

- (7) Ensures that all other suppliers score at least 60, separating lower performers from the rest.
- (8) and (10) If the target criterion is being adjusted, its change must be reflected accurately in y_{target}.
- (9) and (11) Limit the change in non-target criteria to maintain balance and prevent excessive influence from any category.

3. Correlation analysis is another method that the Pearson correlation test is used to measure the strength and direction of the relationship between two variables. (James et al., 2013) This method excels when any existing relationships between the criteria are desired to be detected to prevent a criterion from considering the same factor more than once. Some correlations were found in criteria and sub-criteria pairs and shared with the company. The ones that they also suspect and think the results are reasonable are re-evaluated, and changes in weights are discussed.

4. An early detection system has been developed with exponential smoothingmethod to predict future values by applying weighted averages, where more recent observations have greater weight. It is advantageous in the case that finding a new supplier in a short window may cost the company money and prevent comprehensive supplier searching. Hence, the historical data is limited, exponential smoothing is chosen, and as years pass and data increases, more sophisticated methods could be used to predict future performances. (Billah et al., 2006) Ratio of predicting supplier performance for the past years by the early detection system can be seen in Table 18.2, which shows that almost 65% of suppliers' performances are predicted accurately.

5. The current evaluation system has received limited updates, so a literature review has been conducted, and it involves analyzing existing research, methodologies, and case studies relevant to the supplier

Table 18.3: Maximum Difference Analysis

Sample	Mean	Std Deviation
Sample 1	9.1	6.12
Sample 2	9.47	6.03
Sample 3	9.47	6.03

evaluation technique. It is advantageous because it provides different strategies to enhance Beko's supplier evaluation system. Findings, especially about the different aspects of sustainability (financial and social), a criterion that the company cares about and wants to update, are shared with the company.

18.3 Validation Approach

A validation has been conducted to check the robustness and consistency of our solution approaches. Since we are proposing a novel approach, conducting a validation is not straightforward. So, we primarily have relied on expert opinion to support our findings. Additionally, we have used datasets generated by replicating key characteristics of the supplier evaluation data from last year using the jack knifingtechnique. (Conover, 1999)

Validation of alternative computation methods was made using the simulated data. It has three main assessments. First, the maximum ranking differences among the three methodologies were assessed for each supplier. Second, TOPSIS and Euclidean methods were compared against the traditional ranking system. Third, a correlation analysis was conducted to determine the consistency between the ranking methodologies. As a result, the ranking methods exhibited an overall agreement but did not produce identical results. This indicates that their system is robust and gives consistent results; see Tables 18.3-18.5.

Validation of the sensitivity model was conducted using the historical data. The results we obtained indicate that the values obtained in both years are relatively close, demonstrating the model's stability over time. Simulated data is also used in validation. The results obtained from the

Table 18.4: Maximum Difference Analysis of C and D Suppliers

Sample	Mean	Std Deviation
Sample 1	10.23	6.88
Sample 2	7.81	5.01
Sample 3	8.54	5.11

Table 18.5: Comparison of Real and Simulated Data Correlation Findings

Criteria Pair	Real Data	Simulation 1	Simulation 2	Simulation 3
Quality and Logistic	Weak	Moderate	Moderate	Moderate
Project Management and Commercial	Moderate	Moderate	Moderate	Moderate
Commercial and Sustainability	×	Weak	Weak	Moderate
Quality and Sustainability	×	×	Weak	×

simulated dataset showed a strong alignment with the patterns observed in past data. Specifically, the relative ranking of criteria remained largely stable.

Validation of correlation analyses was also conducted using the simulated data. The correlated pairs we found in the actual data also appeared in all resampling datasets. In addition, it is observed that some additional pairs were also correlated, but these pairs were not constant for each dataset. As a result, no consistent correlation was found apart from the real findings.

These 3 aspects showed us the system in current use is robust from these aspects and gives consistent results. In addition to the above validation methods, we have shared and discussed the results with the company, and they also found these results reflect reality and as they expected, so expert opinion was received.

Validation of the early detection system was conducted using historical data. We predicted the 2020, 2021, 2022, and 2023 values with the early detection system and compared with the actual grades. In this validation, we have focused on the percentage of catching C and D grades. As a result, overall, more than 60% of grades were predicted accurately, and the system's accuracy has improved over the years.

18.4 Outcome and Deliverables

18.4.1 Outcome

This project improves the reliability and foresight of Beko's supplier evaluation process. Key outcomes include a robustness tested scoring system, an early detection mechanism for declining performance, and an improved decision support structure aligned with modern supplier evaluation trends. These improvements allow Beko to proactively manage risks, support strategic decisions, and simplify contract decisions.

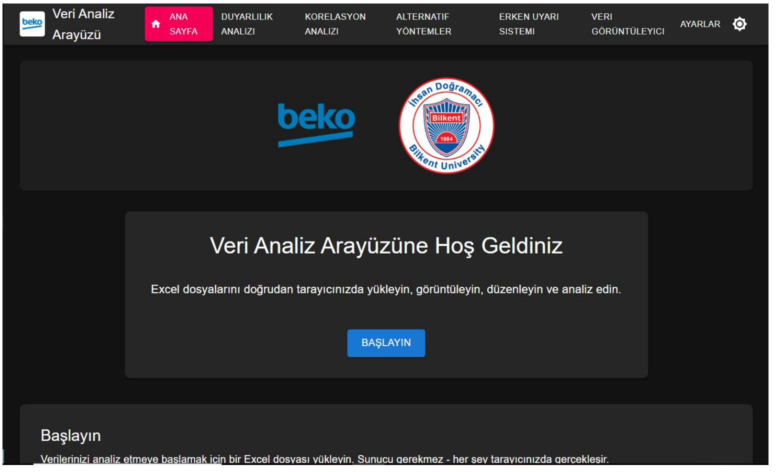


Figure 18.1: User interface

18.4.2 Deliverables

As a central outcome of this project, a decision support system (DSS) has been developed; see Figure 18.1 for a glimpse. This system integrates multiple analytical tools, including alternative computation methods, which allow the company to generate comparative rankings and validate current scoring mechanisms. Alongside these tools, sensitivity and correlation analysis modules are embedded, enabling users to assess the system's results and upper/lower bounds for weights under different configurations and to detect any correlation between criteria.

Another core component of the system is the early detection module, which applies exponential smoothing to predict future supplier performance. This predictive approach offers timely insights, allowing Beko to take proactive action before performance declines become critical. The module has been fine-tuned using historical data from 2015 to 2023, and its predicting accuracy has been validated through performance metrics, particularly focusing on matching C and D grade predictions.

Additionally, a detailed literature review has been conducted to align the system with global trends in supplier management, including sustainability and social responsibility.

Besides these deliverables, an executive summary report is delivered, which includes details and results of analyses of the system. This summary is beneficial during the meetings with top management and within the department, hence providing analytical details about the system and possible results that any change in the current system may give.

18.5 Integration and Pilot Study

The developed decision support system has been packaged for flexible deployment. The system supports various integration options, including standalone use, REST API connectivity, embedding within existing platforms, and integration. Technical documentation and implementation guides have been prepared, ensuring ease of customization and long-term usability based on Beko's operational needs. The decision support mechanism is designed to work with historical supplier data, which can be uploaded in the standard spreadsheet format that the company uses in the current system.

In April, we received new supplier performance data for 2024, which was calculated by using the current system. A pilot study with this data was conducted synchronously by us and the company. After using this data in our decision support tool with all modules and discussing the results with the Industrial Advisor, we received the feedback that the results are reasonable by showing robustness and consistency of the systems and predicting future performance of suppliers with 56.2% accuracy.

18.6 Benefits and Benchmarking

This project helps Beko's supplier evaluation system by increasing its reliability and proving consistency. Applying alternative computation methods, sensitivity analysis, and correlation analysis helped Beko test their current system from different aspects and ensure its robustness. An early detection system helps Beko gain insight into suppliers' future performances, alert them about declining performances, and start searching for new supplier processes earlier, which may help solve major limitations that cause problems about terminating contracts, hence dependent on suppliers.

After showing the decision support system to the Industrial Advisor, it is told that it is helpful for them to discuss weights and see how potential changes in weight could be beneficial. Also, they mentioned that rules in current use that determine contract terminations according to supplier performances could be changed while adding new action plans, hence getting insights about future performances. They said that this system is beneficial for them during decision-making processes within the Directorate.

There are 5 different aspects of the solution approach. By applying alternative computation methods, the project generates new supplier rankings and compares them with Beko's current evaluations, offering a means of validation and potential improvement. Hence, offering two new computation methods, results should be compared with the system in current use, and supplier classifications could be determined accordingly. To classify suppliers as C or D, the company may expect to see the supplier classified as C or D in all of the methods; if some methods generate different results, then this supplier could be classified in a different category where Beko could examine closely and give alerts about declining performances. Through the sensitivity analysis, the upper and lower bounds of criteria could be determined. If an upper or a lower bound has dramatic changes than actual weight, this could be commented as that criterion is not assessing suppliers as expected and does not have a significant impact on grades; on the other hand, if upper and lower bounds are very close to actual weight, this could be commented as this criterion is strictly determining grades of suppliers. We expect to see around 10% change in actual weights. Finding correlations may signify that some criterion has more weight than actual, hence assessing some suppliers' features more than once under different criteria. Repeating correlations should be examined closely, and findings about historical correlations were shared with Beko. These solutions approach aspects help Beko assess the current system from different perspectives and produce more reliable outcomes. Developing an early detection system for supplier grades supports proactive risk identification, contributing to more effective supplier management. As the Industrial Advisor stated, this system could be helpful for them to alert suppliers whose performance is declining and change the ruleset accordingly while bringing new action plans. Insights gained from an extended literature review ensure that the system is aligned with proven practices and global standards. Altogether, these efforts are expected to significantly strengthen Beko's supplier evaluation process and support its operational goals.

18.7 Conclusion

Our aspects for solution approach assesses the current system of Beko while helping them to generate more reliable and consistent results, gives insights about the future performances of suppliers, and offers new sub-criteria to align the system with literature and company goals.

In conclusion, the project successfully achieves its objective of improving the supplier performance system of the Directorate of Small Domestic Appliances while offering new decision support tools. Our aspects for solution approach can be seamlessly integrated into the company's planning system, along with the recommendations and benchmarking provided above.

Bibliography

Beko (2025). Overview. Accessed: 21 April 2025.

Billah, B., R. J. Hyndman, and A. B. Koehler (2006). Empirical information criteria for selecting between forecasts. *International Journal of Forecasting 22*(2), 239–248.

Conover, W. J. (1999). *Practical Nonparametric Statistics*, Volume 350. John Wiley & Sons.

James, G., D. Witten, T. Hastie, and R. Tibshirani (2013). *An Introduction to Statistical Learning: with Applications in R.* Springer.

Pitchipoo, P., P. Venkumar, and S. Rajakarunakaran (2013). Modeling and development of a decision support system for supplier selection in the process industry. *Journal of Industrial Engineering International 9*, 23.

Thakkar, J. J. (2021). *Multi-Criteria Decision Making*, Volume 336 of *Studies in Systems, Decision and Control.* Springer Nature Singapore Pte Ltd.

Appendix: Mathematical Model

Parameters

- n: Number of suppliers
- k: Number of criteria
- $w_{\text{old,criteria}}$: Old weight of a criterion
- $\text{score}_{i,\text{criteria}}$: Performance score of supplier i in each criterion
- target: Criterion selected for focused weight adjustment

Decision Variables

- $w_{\text{new,criteria}}$: New weight for each criterion
- y_{criteria}: Absolute weight change
- new_total_score_i: Total score of supplier i with new weights

Mathematical Model

$$\text{Maximize} \quad \sum_{\text{criteria}} y_{\text{criteria}} \tag{1}$$

Subject to:

$$\sum_{\text{criteria}} w_{\text{new,criteria}} = 1 \tag{2}$$

$$y_{\text{criteria}} \geq w_{\text{new,criteria}} - w_{\text{old,criteria}} \tag{3}$$

$$y_{\text{criteria}} \geq w_{\text{old,criteria}} - w_{\text{new,criteria}} \tag{4}$$

$$\text{new\_total\_score}_i = \sum_{\text{criteria}} \text{score}_{i,\text{criteria}} \cdot w_{\text{new,criteria}} \quad \forall i \tag{5}$$

$$\text{new\_total\_score}_i \leq 60 \quad \forall i \in \{\text{worst 10 suppliers}\} \tag{6}$$

$$\text{new\_total\_score}_i \geq 60 \quad \forall i \in \{\text{remaining suppliers}\} \tag{7}$$

$$y_{\text{target}} \leq |w_{\text{new,target}} - w_{\text{old,target}}| \tag{8, 10}$$

$$y_{\text{criteria}} \leq |w_{\text{new,criteria}} - w_{\text{old,criteria}}| \quad \forall \text{criteria} \neq \text{target} \tag{9, 11}$$

Tesis İçi Lojistikte Forklift Araçlarının Sayısı ve Görev Dağılımının Optimizasyonu Tepe Betopan

19

Proje Ekibi
İpek Altınova, Elif Demir, Elif Kurtulmaz
Başak Ödemiş, Kerim Sayan, Hayrettin Arda Şeref, Simay Turgut

Şirket Danışmanı
Çağatay Çaparlı
Planlama ve Lojistik Yöneticisi

Akademik Danışman
Dr. Öğr. Üyesi Gizem Özbaygın
Endüstri Mühendisliği Bölümü

Özet

Tepe Betopan'ın yeni fabrikasında amaç, önceden belirlenmiş forklift yollarına uygun sayıda ve tipte forklift atayarak malzeme taşıma sistemini etkili bir şekilde tasarlamaktır. Belirli istasyon çiftleri arasındaki malzeme akışı, birden fazla zaman dilimi boyunca değerlendirilmiş ve forklift yük tahsisleri buna göre optimize edilmiştir. Bu amaçlar doğrultusunda, gerekli verilere erişmek için SAP veritabanı ve sorunu çözmek için Google OR-Tools kullanılmıştır. Önerilen çözüm, fabrikanın forklift hareket verimliliğine katkıda bulunmayı amaçlamaktadır.

Anahtar Sözcükler: Malzeme akışı, forklift yolları, forklift atamaları, forklift yük tahsisi.

Design and Application of Inspection System for Mechanics Department

Abstract

In Tepe Betopan's new factory, the aim is to effectively design the material handling system by assigning an appropriate number and type of forklifts to predetermined forklift paths. Material flow between specific station pairs has been evaluated over a multi-period planning horizon, and forklift load allocations have been optimized accordingly. For these purposes, the SAP database was used to access the necessary data and Google OR-Tools was used to solve the problem. The proposed solution aims to contribute to the forklift movement efficiency of the factory.

Keywords: Material flow, forklift paths, forklift assignments, load allocation.

19.1 Company Information

Tepe Betopan was founded in 1984 under the roof of Bilkent Holding. Its vision is to be a company that quickly adapts to technological developments, drives changes, and sustainably grows to add value to the domestic and international construction industry. As provided in the company's official website, Tepe Betopan (2025) produces nonflammable, shock-absorbing, and non-bugging products. Tepe Betopan established the first cement-bonded particleboard factory, Betopan Factory, in Turkey to produce their registered brand Betopan, and the capacity of the Betopan factory is stated to be 50,000 m^3.

In 2014, the Tepepan Factory, with a capacity of 50,000 m^3, opened in Ankara ASO 2. OSB. In 2023, 1,246,943 items were produced in a variety of sizes under different labels. The products are offered to all regions in Turkey by 83 dealers and exported to more than 20 countries across 4 continents.

Tepe Betopan is expanding its facilities and preparing to open the Betopan-2 Factory. It is essential to establish clear paths for forklifts within the plant.

19.2 Current System and the Problem

19.2.1 Current System Analysis

To understand the modus operandi of Tepe Betopan, we analyzed the material handling data for 2023 that was recorded in the SAP system. The data includes several key elements: the types of materials, date and time of forklift operations, stations [3051 (press oven), 3052 (semi-finished goods depot), 3053 (rotary kiln), 3054 (separation and packaging depot), and 3056 (shipping depot)], direction of movements, and batch numbers.

We conducted data analysis in multiple steps for the dataset of 286,726 rows. First, we examined the total volume in cubic meters entering and exiting, forklift operations used, and identified any imbalances. Our analysis revealed that the inflows and outflows of volume are relatively close to each other.

The number of forklift movements between stations 3052–3053 and 3054–3056 is higher than that of other routes, suggesting possible congestion. An observed imbalance between materials exiting and entering storage underscores the need to explore historical data.

A month-by-month analysis was conducted to evaluate consistency. This approach led to the computation of average daily volume movements and forklift operations per storage unit for each month. Each storage unit was analyzed for its throughput.

Average hourly volume movements and forklift operations were determined for each storage unit. This quantification provides essential parameters for a robust operational model.

In conclusion, the rigorous examination of the 2023 material handling data facilitates a comprehensive understanding of forklift scheduling on a monthly, daily, and hourly basis. This analytical framework serves as the foundation for constructing a mathematical model, which is enhanced through simulation and validation processes.

19.2.2 Problem Definition

In the current operational framework of Tepe Betopan's factory, material handling is mainly carried out by forklifts operating between five stations: 3051, 3052, 3053, 3054, and 3056. A notable issue is the under-utilization of some forklifts, highlighting the need for optimization in the new factory.

Given the fixed machine layout and established material flow, alternative forklift routes are limited. In the previous facility, there was one storage station per type. In the new one, the number of 3052 depots is increased to six. Therefore, two scenarios were created: best case and worst case.

In the best-case scenario, the 3052 depot minimizing total distance to 3051 and 3053 was selected. In the worst case, the opposite. These two scenarios aim to provide forklift number recommendations. The number of forklifts is determined based on the shortest and longest distances between 3052 and adjacent stations.

While defining the routes is the first step, real efficiency depends on optimal forklift assignment to minimize the number needed while meeting requirements.

Strategic decisions regarding timing and capacity utilization are also critical. Initial data indicates a 1.5x increase in workload compared to the old facility.

Since transport occurs only forward between stations, there are 14 designated paths. Multiple trips may be needed, making task-specific forklift assignments necessary.

19.2.3 Critical Assumptions and Major Constraints

This section outlines the main assumptions and constraints guiding our solution approach.

- The transportation schedule must follow strict hourly intervals due to the lack of intermediate storage. Materials cannot be retained and must be moved immediately within the allocated time slots.
- The workflow progresses sequentially from station 3051 to 3056 (3051 $\rightarrow$ 3052 $\rightarrow$ 3053 $\rightarrow$ 3054 $\rightarrow$ 3056). There is minimal movement from station 3055; thus, it is assumed that no material flow originates there. Additionally, materials do not revert to previous stations once processed.
- Time periods are segmented hourly, and each forklift must complete its assigned load within that hour to ensure timely processing and efficiency.
- Forklifts operate at a constant speed of 10 km/h as specified by the Integrated Managed Systems Manager, ensuring safe and efficient movement.
- Forklift maintenance is excluded from our model, as minor disruptions (under 30 minutes) are not expected to impact workflow significantly.
- Although six 3052 stations exist, for best/worst case analysis, we assume only one is active, considering both the farthest and closest to define a forklift requirement range.

Major Constraints:

- The factory layout is fixed and cannot be modified.
- The workflow is forward only.

19.3 Our Solution Approach

We began by identifying the most efficient routes between consecutive station pairs to support rapid forklift-based transfers.

Our factory layout analysis revealed six 3052 depots. Four are near 3051 and 3053, while two are farther away. Given the unknown usage frequency of the distant depots, we developed best and worst case scenarios. In both, we assume a single 3052, the closest one for the best case and the farthest for the worst case. Distances were measured using This part of the design was created using BricsCAD (2025) and presented in Figures 19.1 and 19.2.

This dual-scenario method allowed us to define a range for forklift requirements. In the best case, we minimized travel distances; in the worst case, we maximized them. Without specific depot usage data, this approach offers robustness across operating conditions.

We then explored forklift alternatives in consultation with the company's purchasing team. The current models—Doosan D70S-9 (7 tons) and Clark C50s (5 tons)—were converted into cubic meters using density formulas. We evaluated additional forklift models from both brands, covering diesel and electric types as can be seen Figures 19.3 and 19.4. Our model only deals with the capacities and the model, brand is left to the company because of the budget.

Our problem aligns with a modified version of the assignment problem, where tasks are defined as volume transported over a path within a time period. The model supports assigning one forklift to multiple tasks or several forklifts to one task, depending on capacity needs.

We calculated the number of trips required per task by dividing total volume by forklift capacity. Given constant forklift speed and fixed distances, total task time was derived and used to calculate utilization which is defined as the ratio of the forklift's total working time to the total available time in a 24-hour period.

A mathematical model was implemented using Gurobi Optimization, LLC (2025) in Python and adapted to OR-Tools (2025) for flexibility and accessibility. Once optimal forklift assignments are identified, unassigned forklifts are excluded. The company can update production data and rerun the model to obtain new forklift plans as needs evolve.

19.3.1 Mathematical model

Parameters are:

- i: Index of paths ($i \in \{1, 2, 3, 4\}$),
- k: Index of forklifts ($k \in \{1, 2, \ldots, m\}$). Here, the capacity of forklifts

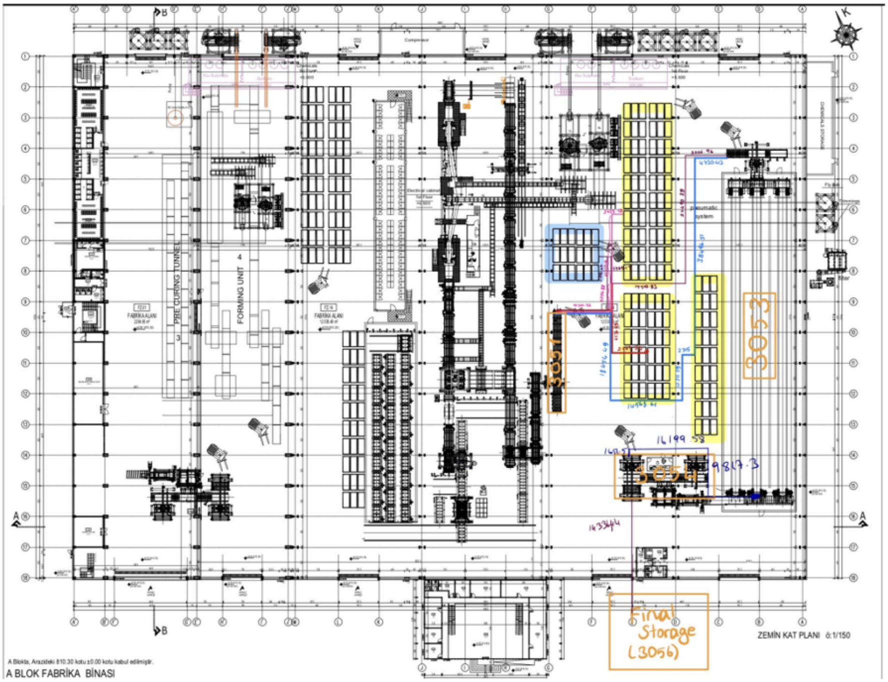


Figure 19.1: Best Case Scenario

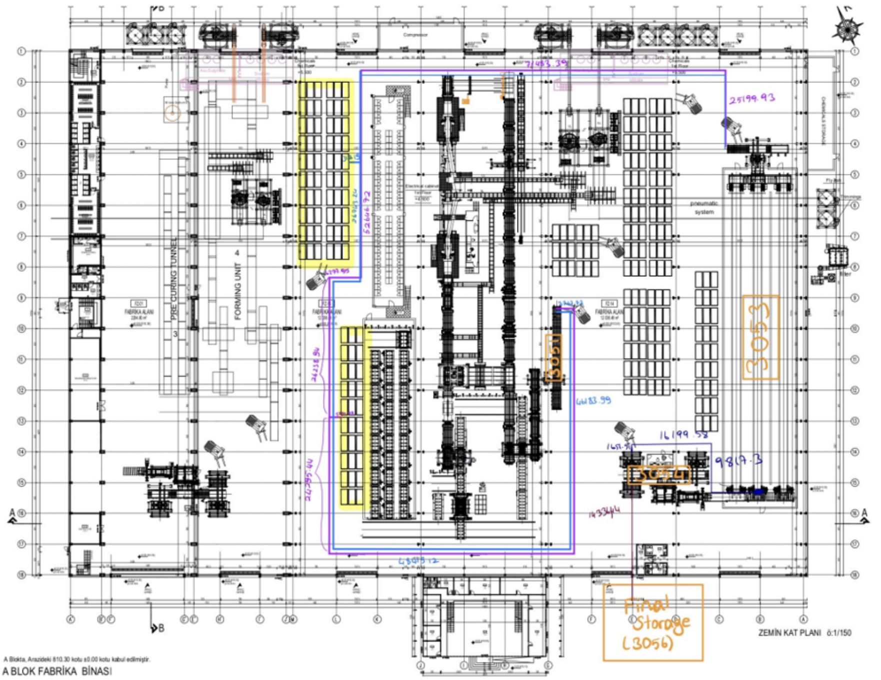


Figure 19.2: Worst Case Scenario

Model	Load Capacity	Engine Power	Fuel Type	Fuel Consumption	Estimated Price (EUR)	Estimated Price (TL)
S30	3,000 kg (3 tons)	48 kW	Diesel	3.5 - 4.0 Liters/Hour	34,000	1,292,000
S35	3,500 kg (3.5 tons)	52 kW	Diesel	4.0 - 4.5 Liters/Hour	36,000	1,368,000
C40	4,000 kg (4 tons)	55 kW	Diesel	4.5 - 5.0 Liters/Hour	40,000	1,520,000
C45	4,500 kg (4.5 tons)	60 kW	Diesel	5.0 - 5.5 Liters/Hour	44,000	1,672,000
C50s	5,000 kg (5 tons)	65 kW	Diesel	5.5 - 6.0 Liters/Hour	48,500	1,843,000
C55s	5,500 kg (5.5 tons)	70 kW	Diesel	6.0 - 6.5 Liters/Hour	52,500	1,995,000
C60	6,000 kg (6 tons)	75 kW	Diesel	6.5 - 7.0 Liters/Hour	57,500	2,185,000
C70	7,000 kg (7 tons)	80 kW	Diesel	7.0 - 7.5 Liters/Hour	62,500	2,375,000
C75	7,500 kg (7.5 tons)	85 kW	Diesel	7.5 - 8.0 Liters/Hour	66,500	2,527,000
C80	8,000 kg (8 tons)	90 kW	Diesel	8.0 - 8.5 Liters/Hour	70,000	2,660,000
GEX30L	3,000 kg (3 tons)	50 kW	Electric	N/A	40,000	1,520,000
GEX40	4,000 kg (4 tons)	55 kW	Electric	N/A	44,000	1,672,000
GEX45	4,500 kg (4.5 tons)	60 kW	Electric	N/A	47,500	1,805,000
GEX50	5,000 kg (5 tons)	65 kW	Electric	N/A	50,000	1,900,000

Figure 19.3: Clark Forklift Model and Prices

Model	Load Capacity	Engine Power	Fuel Type	Fuel Consumption	Estimated Price (EUR)	Estimated Price (TL)
D60S-9	6,000 kg (6 tons)	55 kW & 80.9 kW	Diesel	5 Liters/Hour	50,000	1,900,000
D70S-9	7,000 kg (7 tons)	55 kW & 80.9 kW	Diesel	5 Liters/Hour	55,000	2,100,000
D80S-9	8,000 kg (8 tons)	80.9 kW	Diesel	6 Liters/Hour	62,500	2,400,000
D90S-9	9,000 kg (9 tons)	80.9 kW	Diesel	6 Liters/Hour	75,000	2,900,000

Figure 19.4: Doosan Forklift Model and Prices

may change across k. For example, k = 1,...,n may denote the types of forklifts with capacity m, k = (n+1),...,p may denote the types of forklifts with capacity q.

- t: Index of periods ($t \in \{1, 2, \ldots, 24\}$),
- C_k: Capacity of forklift k (in cubic meters),
- Q_{it}: Amount of volume to be moved on path i in period t,
- M_{ikt}: Number of tours needed to be traveled on path i by forklift k in period t to transport all the materials,
- d_i: Duration of a trip on path i, including load/unload durations (in minutes)

Decision variables are:

$$x_{ikt} = \begin{cases} 1, & \text{if forklift } k \text{ is assigned to path } i \text{ in period } t, \\ 0, & \text{otherwise,} \end{cases}$$

f_{ikt} : Amount of volume forklift k will carry on path i in period t,

z_{ikt} : Number of times forklift k transports materials on path i in period t,

$$y_{kt} = \begin{cases} 1, & \text{if forklift } k \text{ is used in period } t, \\ 0, & \text{otherwise,} \end{cases}$$

$$F_k = \begin{cases} 1, & \text{if forklift } k \text{ is used in any period} \\ 0, & \text{otherwise,} \end{cases}$$

The model is:

$$\text{Minimize} \quad \sum_k F_k, \tag{1}$$

subject to:

$$\sum_i x_{ikt} \leq 4y_{kt}, \qquad \forall k, \forall t \tag{2}$$

$$z_{ikt} \leq M_{ikt} \cdot x_{ikt}, \qquad \forall i, \forall k, \forall t \tag{3}$$

$$f_{ikt} \leq C_k \cdot z_{ikt}, \qquad \forall i, \forall k, \forall t \tag{4}$$

$$\sum_k f_{ikt} = Q_{it}, \qquad \forall i, \forall t \tag{5}$$

$$\sum_i z_{ikt} \cdot d_i \leq 60, \qquad \forall k, \forall t \tag{6}$$

$$F_k \geq y_{kt}, \qquad \forall k, \forall t \tag{7}$$

$$x_{ikt} \in \{0, 1\}, \qquad \forall i, \forall k, \forall t \tag{8}$$

$$y_{kt} \in \{0, 1\}, \qquad \forall k, \forall t \tag{9}$$

$$f_{ikt}, z_{ikt}, v \in \mathbb{Z}_{\geq 0}, \qquad \forall i, \forall k, \forall t \tag{10}$$

Constraint (2) ensures that if a forklift is used in that period, the maximum number of paths that forklift is assigned to is 4. Constraint (3) denotes that the number of trips z_{ikt} made by forklift k on path i during period t should not exceed the number of trips needed M_{ikt} to transport all the materials, if that the forklift is assigned to the path at that time period. Constraint (4) ensures that the amount of volume transported by forklift k on path i during period t should not exceed the forklift's capacity times the number of trips traveled by the forklift, which is the max amount of volume that can be carried by the forklift on path i at that time period. Constraint (5) ensures that the amount of volume transported on path i during period t should meet the demand Q_{it}. Constraint (6) ensures that the total time spent by forklift k on trips across all paths i during period t can not exceed 60 minutes, which is our time period. Constraint (7) ensures that if a forklift is not being used, it is not assigned to any period. Constraints (8), (9), and (10) are non-negativity and binary constraints.

When coding this model to Python-Gurobi and OR-Tools, we also printed the utilizations of the assigned forklifts. In our model, utilization is defined as

$$\frac{100 \times \sum_t \sum_i z_{ikt} \cdot d_i}{24 \times 60} = \text{Utilization}, \quad \forall k.$$

19.4 Verification

In this section, we examined how our code functions and whether it provides expected results under various scenarios. To verify our model, we adjusted input parameters systematically and tested specific situations. We began with a toy problem that could be solved by inspection. Using 6 forklifts, each with a 4 m^3 capacity, and 16 m^3 of volume to be moved per path and period, we showed that one forklift could complete all tasks. The model returned the expected result: one forklift assigned across all paths and periods, performing four trips each time. Next, we tested continuity by changing RHS values. Lowering the 60-minute time constraint to 30 made one forklift insufficient. The model then correctly assigned two forklifts and distributed their tasks across paths and periods, confirming accurate adjustment.

We then altered forklift capacities. Five forklifts had a reduced capacity of 2 m ^{3} while one remained at 4 m ^{3}. The model correctly selected the 4 m^3 forklift. When all were set to 0.5 m ^{3}, the model returned an infeasible result, as expected. This confirmed that our model selects the correct forklift based on capacity. To check for redundancy, we commented out constraints individually and observed that each constraint influenced at least one variable.

For degeneracy testing, we modified the objective function coefficient. Increasing it to 1,000,000 did not affect the solution, while decreasing it to -1,000,000 caused all forklifts to be used, which was logical given the minimization goal. Lastly, we conducted consistency testing by varying load levels. The model handled low loads effectively and adjusted as loads increased, until fleet capacity was exceeded—at which point it signaled the need for more forklifts or parameter changes. These tests confirmed that our model and code function reliably under varying conditions and successfully minimize forklift use while satisfying operational requirements. The next step is validation, incorporating real-life parameters from our data analysis.

19.5 Validation

Our validation process began with a theoretical review, particularly the determination of input data. A key parameter, Q_{it}, represents the volume (in cubic meters) to be transported along path i during time period t.

Initially, we assumed uniform hourly pallet movement. However, after analyzing time-stamped 2023 data, we questioned this assumption. We selected March, June, and September, focusing on 9–10 AM, 3–4 PM, and 11 PM–12 AM. Pivot tables revealed significant volume fluctuations within the same hour across different days. This conclusion was expected even without extensive statistical testing. As a result, we chose to utilize empirical distribution. The following paragraph provides further explanation.

In order to generate our parameter Q_{it}, we first require an empirical distribution matrix. This matrix has the same dimensions as Q_{it}, specifically 4x24, where 4 refers to the number of paths and 24 corresponds to the number of periods. The elements of this empirical distribution matrix are pairs of the form $(p_1 v_1, p_2 v_2, \dots)$, where $p_1, p_2, \dots$ represent cumulative probabilities and $v_1, v_2, \dots$ represent the transported volumes (in cubic meters) corresponding to each probability. Each row of this empirical distribution matrix corresponds to a different path, and for each path, the empirical distribution parameters are provided for every hour. We have developed a code that randomly generates Q_{it} using the empirical distribution matrix. Specifically, the element in the first row, first column of Q_{it} is randomly selected from the first row, first column of the empirical distribution matrix. Similarly, the element in the first row, second column of Q_{it} is randomly selected from the first row, second column of the empirical distribution matrix, and this pattern continues for all rows and columns of Q_{it}.

Next, in coordination with the company's purchasing department, we determined forklift capacity values for the C parameter. Since the new factory will use forklifts of equal capacity, we explored a range of volume capacities derived from forklift weight (tons) and average material density (1475 kg/m^3). This gave us 11 candidate capacities (in m^3): 2.034, 2.373, 2.712, 3.051, 3.390, 3.729, 4.068, 4.746, 5.085, 5.424, 6.102.

We entered each capacity into the model, testing different quantities to determine the minimum number of forklifts needed per case.

For travel time and tours, we calculated path distances using AutoCAD and forklift speed (10 km/h). This allowed us to compute the time per tour and determine the number of tours required by dividing Q_{it} values by capacity.

Using this data, we ran our model. In the best-case scenario, forklift capacities of 2.034–3.051 m^3 require 2 forklifts; higher capacities need only

1. In the worst case, capacities up to 3.390 m^3 require 2 forklifts, and larger ones still need only 1.

The model also displayed which forklifts were assigned to which paths and periods. Seeing consistent and feasible results, we advanced to operational validation as can be seen in Figure 19.5.

We have tested the model with realistic input values: periods, paths, travel times, and transported volumes. The model performed reliably.

Lastly, since the factory is not yet operational, we developed a simulation model to visualize forklift movement based on our assignments. This will be shared with the company for expert evaluation. If their feedback confirms alignment between the model and operational feasibility, we will validate the credibility of our approach.

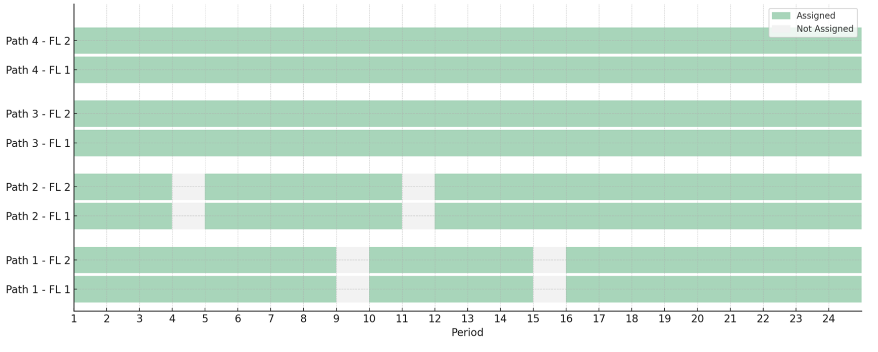


Figure 19.5: Gantt chart of forklift assignments when capacity is 2.034 m^3

19.6 Simulation

Initially, Q_{it} values representing the volume (in m^3) to be transported along path i during period t were logically derived from a toy problem. However, actual volumes are not simply 1.5 times historical data; they vary with randomness while following past patterns.

To reflect this variability, we used empirical distributions instead of theoretical ones, as Arena's Input Analyzer yielded low p-values for all fitted distributions. We created 24 empirical distributions, one per hour, for each of the four paths (3051–3052, 3052–3053, 3053–3054, 3054–3056). Using Excel pivot tables, we calculated volume frequencies and their cumulative probabilities, grouped similar values, and generated a practical 4×24 Q_{it} matrix.

Values from this matrix were generated via Python rather than directly inputting schedules into Arena, allowing consistency with the randomness used in the mathematical model. The simulation involved four Create modules (one per path), each producing 2 m^3 entities. These were batched, routed to decision modules using 24 time-based conditions, and sent to process modules that matched the optimal forklift assignments for each path and hour. Forklift allocation reflected either single or multiple resources depending on the task, then proceeded to a Dispose module.

Randomness in the simulation reflects real-world fluctuations, while code-based randomness allowed performance testing under different Q_{it} inputs. Occasionally, mismatches occurred—e.g., the model assigned zero forklifts while simulation volume was non-zero. To detect these cases, we used a Record module to track unassigned batches. However, forklifts often rerouted post-task, alleviating concerns.

Verification began with a toy problem. Forklifts operated without delays or queue overflows, confirming correctness within Arena's 150-entity student model limit.

For consistency testing, we altered batch sizes: 3 m^3 caused queuing delays due to 2 m^3 arrivals, while 1 m^3 maintained flow but required more tours. Degeneracy tests showed that high Q_{it} values triggered entity limits, while low values decreased utilization as expected. Modifying tour times also produced logical outcomes—longer durations reduced service capacity, while shorter ones improved utilization.

During peak hours, forklift utilization reached 100%, with an average of 40%. As there is no intermediate storage, forklifts must handle full volume at all times, making peak demand a key driver in determining fleet size. These utilization figures validate our modeling approach.

19.7 Sensitivity Analysis

The purpose of the sensitivity analysis is to determine how responsive our model is to changes in production volume (in cubic meters). The focus is on identifying how the minimum number of forklifts required varies as production levels increase.

First, we established the number of forklifts needed at standard production levels, which are defined as 1.5 times the current output of the Bilkent Campus factory. Then, we manually increased the Q matrix by multipliers (1.1, 1.2, 1.3, ...) until the number of forklifts required increased. This process was repeated for each forklift capacity. The findings are as shown in Figure 19.6:

These results illustrate the model's responsiveness to scaling production and its ability to adjust forklift assignments accordingly.

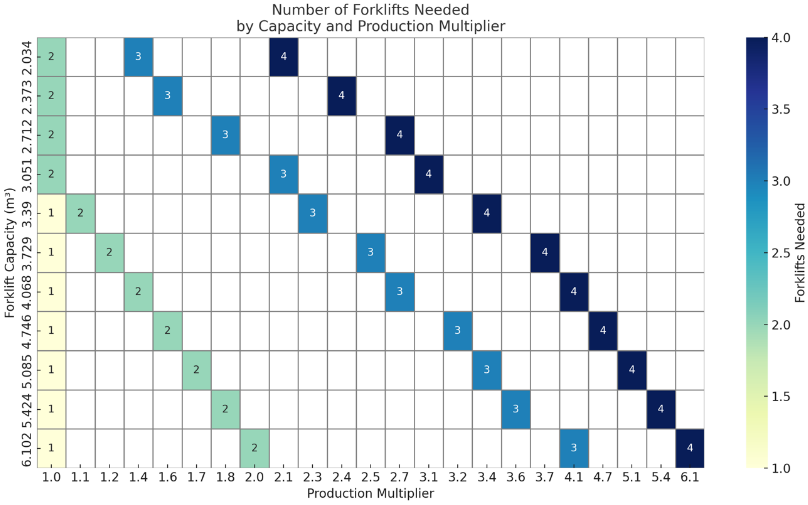


Figure 19.6: Forklift requirement change according to production change

19.8 Project Outcomes and Benefits

The outcome of the project will provide Tepe Betopan with strategic insights for operational planning and an optimized forklift assignment plan tailored for their new factory. By running our mathematical model for various forklift capacity sets, we minimize the number of forklifts needed and determine the optimal quantity to be purchased. These strategic results were shared in a detailed report including forklift models, their capacities, the quantities required, and the corresponding total purchase costs. This enables Tepe Betopan to compare different options and choose the most cost-effective forklift set that aligns with their operational needs.

The optimized assignment plan is generated using our model, assigning forklifts to specific paths and periods for each capacity set. The results will be reported comprehensively, including the assignment schemes and projected utilization rates. Additionally, simulation results—such as peak and average utilization—will offer further insights into the efficiency of the proposed plans as shown in Figure 19.7

To support future decision-making, we developed an adaptive optimization code in Google OR-Tools. Tepe Betopan will be able to re-run the model with updated inputs such as different forklift capacities, quantities, or changes in material flow. A clear user manual and a tutorial video will guide the company on how to input data, run the model, and interpret the results.

The benefits to the company can be evaluated in terms of utilization, reduction of unnecessary movements, and cost savings. Our approach focuses on maximizing forklift utilization and preventing idle times by finding

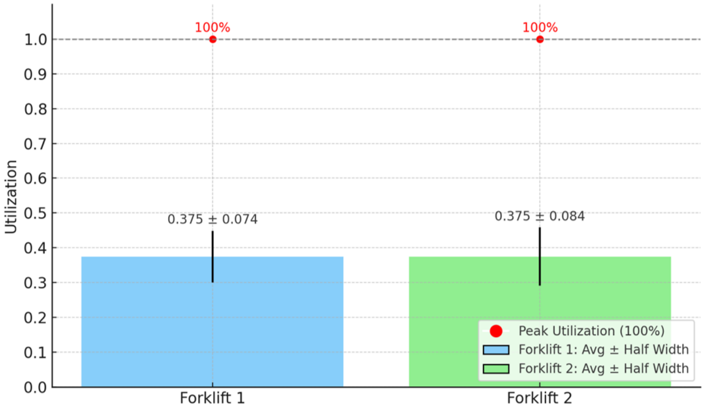


Figure 19.7: Utilization of forklifts on average and during the busiest period

optimal assignments. It also aims to eliminate unnecessary movements and increase operational efficiency.

However, it should be noted that while our assignment plan shows which forklift is assigned to which paths in each period, it does not dictate the order of tasks. That responsibility will remain with the forklift operators, based on real-time factory conditions.

19.9 Implementation Plan and Pilot Study

Since the new Tepe Betopan factory was not operational at the time of our project, we conducted a pilot study at the current Bilkent production facility to validate the effectiveness of our models. For this purpose, Tepe Betopan provided us with forklift operation data from February of the previous year, detailing the working hours of the three forklifts currently in use.

It is important to note that all three forklifts used in the existing factory are of the larger type, capable of carrying two pallets (equivalent to 3.6 m^3) at once, identical to the forklifts modelled in our optimization and simulation studies. Using the historical data, we first calculated the average utilization and peak utilization values for each forklift over the month. This analysis revealed that the forklifts operated at an average utilization of approximately 30.54 percent, with peak utilizations around 60 percent during the busiest times.

Following this, we applied our optimization model, originally designed for the new factory, to the Bilkent facility. The model generated an optimal number of forklifts and task assignments across the working hours. The results indicated that only one forklift would be sufficient to handle the workload at the Bilkent factory. To validate the feasibility of this solution under realistic operating conditions, we implemented the forklift assignments produced by our optimization model into the Arena simulation environment. The simulation demonstrated that, with the optimized assignments, the single forklift achieved an average utilization of 47 percent, and the peak utilization reached 100 percent during the busiest periods.

These findings highlight the strengths of our approach. By integrating mathematical optimization and simulation, we were able to significantly improve operational efficiency using fewer resources. The pilot study not only validated our models in a real-world setting but also reinforced their value for the upcoming factory. If the new Tepe Betopan facility experiences comparable enhancements, it is probable that there will be notable increases in efficiency and decreases in costs.

19.10 Conclusion

In conclusion, if there is a significant change in the company's production volume, they can reach the optimal number of forklifts by using the user guide we have prepared for the company. They can also reach the optimal number of forklifts by re-running the code we have prepared according to the desired capacities of forklifts and determine the appropriate capacity for themselves. Thanks to our project, the company will reduce the use of unnecessary forklifts and will use the optimal number of forklifts even if there is a change in production volume.

Bibliography

BricsCAD (2025). *BricsCAD: All-in-One CAD Software*. BricsCAD. https://www.bricsys.com.

Gurobi Optimization, LLC (2025). *Gurobi Optimizer Reference Manual*. Gurobi Optimization, LLC. https://www.gurobi.com.

OR-Tools (2025). *Google OR-Tools*. OR-Tools. https://developers.google.com/optimization.

Tepe Betopan (2025). Tepe betopan resmi web sitesi. https://www.betopan.com.tr/tr.

20 | Üretim Planlama Karar Destek Sistemi

Bakioğlu Holding

Proje Ekibi

Pınar Aydınelli, Ahmet Değirmencioğlu, Liya Fındık, Fatma Küçük, Onurhan Ünal, Cem Yeni, Buse Yüksekkayalı

Şirket Danışmanı
Beste Yıldız
Proje Geliştirme Uzman Mühendisi

Akademik Danışman
Dr. Emre Uzun
Endüstri Mühendisliği Bölümü

Özet

Bakioğlu Holding'in Bareks Plastik fabrikalarında karar verme düzeninde sistematik bir yazılım altyapısının bulunmaması üretim süreçlerinde zaman zaman aksamaların yaşanmasına ve optimize edilmiş üretim planlamasının yapılamamasına neden olabilmektedir. Bu projede öncelikle şirketin problemleri analiz edilmiş, şirketin üretim sürecinin nasıl işlediğine dair bilgiler alınmış ve eldeki mevcut bilgilere göre bir matematiksel model tasarlanmıştır. Ancak matematiksel modelin kompleks doğasından dolayı alternatif olarak bir sezgisel algoritma, şirketin kullanımı için tasarlanmıştır. Bu tasarımın amacı şirketin olabildiğince zamanında üretim yapabilmesine yardımcı olmak, makinelerin boş kaldığı süreleri olabildiğince azaltmak, ürünlerin terminlerinden önce teslim edilmesine yardımcı olmak ve karar verme sürecinin bir nebze olsun otomatize olmasına yardımcı olmaktır. Öncelikle hem model hem de sezgisel algoritma şirket verileriyle test edilmiş, ardından sezgisel algoritmanın kullanılacağı bir kullanıcı arayüzü tasarlanmıştır.

Anahtar Sözcükler: Planlama, Kullanıcı Arayüzü, Karar Destek Sistemi, Sezgisel Yaklaşım, Gecikme

Production Planning Decision Support System

Abstract

Lack of a dedicated computing system to support decision making occasionally causes disruptions in production or production plans not fully optimized. In this project, the company's problems were first analyzed, information was obtained on how the company's production process worked, and a mathematical model was designed according to the available information. However, due to the complex nature of the mathematical model, an alternative heuristic algorithm was designed. The purpose of this design is to help the company produce on time as much as possible, minimize the idle times of the lines, help deliver the products before the deadlines, and help automate the decision-making process. Both the model and the heuristic algorithm were tested with company data, and then a user interface was designed to use the heuristic algorithm.

Keywords: Planning, User Interface, Decision Support System, Heuristic Approach, Tardiness.

20.1 Company Information

Bakioğlu Holding is a multi-faceted holding company based in İzmir. Bareks Plastic and Polyethylene is one of the companies under Bakioğlu Holding that was founded in 2002 and their main goal is to produce multi-layered polyethylene films designed for printing and lamination that is suitable for food packaging. Bareks is listed as one of the "Top 1000 Exporters" in Türkiye. Bareks is a well known global Polyethylene Film manufacturer as its export share reached up to 85% and works in "delivery on time" principle for its customers with close location to İzmir ports and ability to store in Europe. Bareks, as being a preferred partner in both domestic and international market, targets to manufacture 70.000 tons in 2025. The company has two factories in Çiğli and Menemen and they have 9 production lines. They can produce both transparent and colored packages. The plant produces materials based on the type and category of packages requested by the customer

20.2 Current System and the Problem

20.2.1 Current System Analysis

As mentioned in the "Company Information" section, Bareks has two factories in Menemen and Çiğli that are open 7/24. There are 9 production lines, 6 of which are located in Menemen and the rest are in Çiğli. The company works with a make to order principle, they work without any stock. The average speeds of lines 1, 4, 11, 12, 13, 14 are 550 kg/h, the average speeds of lines 3 and 17 are 250 kg/h and the average speed of line is 450 kg/h as seen in Table 20.1. The production is 7/24 and they aim to complete the production in compliance with the due dates set on the orders. During the production process, the setup times of lines during the transition from one product to another, the product's length, width, layflat value, raw material and film types are all considered.

Table 20.1: Production Line Speed Matrix

Lines	Average Speed (kg/h)
1, 4, 11, 12, 13, 14	550
3, 17	250
15	450

20.2.2 Problem Definition

When production lines start to work again and different orders start to arrive, to meet the requirements of the orders, a setup time will be required. Setup time switches based on what product is produced in a line after another product. If the company produces more than the demand, they need to rent external warehouse space. This contradicts with their make-to-order production philosophy. They want to minimize tardiness of jobs and they also want to minimize the early production. This means that the company wants to produce on time, complying with the deadlines. A product can be produced in multiple lines as the production lines are quite flexible. The current system lacks a systematic approach to job scheduling, resulting in frequent tardiness, excessive idle times, and reliance on engineer experience. Therefore, from time to time, they observe jobs that are completed late and idle production lines An algorithm focusing on minimizing tardiness and earliness of jobs, minimizing the time lost setting up the lines and minimizing the amount of time that a line sits idle is offered to the company.

20.3 Proposed Solution Strategy

This project aims to optimize production schedule of the company to minimize total setup times and idle times of the lines, earliness and tardiness of the jobs while ensuring that the jobs are assigned to the right production line. There are over 700 products that are produced in 9 lines, there are constraints in place that are defined by the company. Before those constraints, since there is a big variety of data to work with, we made some assumptions. Those assumptions being:

- The date of the given order is accepted as the start date of the production program.
- Each line operates independently of each other.
- External interruptions are ignored.
- Unless told otherwise, setup times of lines are assumed to be constant.

Data was obtained from the company including sample order details, product-specific constraints and operational rules. The mathematical model was then established by defining products, lines and sample orders. The model processed data using a mathematical framework based on the Mixed Integer Linear Programming (MILP). The parameters, including things such as processing time, setup times of lines, due date etc. were established along with the decision variables. The dummy data was prepared to see how effective the model would work in a testing scenario.

The model was coded in Python and Gurobi was chosen as the solver since it is a widely used solver and it has been proven to be effective in solving optimization problems. But the model's complexity was a big problem as an output could not be obtained in a fast manner. Trying to run the model with a 50 job data set, the computers had memory errors after 20 minutes of trying to solve the program. To tackle this problem, a heuristic approach had to be developed. This was done so that the program could work with larger amounts of data and that the team could get faster results that are close to an optimal solution. The heuristic was coded in Python 6.0.2 and developed using the Spyder IDE. The heuristic approach is coded in such a way that an Excel file is both an input and output in the system, just how the company wants to run their system moving forward.

20.3.1 Mathematical Model

A very simple explanation of the solution method is given in Figure 20.1. The model considers various factors such as line compatibility and product sequences, that must be followed. For example, certain products cannot be produced in certain lines, some products have no such restriction. The decision variables include variables like completion time of a material, beginning time of a material in a line, tardiness of a job and whether a material is processed on a line in a specific order. The objective function is minimizing idle time of the lines, product delay times and early production times by giving weights to these parameters.

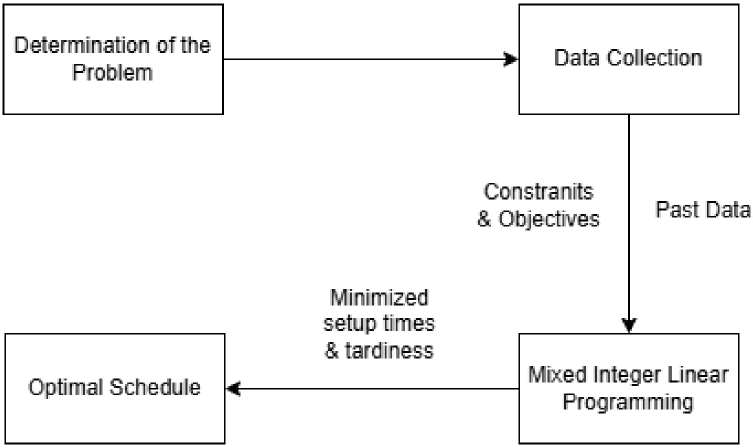


Figure 20.1: Simplified Concept of the Solution Approach

In the mathematical model, there are over 30 constraints. The mathematical model's objective function and constraints are shown in Appendix 20.A. First constraint is the calculation of the completion time of a job. Second constraint guarantees that each job can only be assigned to one line and one position. Third constraint ensures that there can only be at most one job in a position. Fourth constraint ensures material-line compatibility. Fifth constraint links the start time variable with the assignment variable. Sixth constraint ensures that the beginning time of a material is greater than or equal to the completion time of the previous material. Seventh, eighth and ninth constraints are the tardiness and earliness of a product and the idle time of a line. The following four constraints ensure sequential assignment on a line. Fourteenth constraint ensures that a no job can be scheduled unless all previous positions on the line are filled. Next 13 constraints are regarding the double corona production and layflat value of a product. If the layflat of a product is bigger than a certain value, certain lines are not able to produce that material. Twenty eighth constraint is the odor constraint. If a material is odor-emitting and there is an odor-sensitive product planned right after that material, there must be a 480 minute gap between the production of these two materials. Twenty ninth constraint puts an upper limit on the tardiness value. Next five constraints are the non-negative parameters and decision variables and the final two constraints are the binary variables. The mathematical model is addressed with the help of Mixed Integer Linear Programming. Our aim was to minimize the said objective function by taking into account linear constraints according to Modos (2021).

20.3.2 Heuristic Approach

A heuristic approach needed to be developed since the team could only work with limited amount data. Even if this may not give the optimal solution, it works much faster compared to the model, it provides near-optimal solutions and it works with a bigger interval of datasets. This heuristic approach takes inspiration from Ersan (2022) and Lee and Pinedo (1997)'s work on parallel machine scheduling heuristics. The first two steps of the heuristic algorithm is laid out in Appendix 20.B. There are three main things that takes place in the heuristic. We first start with initializing the makespan for each machine then we filter the jobs based on their eligibility. We then calculate the start times of the jobs based on their processing time. The processing time is calculated based on the production amount (based on kg) divided by the speed of the line which is then multiplied by 60 to give an output in minutes. The jobs are then shifted based on their deadline to minimize earliness, the algorithm then attempts to optimize the assignments for jobs that can be produced in multiple lines. Then finally, we consider the odor and color constraints in the Excel file that is optimized with the help of the heuristic approach.

20.4 Verification and Validation

The verification process was about checking if the model complied with the constraints we set and if the heuristic algorithm worked with extreme numbers of data. The model's simplified version was first tested with a 20 job data set, then the number of jobs were gradually increased to see how the model would respond. During this process, parameters like the weights of earliness, tardiness, idle time and setup time were constantly changed as well as the layflat values. It was observed that the model complied with all of the constraints. For the verification of the heuristic approach, the tests were made with an interval of 20-300 jobs. The layflat values were variable as well as the amount of material produced, product-line compatibility etc.

In the validation part, the company data was integrated to the model and heuristic approach and compared the outputs. The mathematical model worked better with a smaller data set, having a smaller objective function value and less tardy jobs. As the number of jobs increased, so did the number of tardy jobs. But with the company data integrated to the heuristic approach, while number of tardy jobs rises with the number of jobs, it is a less exponential increase compared to the model's output. So even with a bigger number of jobs, the heuristic approach can give a solution that is close to being the optimal.

20.5 Benchmarking

In this part, the number of tardy jobs from the outputs of the model and the heuristic approach are compared. In the 20 job test, both the model and the heuristic algorithm have no tardy jobs. Running the 30 job data set, the model's output shows 3 jobs that are estimated to be completed late. While in the heuristic algorithm, there are again no tardy jobs seen. With the 40 job data set, which is the maximum number of data that the model could run with, there are 6 tardy jobs in the model while there is 1 tardy job in the heuristic algorithm. As seen in the in the results of the model, the 30 job data set has 10% of its jobs that are tardy. The 40 job data set has 15% of its jobs that are tardy. For the heuristic algorithm, a 10% and 12.5% improvement is seen in the respective datasets. For the respective datasets, 3 jobs in the 30 job set and 5 jobs in the 40 job set are now produced before their deadlines instead of being produced later than their deadlines.

20.6 Project Outcome and Deliverables

The focus of this project was to create a decision-making support system with the help of a heuristic algorithm. This provided the team with decisions about what product should be produced where and when it should be produced depending on the company constraints and the compatibility rules. It was a priority to minimize the earliness and tardiness of jobs while also minimizing the times lost in setup and idle times of the lines, so that the efficiency of said lines would be increased. This also resulted in a more balanced workload. Testing this approach showed that the goal of more balanced workload was achieved. One of the main goals of the company was to have a system that could work with unplanned orders coming through that have tight deadlines. The tests have also shown the team that the support system is capable of handling sudden changes in the production planning horizon. Depending on the deadlines of the jobs, the number of tardy jobs were managed to be minimized in the test runs which was one of the most important points of this project. The company can now implement this system to help them in their decision-making process while helping them potentially reduce costs and helping them interpret data more accurately.

20.6.1 User Interface

After deciding on the heuristic algorithm as the go-to solution approach, a User Interface was built. This User Interface was built on Spyder which is an integrated development environment (IDE) in the Python language. Since both the company and the department required the usage of an open-

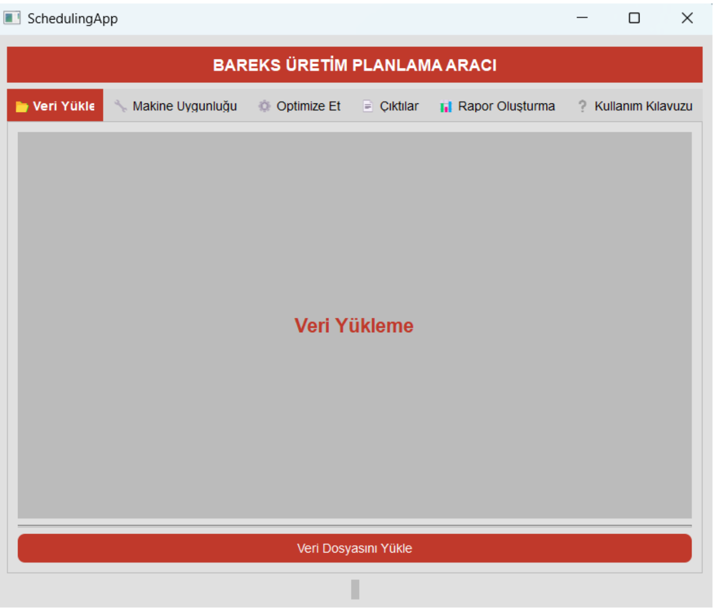


Figure 20.2: The First Tab of the UI

source platform in building this interface, Spyder was chosen since members of the team had previous familiarity with the IDE.

The User Interface starts with the first tab seen in Figure 20.2 where the user uploads a specifically formatted Excel sheet to the system seen in Figure 20.3. This Excel sheet contains vital information like the deadline date of the material's delivery, which line can produce material and its processing time and the material's layflat value. In the second tab, the user can open or close the production lines based on their availability at that time. If a line's closed, it will not be counted in the production process and the algorithm will not count that line. In the third tab, the Excel sheet is optimized by the algorithm. The fourth tab shows the results in written manner and in a Gantt Chart form. In the fifth tab, the user can obtain the results in an Excel sheet form and the final tab is the user manual which explains the process of how to run the interface.

20.7 Conclusion

The proposed support system by the team balances the workload between production lines while minimizing the number of tardy jobs. The system also works in scenarios where there are unplanned orders from customers that might have tight deadlines. The algorithm can re-optimize the proposed schedule despite these challenges. The results from the test runs suggest that the company can have more timely production without compromising with the deadlines while also keeping their production lines working as much as possible, minimizing their idle times. The company can run this system with a dataset of 20 jobs or they can run this with a dataset of over 400 jobs which is about the monthly average of jobs done by the company.

Bibliography

Ersan, T. (2022). Unrelated Parallel Machine Scheduling With Sequence-Dependent Setup Times And Machine Eligibility: An Application At Euro Gıda. https://gcris.ieu.edu.tr/bitstream/20.500.14365/186/1/186.pdf.

Lee, Y. H. and M. Pinedo (1997). Scheduling jobs on parallel machines with sequence-dependent setup times. *European Journal of Operational Research 100*(3), 464–474.

Modos, I. (2021). Mixed Integer Linear Programming: Formal Definition and Solution Space. https://towardsdatascience.com/mixed-integer-linear-programming-formal-definition-andsolution-space-6b3286d54892.

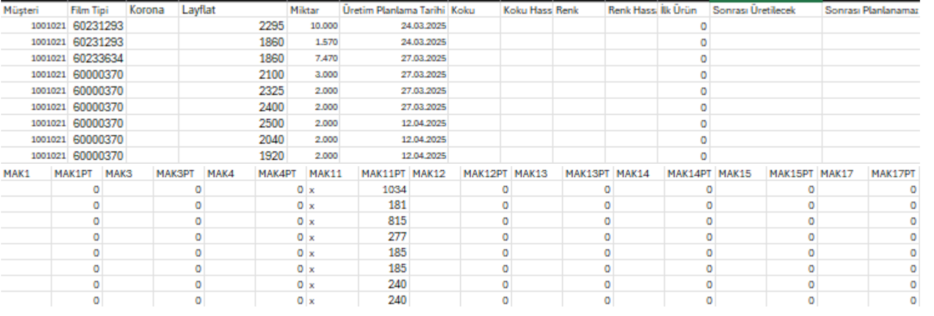
Appendices

20.A The Mathematical Model

$$\min \quad w_I \sum_{l \in M} idletime_l + w_T \sum_{j \in N} T_j + w_E \sum_{J \in N} EA_j + w_S \sum_{k \in N} \sum_{j \neq k} \sum_{l \in M} s_{lkj} Y_{kjl} \tag{20.1}$$

s.t.

$$C_j = \sum_{l \in M} \sum_{i} (B_{jl} + p_{jl} X_{jli}) \quad \forall j \in N \tag{20.2}$$



Müşteri	Film Tipi	Korona	Layflat	Miktar	Üretim Planlama Tarihi	Koku	Koku Hass	Renk	Renk Hass	İlk Ürün	Sonrası Üretilecek	Sonrası Planlanamaz
1001021	60231293		2295	10.000	24.03.2025					0		
1001021	60231293		1860	1.570	24.03.2025					0		
1001021	60233634		1860	7.470	27.03.2025					0		
1001021	60000370		2100	3.000	27.03.2025					0		
1001021	60000370		2325	2.000	27.03.2025					0		
1001021	60000370		2400	2.000	27.03.2025					0		
1001021	60000370		2500	2.000	12.04.2025					0		
1001021	60000370		2040	2.000	12.04.2025					0		
1001021	60000370		1920	2.000	12.04.2025					0		

MAK1	MAK1PT	MAK3	MAK3PT	MAK4	MAK4PT	MAK11	MAK11PT	MAK12	MAK12PT	MAK13	MAK13PT	MAK14	MAK14PT	MAK15	MAK15PT	MAK17	MAK17PT
	0		0		0	x	1034		0		0		0		0		0
	0		0		0	x	181		0		0		0		0		0
	0		0		0	x	815		0		0		0		0		0
	0		0		0	x	277		0		0		0		0		0
	0		0		0	x	185		0		0		0		0		0
	0		0		0	x	185		0		0		0		0		0
	0		0		0	x	240		0		0		0		0		0
	0		0		0	x	240		0		0		0		0		0

Figure 20.3: Excel sheet used in the optimization

$$\sum_{l\in M}\sum_{i\in I} X_{jli} = 1 \quad \forall j \in N \tag{20.3}$$

$$\sum_{j\in N} X_{jli} \leq 1 \quad \forall l \in M, i \in I \tag{20.4}$$

$$\sum_{i\in I} X_{jli} \leq e_{jl} \quad \forall j \in N \quad ,\forall l \in M \tag{20.5}$$

$$B_{jl} \leq BM \sum_{i} X_{jli} \quad \forall j \in N \quad ,\forall l \in M \tag{20.6}$$

$$B_{jl} \geq B_{kl} + p_{kl} + s_{lkj} - BM(1 - Y_{kjl}) \quad \forall j, k \in N,\ j \neq k, \forall\ l \in M \tag{20.7}$$

$$T_j \geq C_j - d_j \quad \forall j \in N \tag{20.8}$$

$$EA_j \geq d_j - C_j \quad \forall j \in N \tag{20.9}$$

$$idletime_l = A_l - \sum_{j\in N}\sum_{i\in I} p_{jl}X_{jli} - \sum_{k\in N}\sum_{j\neq k} s_{lkj}Y_{kjl} \quad \forall l \in M \tag{20.10}$$

$$Y_{kjl} = \sum_{i=1}^{n} X_{kli}X_{jli+1} \quad \forall k, j \in N, k \neq J, \forall l \in M \tag{20.11}$$

$$Y_{kjl} \leq \sum_{i=1}^{n} X_{kli} + X_{jli+1} \quad \forall k, j \in N, k \neq J, \forall l \in M \tag{20.12}$$

$$\sum_{i\in I} X_{kjl} + \sum_{i\in 1} X_{jli} \geq 2Y_{kjl} \quad \forall l \in M, \forall j, k \in N, j \neq k \tag{20.13}$$

$$Y_{kjl} \geq \sum_{i=1}^{n} X_{kli} + X_{jli+1} - 1 \quad \forall k, j \in N, k \neq J, \forall l \in M \tag{20.14}$$

$$\sum_{j} X_{jl(i+1)} \leq \sum_{j} X_{jli} \quad \forall l \in M \quad ,\forall i \tag{20.15}$$

$$\sum_{i\in I} X_{j8i} \geq k_j \quad \forall j \in N \tag{20.16}$$

$$L_j - 1500 \leq BM * z_{1500j} \quad \forall j \in N \tag{20.17}$$

$$L_j - 1500 \geq -BM(1 - z_{1500j}) \quad \forall j \in N \tag{20.18}$$

$$\sum_{i\in I} X_{j9i} \leq 1 - z_{1500j} \quad \forall j \in N \tag{20.19}$$

$$L_j - 1550 \leq BM * z_{1550j} \quad \forall j \in N \tag{20.20}$$

$$L_j - 1550 \geq -BM(1 - z_{1550j}) \quad \forall j \in N \tag{20.21}$$

$$\sum_{i\in I}(X_{j9i} + X_{j2i}) \leq 1 - z_{1550j} \quad \forall j \in N \tag{20.22}$$

$$L_j - 2550 \leq BM * z_{2550j} \quad \forall j \in N \tag{20.23}$$

$$L_j - 2550 \geq -BM(1 - z_{2550j}) \quad \forall j \in N \tag{20.24}$$

$$\sum_{i \in I}(X_{j2i} + X_{j3i} + X_{j7i} + X_{j9i}) \leq 1 - z_{2550j} \quad \forall j \in N \tag{20.25}$$

$$L_j - 2560 \leq BM * z_{2560j} \quad \forall j \in N \tag{20.26}$$

$$L_j - 2560 \geq -BM(1 - z_{2560j}) \quad \forall j \in N \tag{20.27}$$

$$\sum_{i \in I}(X_{j2i} + X_{j3i} + X_{j7i} + X_{j9i}) \leq 1 - z_{2560j} \quad \forall j \in N \tag{20.28}$$

$$B_{jl} \geq B_{kl} + (p_{kl} * X_{kli}) + 480X_{kli}, \quad \forall l \in M \tag{20.29}$$

$$T_j \leq 50000, \quad \forall j \in N \tag{20.30}$$

$$C_j \geq 0 \quad \forall j \in N \tag{20.31}$$

$$T_j \geq 0 \quad \forall j \in N \tag{20.32}$$

$$EA_j \geq 0 \quad \forall j \in N \tag{20.33}$$

$$B_{jl} \geq 0 \quad \forall j \in N \quad , \forall l \in M \tag{20.34}$$

$$idletime_l \geq 0 \quad \forall l \in M \tag{20.35}$$

$$X_{jli} \in \{0, 1\} \tag{20.36}$$

$$Y_{kjl} \in \{0, 1\} \tag{20.37}$$

20.B Heuristic Algorithm

Phase 1: Pre-Processing

- m = number of lines
- n = number of products
- p = average processing time
- s = average setup time
- d = average due date
- d_{max} = maximum due date
- d_{min} = minimum due date
- $c_{max} = \max\{c_1, c_2\}$ = maximum makespan
- $\mu = \frac{n}{m}$ = product-line factor
- $\eta = \frac{s}{p}$ = setup time severity factor
- $\beta = 0.4 + \frac{10}{\mu^2} - \frac{n}{7}$ = coefficient accounting for setup effects on makespan

- $c_1 = \sum p_{j1} + \frac{\sum p_{j(1,2)}}{2} + (s * \beta)$
- $c_2 = \sum p_{j2} + \frac{\sum p_{j(1,2)}}{2} + (s * \beta)$
- $\tau = 1 - \frac{d}{C_{max}}$
- $R = \frac{d_{max} - d_{min}}{C_{max}}$

Phase 2: Dispatching
The job index $J_j(t, l)$ for job j on machine l at time t is given by:

$$J_j(t,l) = \left(\frac{1}{p_j}\right) \exp\left(-\frac{\max(d_j - p_j - t, 0)}{k_1 p}\right) \cdot \exp\left(-\frac{s_{lj}}{k_2 s}\right)$$

where

- p_j is the processing time for material j
- d_j is the due date for material j
- t is the time
- $k_1 = 1.2\ln(\mu) - R$
- $k_2 = \frac{\tau}{A_2\sqrt{\eta}}$

  where,

  - $A_2 = 1.8$ if $\tau < 0.8$
  - $A_2 = 2.0$ if $\tau >= 0.8$

  - Subtract 0.5 from k_1 if $\tau < 0.5$.
  - Subtract 0.5 from k_1 if $\eta < 0.5$ and $\mu > 5$.
- s_{lj} is the setup time between job l and job j.
- p is the average processing time.
- s is the average the setup time.

21 Üretimde İş Gücü Planlaması Karar Destek Sistemi

Beko Elektronik İşletmesi

Proje Ekibi
Gizem Akmaz, Emir Kerem Elmalı, Alara Günel,
Armağan Sarıışık, Begüm Tan, Behçet Çağlar Ulutaş, Cansu Yorgancı

Şirket Danışmanları
Ömer Faruk Ünal ve Elvan Uslu
Üretim Mühendisliği

Akademik Danışman
Mis. Dr. Öğr. Üyesi Andrea Pizzuti
Endüstri Mühendisliği Bölümü

Özet

Beko Elektronik Fabrikası, Tekirdağ'da yer alan ve televizyon üretiminde yüksek kapasitesiyle faaliyet gösteren önemli bir üretim merkezidir. Mevcut durumda vardiya planlaması, her ayın başında yaklaşık iki gün süren ve büyük ölçüde deneme-yanılma esasına dayanan manuel yöntemlerle yapılmaktadır. Bu proje, fabrikanın iş gücü planlama süreçlerini iyileştirmeyi ve daha sistematik bir yapıya kavuşturmayı amaçlamaktadır. Proje kapsamında, vardiya süreleri, fazla mesai ve ek vardiya gereksinimleri göz önünde bulundurularak, üretim verimliliğini artıracak bir vardiya planı geliştirilmiştir. Geliştirilen model, iş gücü kullanımını eniyilemek, fazla mesaiyi enazlamak ve üretim verimliliğini artırmak için matematiksel ve mühendislik temelli bir çözüm sunmaktadır. Ayrıca, oluşturulan karar destek sistemi, fabrika yöneticilerine doğru iş gücü planlaması için gerekli verileri sağlar. Bu modelin uygulanması, iş gücü maliyetlerinin azaltılmasına ve üretim verimliliğinin artırılmasına olanak tanıyacaktır.

Anahtar Sözcükler: İş gücü planlaması, vardiya planlaması, iş gücü verimliliği, sezgisel yöntemler, talep karşılanması

Decision Support System for Production Workforce Planning

Abstract

Beko Electronics Factory, located in Tekirdağ, is a major production facility operating with high capacity in television manufacturing. Currently, shift planning is conducted manually through a trial-and-error process that takes approximately two days at the beginning of each month. This project aims to improve the factory's workforce planning processes and establish a more systematic structure. Within the scope of the project, a more efficient shift schedule has been developed by taking into account shift durations, overtime, and additional shift requirements. The proposed model offers a mathematical and engineering-based solution to improve labor utilization, minimize overtime, and increase production efficiency. Additionally, the decision support system provides factory managers with the necessary data for accurate workforce planning. Implementing this model will enable a reduction in labor costs and an improvement in production efficiency.

Keywords: Workforce planning, shift scheduling, labor efficiency, heuristic methods, demand fulfillment

21.1 Beko and System Analysis

21.1.1 Company Description

Beko Electronics is a manufacturing facility located in Tekirdağ, Turkey, operating under Beko Global, a subsidiary of Koç Holding. The factory specializes in television production, with an annual capacity of up to 1.000.000 units. In addition to televisions, the facility contributes to the production of various home appliances and consumer electronics. Its production scale places it among the largest manufacturing sites in Turkey and Europe. Beko Electronics distributes products to over 130 countries across multiple regions, including Europe, the Middle East, Africa, and Asia (Beko, 2023).

This project was developed to support workforce planning for television production lines at Beko Electronics. A decision support system was designed to assist with shift scheduling and workforce allocation, helping to reduce overtime, improve resource utilization, and control labor costs. Additionally, the system provided data-driven insights to enhance planning decisions related to labor management.

21.1.2 System Analysis

The factory's production processes include electronic circuit assembly and television assembly lines. Although there are six television production lines, four are considered in this project. Production line personnel operate in three shifts: 08:00–16:00, 16:00–00:00, and 00:00–08:00, with each shift including a 50-minute break, resulting in 430 minutes of active working time. Factory employees are contract workers, and recruitment or dismissal during the planning process is based on the demand forecast for the next three months.

The current production planning process at Beko Electronics is managed manually, with the production plan created at the beginning of each month. This process takes approximately two days and is time-consuming. Moreover, manual planning is prone to errors and may not generate the most efficient production sequence, resulting in excessive labor usage and higher operational costs.

In the current system, shift planning is based on the assumption that only the first shift will be utilized. Additional shifts are introduced if the first shift proves insufficient to meet production demand. Since this approach is done manually, it lacks a systematic structure and may not consistently yield the most efficient outcomes. It can result in higher labor requirements. Moreover, the reliance on manual planning through Excel and a trial-and-error method can lead to human errors, such as incorrect workforce allocation or production line mismatches.

21.2 Problem Definition and Deliverables

The main problem is the inability to efficiently plan the workforce in production. The current manual system fails to fully meet production capacity, leads to unnecessary labor usage, and increases costs through reliance on overtime and extra shifts. Therefore, developing an improved workforce planning approach for each shift over a three-month horizon is necessary. The primary objective of the project is to establish a mathematically grounded method for generating effective workforce and shift planning decisions. The model accounts for operational constraints such as line-specific product compatibility, employee availability, shift limits, overtime regulations, and production targets.

The main deliverable is a user-friendly decision support system designed to assist workforce planning across television production lines. Developed using Python, Gurobi, and CBC, the system operates with a single Excel input file and generates detailed three-month labor and shift allocation plans. It provides key outputs, including demand fulfillment, UPPH, workforce changes, and overtime usage. Results can be exported to Excel and optionally shared via email through the interface. To enhance usability, the system includes a visually guided manual, enabling planners to use the tool without technical expertise. Additionally, it supports scenario-based

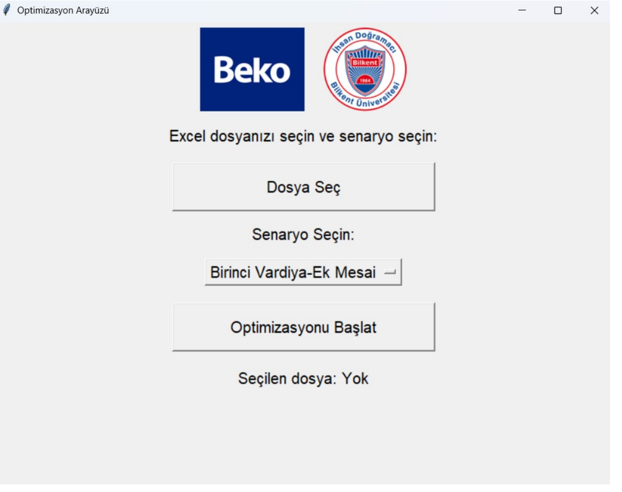


Figure 21.1: User Interface of the Decision Support System

analysis, allowing flexible adjustments to varying production demands and constraints. The main page of the decision support system is shown in Figure 21.1.

21.3 Proposed Solution Strategy

21.3.1 Critical Assumptions

Critical assumptions made during the model development process include treating each of the four primary production lines as independent units, each capable of producing specific products. Only the third line can do two different processes such as back module and last assembly, it is seperated to two different lines to solve the problem and they act like lines 3 and 4. The model assumes that the production rate for each product is calculated based on the assumption that the product is produced on the assigned line for an entire shift. Furthermore, it is assumed that raw materials will always be available at the start of production, and no raw material shortages will occur. Additionally, it is assumed that there are no interruptions from general maintenance during production planning, and that all employees are contract workers for a month.

21.3.2 Major Constraints

Real-world production constraints have been carefully incorporated into the model. Products are assigned to different lines, with line-specific capabilities taken into account, particularly due to varying product types and sizes. For example, certain lines can only produce specific products, such as small and medium-sized televisions, while others are restricted from producing larger models. The shift duration is another key constraint; each shift lasts for 8 hours (480 minutes), with a 50-minute break, resulting in 430 minutes of active working time. Setup times are deducted from this available time, and the maximum daily working hours are capped at 11 hours, with a weekly maximum of 45 hours and an annual overtime limit of 270 hours. For the overtime and second shift options, an employee cannot work overtime in two consecutive days.

21.3.3 Objectives

The primary objective of this project is to support more effective workforce planning at Beko Electronics by developing a decision support system for shift scheduling. To achieve this, the project introduces three distinct planning scenarios, each designed to evaluate the impact of workforce size, production costs, and backlog under different operational conditions. These models assist in identifying cost-conscious workforce and shift arrangements that can meet production demand while reducing delays and avoiding excessive labor use.

A secondary objective is to generate practical and efficient shift schedules that align with monthly production targets. These schedules are developed in coordination with the cost-focused models to minimize overtime, reduce the need for temporary workers, and make better use of available staff.

Overall, the system is designed to support more structured, adaptable, and cost-efficient workforce planning without altering production line configurations or capacities.

21.3.4 Solution Approach

The solution approach involves developing a mathematical model to allocate sufficient workforce to each production line while meeting production targets. Due to the computational complexity of the problem, a heuristic procedure is applied to reduce runtime and generate feasible solutions efficiently. To simplify the problem, it is divided into three scenario models, each using inputs such as the line-product matrix and production data to calculate the optimal number of active days per line. The outputs of these models are then used as inputs for the schedule models. Solving the schedule models yields the final workforce plan. The CBC solver was used to validate the model and generate feasible schedules, balancing shift durations, workforce capacity, and product-line compatibility while improving production efficiency and reducing labor costs.

Conceptual Model

The conceptual model starts with production planning data, which is separately processed by three scenario models: First Shift with Overtime, First and Second Shift, and First, Second, and Third Shift. Their outputs are then fed into the schedule model to generate workforce schedules, which are evaluated against operational objectives and constraints to support final decision-making.

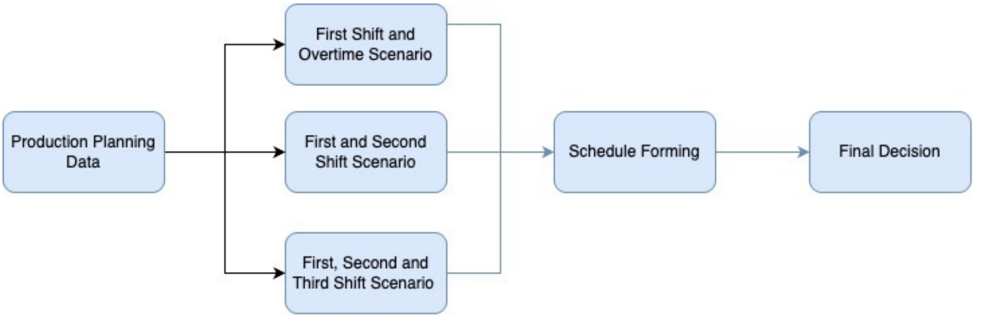


Figure 21.2: Conceptual Model of the Workforce Planning Decision Support System

Mathematical Models

Table 21.1: Set definitions

Sets	**Description**
$I = \{1, 2, 3\}$	Set of months.
$J_i = \{1, 2, \ldots, \lvert J_i \rvert\}$	Set of days in month i.
$K = \{1, 2, 3, 4, 5\}$	Set of production lines.
$L = \{1, 2, \ldots, 568\}$	Set of products.
$S = \{1, 2, 3\}$	Set of shifts.

Table 21.2: Parametre definitions

Parameters	**Description**
E_l	Total excess inventory of product l from previous month.
W	Initial number of workers in the system.
B_k	Number of workers assigned to line k.
C^O	Cost of overtime worker per hour.
C^R	Cost of regular time worker per month.
C^I	Cost of inventory.

C^B	Cost of backlog per item.
C^H	Cost of recruiting one worker.
C^F	Cost of releasing one worker.
Sd	Duration of a regular shift.
Od	Duration of overtime.
T_l	Time needed to produce product l.
D_{il}	Demand for product l in month i.
AD_{isk}	Number of days line k is active in month i, shift s.
M	A sufficiently large number used for constraint formulations.
P_{kl}	$= \begin{cases} 1, & \text{if product } l \text{ can be produced on line } k, \\ 0, & \text{otherwise} \end{cases}$

Table 21.3: Decision variables

Decision Variables	Description
e_{il}	Excess product l at the end of month i, $\forall i \in I, l \in L$.
w_i	Total number of workers in month i, $\forall i \in I$.
w_i^{FS}	Workers in the first shift in month i, $\forall i \in I$.
w_i^{SS}	Workers in the second shift in month i, $\forall i \in I$.
w_i^{TS}	Workers in the third shift in month i, $\forall i \in I$.
h_i	Number of workers recruited at the beginning of month i, $\forall i \in I$.
f_i	Number of workers released at the beginning of month i, $\forall i \in I$.
b_{il}	Unmet demand for product l in month i, $\forall i \in I, l \in L$.
o_{ik}	Overtime in month i for line k, $\forall i \in I, k \in K$.
fs_{ik}	First shift in month i for line k, $\forall i \in I, k \in K$.
ss_{ik}	Second shift in month i for line k, $\forall i \in I, k \in K$.
ts_{ik}	Third shift in month i for line k, $\forall i \in I, k \in K$.
p_{ijkl}^F	Product l produced in the first shift, $\forall i, j, k, l$.
p_{ijkl}^O	Product l produced in overtime, $\forall i, j, k, l$.
p_{ijkl}^S	Product l produced in the second shift, $\forall i, j, k, l$.
p_{ijkl}^T	Product l produced in the third shift, $\forall i, j, k, l$.
emp	Maximum number of employees needed on any day of the month.
g_{ik}^{FS}	$\begin{cases} 1, & \text{if line } k \text{ is used in the first shift in month } i \\ 0, & \text{otherwise} \end{cases}$

g_{ik}^{SS}	$\begin{cases} 1, & \text{if line } k \text{ is used in the second shift in month } i \\ 0, & \text{otherwise} \end{cases}$
g_{ik}^{TS}	$\begin{cases} 1, & \text{if line } k \text{ is used in the third shift in month } i \\ 0, & \text{otherwise} \end{cases}$
x_{sjk}	$\begin{cases} 1, & \text{if line } k \text{ is used in shift } s \text{ on day } j \\ 0, & \text{otherwise} \end{cases}$

Mathematical Model for First Shift and Overtime

$$\text{Minimize: } \sum_{i\in I} C^R w_i + \sum_{i\in I}\sum_{k\in K} B_k C^O O do_{ik} + \sum_{i\in I}\sum_{l\in L} C^B b_{il} + \sum_{i\in I}\sum_{l\in L} C^I e_{i,l} + \sum_{i\in I} C^H h_i + \sum_{i\in I} C^F f_i \tag{21.1}$$

$$w_1 = W + h_1 - f_1 \tag{21.2}$$

$$\sum_{j\in J_1}\sum_{k\in K}(p_{1jkl}^F + p_{1jkl}^O) + E_l + b_{1l} - e_{1l} = D_{1l}, \quad \forall\, l \in L \tag{21.3}$$

$$w_i = w_{i-1} + h_i - f_i, \quad \forall\, i \in \{2,3\} \tag{21.4}$$

$$\sum_{j\in J_i}\sum_{k\in K}(p_{ijkl}^F + p_{ijkl}^O) + e_{i-1l} + b_{il} - e_{il} = D_{il}, \quad \forall\, i \in \{2,3\};\ l \in L \tag{21.5}$$

$$\sum_{k\in K} B_k fs_{ik} \le |J_i| w_i, \quad \forall\, i \in I \tag{21.6}$$

$$\sum_{k\in K} B_k o_{ik} \le \lfloor \frac{|J_i|}{2} \rfloor w_i, \quad \forall\, i \in I \tag{21.7}$$

$$\sum_{k\in K} B_k o_{ik} \le 12 w_i, \quad \forall\, i \in I \tag{21.8}$$

$$\sum_{j\in J_i}\sum_{l\in L} T_l p_{ijkl}^F \le Sdfs_{ik}, \quad \forall\, i \in I;\ k \in K \tag{21.9}$$

$$\sum_{j\in J_i}\sum_{l\in L} T_l p_{ijkl}^O \le Odo_{ik}, \quad \forall\, i \in I;\ k \in K \tag{21.10}$$

$$\sum_{k\in K} o_{ik} \le \lfloor \frac{|J_i|}{2} \rfloor, \quad \forall\, i \in I;\ k \in K \tag{21.11}$$

$$\sum_{l\in L} T_l p_{ijkl}^F \le Sd, \quad \forall\, i \in I;\ j \in J_i;\ k \in K \tag{21.12}$$

$$\sum_{l\in L} T_l p_{ijkl}^O \le Od, \quad \forall\, i \in I;\ j \in J_i;\ k \in K \tag{21.13}$$

$$o_{ik} \le 12, \quad \forall\, i \in I;\ k \in K \tag{21.14}$$

$$\sum_{l\in L} T_l(p^F_{ij3l} + p^F_{ij4l}) \leq Sd, \quad \forall\, i \in I;\ j \in J_i;\ k \in K \tag{21.15}$$

$$\sum_{l\in L} T_l(p^O_{ij3l} + p^O_{ij4l}) \leq Od, \quad \forall\, i \in I;\ j \in J_i;\ k \in K \tag{21.16}$$

$$fs_{ik} \leq |J_i|, \quad \forall\, i \in I;\ k \in K \tag{21.17}$$

$$fs_{i3} + fs_{i4} \leq |J_i|, \quad \forall\, i \in I;\ k \in K \tag{21.18}$$

$$o_{i3} + o_{i4} \leq \lfloor \frac{|J_i|}{2} \rfloor, \quad \forall\, i \in I;\ k \in K \tag{21.19}$$

$$o_{i3} + o_{i4} \leq 12, \quad \forall\, i \in I;\ k \in K \tag{21.20}$$

$$p^F_{ijkl},\ p^O_{ijkl},\ fs_{ik},\ o_{ik},\ e_{il},\ b_{il},\ w_i,\ h_i,\ f_i \geq 0, \quad \forall\, i \in I;\ j \in J_i;\ k \in K;\ l \in L \tag{21.21}$$

Mathematical model for First Shift-Overtime scenario is given here. First-Second Shifts and First-Second-Third Shifts scenarios can be seen in Appendices 21.A and 21.B. Constraints (2) and (4) maintain worker count update and tracking. (3) and (5) are balance constraints related to demand fulfillment and inventory. (6), (7) and (8) are worker capacity constraints. (9), (10), (12), (13),(15)and (16) limit production time and shift duration. (11) and (14) limit the usage of overtime. (17), (18), (19) and (20) provide shift usage limits for different lines.

The schedule model uses the outputs of the three models and creates schedules for each of the scenarios. The schedule model can be seen in 21.C.

21.3.5 Validation of Our Approach

To validate the workforce optimization model, we evaluated its structure, assumptions, and outputs against Beko's actual operational data. To better reflect real-life shift operations, our model is structured around three distinct scenarios. This approach captures all operational alternatives without the computational complexity of solving a unified model. The model can be rerun every 15 days to match the company's decision-making cycle. Key parameters such as line-specific workforce levels, working days, and initial employee allocation were derived from real operational data. Additionally, the model supports dynamic updates of demand forecasts, production days, and cost-related inputs, ensuring adaptability to evolving system conditions.

For data validation, the model was tested using Beko's production planning data from the first three months of 2024. It successfully produced a feasible solution, confirming that the actual operational setup lies within the model's feasible solution space. Outputs such as production line schedules, UPPH values, and average workforce numbers were compared against real-life data. The close alignment between model results and actual factory operations supports the model's reliability and applicability for workforce planning. Table 21.4 presents the monthly comparison of actual and model-generated employee numbers, showing that actual values fall within the model's output range across different scenarios (366–376).

21.3.6 Integration and Implementation

Following the development of the decision support system, the implementation phase began under the supervision of Beko's industrial engineers. The mathematical model and user interface were executed using Python, with the open-source CBC (COIN-OR Branch and Cut) solver employed to solve the models. The interface was designed to accept Excel-based inputs, including demand forecasts and product-line compatibility data. A user manual was prepared to guide company personnel, covering input requirements, output interpretation, and instructions for running the three shift planning scenarios. Throughout implementation, engineers actively monitored system performance and provided feedback for final adjustments.

21.3.7 Benefits to the Company

The workforce planning decision support system offers strategic benefits to Beko Electronics by replacing manual, error-prone scheduling with dynamic shift planning based on real demand. It improves workforce allocation, reduces overtime and contract hires, and lowers labor costs.

Benchmarking results show a 12.47% reduction in employee hiring over a three-month horizon, while maintaining full demand fulfillment and comparable Units Per Person Hour (UPPH) levels. Our solution approach achieved a 15.48% improvement in UPPH, increasing from 1.42 under the current system to 1.68. These outcomes demonstrate improved workforce efficiency without compromising production capacity. Additionally, the system can generate shift schedules for all three scenarios simultaneously in under 1.5 minutes. This represents a dramatic improvement, reducing the scheduling process from two full days to mere minutes. The system's interactive interface streamlines scenario selection and automatically generates optimized schedules, allowing decision-makers to evaluate cost-performance trade-offs.

Table 21.4: Monthly Comparison of Actual and Model Employee Numbers

Month	Employee Number (Actual)	Second Scenario	Third Scenario
January	321	313	278
February	336	391	391
March	464	426	429
AVERAGE	**373**	**376**	**366**

By improving human resource utilization and maintaining production efficiency, the decision support system helps Beko minimize operational costs while sustaining high service levels.

21.3.8 Conclusion

The primary objective of this project was to develop a workforce scheduling system to increase production efficiency and minimize labor costs at Beko Electronics. A user-friendly interface was developed using Python, which allowed company personnel to input demand and compatibility data, select a planning scenario, and receive structured output detailing optimal shift plans and workforce adjustments. The system runs three distinct models: First shift + overtime, First + second shift and All three shifts, providing results that reflect projected demand and production capacity over a three-month planning horizon.

The decision support system was implemented with real company data and adjustments were made to enhance functionality. The outputs were compared across scenarios, and the model successfully provided cost-effective shift schedules that satisfied demand. These results guided refinements to the system and demonstrated its potential to support future workforce planning at the factory.

Bibliography

Beko (2023). Annual report 2023. https://www.bekocorporate.com/media/srlh13ru/arcelik_eng23_1405.pdf.

Appendix: Mathematical Models

21.A The First and Second Shifts

Objective Function

$$\begin{aligned}\text{Minimize: } &\sum_{i\in I} C^R w_i + \sum_{i\in I}\sum_{k\in K} C^{SS} ss_{ik} + \sum_{i\in I}\sum_{l\in L} C^B b_{il} \\ &+ \sum_{i\in I}\sum_{l\in L} C^I e_{il} + \sum_{i\in I} C^H h_i + \sum_{i\in I} C^F f_i \end{aligned} \tag{21.22}$$

Constraints

$$w_1 = W + h_1 - f_1 \tag{21.23}$$

$$\sum_{j\in J_1}\sum_{k\in K}(p^F_{1jkl} + p^S_{1jkl}) + E_l + b_{1l} - e_{1l} = D_{1l}, \quad \forall\, l \in L \tag{21.24}$$

$$w_i = w_{i-1} + h_i - f_i, \quad \forall\, i \in \{2,3\} \tag{21.25}$$

$$\sum_{j \in J_i} \sum_{k \in K} (p^F_{i,j,k,l} + p^S_{ijkl}) + e_{i-1l} + b_{il} - e_{il} = D_{il}, \quad \forall\ i \in \{2,3\};\ l \in L \tag{21.26}$$

$$w_i^{FS} + w_i^{SS} \leq w_i, \quad \forall\ i \in I \tag{21.27}$$

$$\sum_{k \in K} B_k fs_{ik} \leq |J_i| w_i^{FS}, \quad \forall\ i \in I \tag{21.28}$$

$$\sum_{k \in K} B_k ss_{ik} \leq |J_i| w_i^{SS}, \quad \forall\ i \in I \tag{21.29}$$

$$\sum_{l \in L} \sum_{j \in J[i]} p^F_{ijkl} \leq M g^{FS}_{ik} \quad \forall\ i \in I;\ k \in K \tag{21.30}$$

$$\sum_{l \in L} \sum_{j \in J[i]} p^S_{ijkl} \leq M g^{SS}_{ik} \quad \forall\ i \in I;\ k \in K \tag{21.31}$$

$$fs_{ik} \leq M g^{FS}_{ik} \quad \forall\ i \in I;\ k \in K \tag{21.32}$$

$$ss_{ik} \leq M g^{SS}_{ik} \quad \forall\ i \in I;\ k \in K \tag{21.33}$$

$$\sum_{j \in J_i} \sum_{l \in L} T_l p^F_{ijkl} \leq Sd fs_{ik}, \quad \forall\ i \in I;\ k \in K \tag{21.34}$$

$$\sum_{j \in J_i} \sum_{l \in L} T_l p^S_{ijkl} \leq \sum_{k \in K} Sd ss_{ik}, \quad \forall\ i \in I;\ k \in K \tag{21.35}$$

$$\sum_{l \in L} T_l p^F_{ijkl} \leq Sd, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.36}$$

$$\sum_{l \in L} T_l p^S_{ijkl} \leq Sd, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.37}$$

$$\sum_{l \in L} T_l (p^F_{ij3l} + p^F_{ij4l}) \leq Sd, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.38}$$

$$\sum_{l \in L} T_l (p^S_{ij3l} + p^S_{ij4l}) \leq Sd, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.39}$$

$$fs_{ik} \leq |J_i| g^{FS}_{ik}, \quad \forall\ i \in I;\ k \in K \tag{21.40}$$

$$ss_{ik} \leq |J_i| g^{SS}_{ik}, \quad \forall\ i \in I;\ k \in K \tag{21.41}$$

$$fs_{i3} + fs_{i4} \leq |J_i| g^{FS}_{ik}, \quad \forall\ i \in I;\ k \in K \tag{21.42}$$

$$ss_{i3} + ss_{i4} \leq |J_i| g^{SS}_{ik}, \quad \forall\ i \in I;\ k \in K \tag{21.43}$$

$$g^{FS}_{ik},\ g^{FS}_{ik} \in \{0,1\}, \quad \forall\ i \in I;\ k \in K \tag{21.44}$$

$$\begin{gathered} p^F_{ijkl},\ p^S_{ijkl},\ fs_{ik},\ ss_{ik},\ e_{il},\ b_{il}, \\ w_i,\ w_i^{FS},\ w_i^{SS},\ h_i,\ f_i \geq 0, \quad \forall\ i \in I;\ j \in J_i;\ k \in K;\ l \in L \end{gathered} \tag{21.45}$$

21.B The First, Second, and Third Shifts

Objective Function

$$\text{Minimize: } \sum_{i\in I} C^R w_i + \sum_{i\in I}\sum_{k\in K} C^{SS} ss_{ik} + \sum_{i\in I}\sum_{k\in K} C^{TS} ts_{ik} + \sum_{i\in I}\sum_{l\in L} C^B b_{il} + \sum_{i\in I}\sum_{l\in L} C^I e_{il} + \sum_{i\in I} C^H h_i + \sum_{i\in I} C^F f_i \quad (21.46)$$

Constraints

$$w_1 = W + h_1 - f_1 \quad (21.47)$$

$$\sum_{j\in J_1}\sum_{k\in K}\left(p^F_{1jkl} + p^S_{1jkl} + p^T_{1jkl}\right) + E_l + b_{1l} - e_{1l} = D_{1l}, \quad \forall\, l \in L \quad (21.48)$$

$$w_i = w_{i-1} + h_i - f_i, \quad \forall\, i \in \{2,3\} \quad (21.49)$$

$$\sum_{j\in J_i}\sum_{k\in K}\left(p^F_{ijkl} + p^S_{ijkl} + p^T_{ijkl}\right) + e_{i-1l} + b_{il} - e_{il} = D_{il}, \quad \forall\, i \in \{2,3\}; \; l \in L \quad (21.50)$$

$$w_i^{FS} + w_i^{SS} + w_i^{TS} = w_i, \quad \forall\, i \in I \quad (21.51)$$

$$\sum_{k\in K} B_k fs_{ik} \le |J_i| w_i^{FS}, \quad \forall\, i \in I \quad (21.52)$$

$$\sum_{k\in K} B_k ss_{ik} \le |J_i| w_i^{SS}, \quad \forall\, i \in I \quad (21.53)$$

$$\sum_{k\in K} B_k ts_{ik} \le |J_i| w_i^{TS}, \quad \forall\, i \in I \quad (21.54)$$

$$fs_{ik} \le M g_{ik}^{FS}, \quad \forall\, i \in I;\; k \in K \quad (21.55)$$

$$ss_{ik} \le M g_{ik}^{SS}, \quad \forall\, i \in I;\; k \in K \quad (21.56)$$

$$ts_{ik} \le M g_{ik}^{TS}, \quad \forall\, i \in I;\; k \in K \quad (21.57)$$

$$ts_{ik} \le ss_{ik}, \quad \forall\, i \in I;\; k \in K \quad (21.58)$$

$$\sum_{j\in J_i}\sum_{l\in L} T_l p^F_{ijkl} \le Sd fs_{ik}, \quad \forall\, i \in I;\; k \in K \quad (21.59)$$

$$\sum_{j\in J_i}\sum_{l\in L} T_l p^S_{ijkl} \le Sd ss_{ik}, \quad \forall\, i \in I;\; k \in K \quad (21.60)$$

$$\sum_{j\in J_i}\sum_{l\in L} T_l p^T_{ijkl} \le Sd ts_{ik}, \quad \forall\, i \in I;\; k \in K \quad (21.61)$$

$$B_k g_{ik}^{FS} \le w_i^{FS}, \quad \forall\, i \in I;\; k \in K \quad (21.62)$$

$$B_k g_{ik}^{SS} \le w_i^{SS}, \quad \forall\, i \in I;\; k \in K \quad (21.63)$$

$$B_k g_{ik}^{TS} \leq w_i^{TS}, \quad \forall\ i \in I;\ k \in K \tag{21.64}$$

$$\sum_{l \in L} T_l p_{ijkl}^F \leq Sd g_{ik}^{FS}, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.65}$$

$$\sum_{l \in L} T_l p_{ijkl}^S \leq Sd g_{ik}^{SS}, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.66}$$

$$\sum_{l \in L} T_l p_{ijkl}^T \leq Sd g_{ik}^{TS}, \quad \forall\ i \in I;\ j \in J_i;\ k \in K \tag{21.67}$$

$$\sum_{j \in J_i} \sum_{l \in L} p_{ijkl}^F \leq M g_{ik}^{FS}, \quad \forall\ i \in I;\ k \in K \tag{21.68}$$

$$\sum_{j \in J_i} \sum_{l \in L} p_{ijkl}^S \leq M g_{ik}^{SS}, \quad \forall\ i \in I;\ k \in K \tag{21.69}$$

$$\sum_{j \in J_i} \sum_{l \in L} p_{ijkl}^T \leq M g_{ik}^{TS}, \quad \forall\ i \in I;\ k \in K \tag{21.70}$$

$$\sum_{l \in L} T_l (p_{ij3l}^F + p_{ij4l}^F) \leq Sd, \quad \forall\ i \in I;\ j \in J_i \tag{21.71}$$

$$\sum_{l \in L} T_l (p_{ij3l}^S + p_{ij4l}^S) \leq Sd, \quad \forall\ i \in I;\ j \in J_i \tag{21.72}$$

$$\sum_{l \in L} T_l (p_{ij3l}^T + p_{ij4l}^T) \leq Sd, \quad \forall\ i \in I;\ j \in J_i \tag{21.73}$$

$$fs_{i3} + fs_{i4} \leq |J_i|, \quad \forall\ i \in I \tag{21.74}$$

$$ss_{i3} + ss_{i4} \leq |J_i|, \quad \forall\ i \in I \tag{21.75}$$

$$ts_{i3} + ts_{i4} \leq |J_i|, \quad \forall i \in I \tag{21.76}$$

$$g_{ik}^{FS},\ g_{ik}^{SS},\ g_{ik}^{TS} \in \{0, 1\}, \quad \forall\ i \in I;\ j \in J_i;\ k \in K;\ l \in L \tag{21.77}$$

$$\begin{aligned} &p_{ijkl}^F,\ p_{ijkl}^S,\ p_{ijkl}^T,\ fs_{ik},\ ss_{ik},\ ts_{ik},\ e_{il},\ b_{il}, \\ &w_i,\ w_i^{FS},\ w_i^{SS},\ w_i^{TS},\ h_i,\ f_i \geq 0, \quad \forall\ i \in I;\ j \in J_i;\ k \in K;\ l \in L \end{aligned} \tag{21.78}$$

21.C The Schedule

Objective Function

$$\text{Minimize: } emp \tag{21.79}$$

Constraints

$$\sum_{k \in K} B_k x_{sjk} \leq emp, \quad \forall\ s \in S;\ j \in J_i \tag{21.80}$$

$$\sum_{j \in J_i} x_{sjk} = AD_{isk}, \quad \forall s \in S\ k \in K \tag{21.81}$$

$$x_{sj3} + x_{sj4} \leq 1, \quad \forall\ s \in S;\ k \in K \tag{21.82}$$

$$x_{sjk} \in \{0, 1\}, \quad \forall\ s \in S;\ k \in K \tag{21.83}$$

$$emp \geq 0 \tag{21.84}$$

Veriye Dayalı Satış İçgörüsü ve Anomali Belirleme Karar Destek Sistemi Ortadoğu Rulman Sanayi

22

Proje Ekibi
Ali Ozan Aytar, Cansu Nur Dinç, Sümeyye Karaca, Arda Kılıç, Doğukan Öge, Mert Tümer

Şirket Danışmanı
Dr. Alptekin Demiray
Üretim Planlama ve Bilgi Sistemleri Müdürü

Akademik Danışman
Prof. Dr. Savaş Dayanık
Endüstri Mühendisliği Bölümü

Özet

Ortadoğu Rulman Sanayi, talep tahminlerindeki düşük doğruluk ve ani satış dalgalanmalarını erken tespit edememesi nedeniyle üretim planlaması ve stok yönetiminde verimsizlik yaşamaktadır. Mevcut sistemin geçmiş verileri etkin kullanamaması, stok fazlası ve ürün yetersizliğine yol açmaktadır. Bu projede, satışları doğru bir şekilde tahmin eden ve tahmin edilen veriler üzerinden anomali tespiti yaparak erken uyarılar veren bir karar destek sistemi geliştirilmiştir. Yapılan karşılaştırmalı analizlerde, satış tahmini sonuçları 56% doğrulukla şirket içi tahminlerden daha iyi performans göstermiştir. Ayrıca 250 ürün için yapılan anomali analizinde, sistem birçok üründe trend değişimlerini başarılı şekilde işaretlemiştir.

Anahtar Sözcükler: Talep Tahmini, Anomali Tespiti, Zaman Serisi Analizi, Karar Destek Sistemi, Hibrit Modelleme, Üretim Planlama.

Data-Driven Decision Support System for Sales Insight and Anomaly Recognition

Abstract

Ortadoğu Bearing Industry experiences inefficiency in production planning and inventory management due to low accuracy in demand forecasts and inability to detect sudden sales fluctuations early. The inability of the current system to use historical data effectively leads to excess inventory and product shortages. In this project, a decision support system has been developed that accurately predicts sales and provides early warnings by detecting anomalies based on the estimated data. In the comparative analyses performed, the sales forecast results have outperformed the internal forecasts with an accuracy of 56%. In addition, in the anomaly analysis conducted for 250 products, the system successfully marked trend changes in many products.

Keywords: Demand Forecasting, Anomaly Detection, Time Series Analysis, Decision Support System, Hybrid Modeling, Production Planning.

22.1 Company Information

Ortadoğu Rulman Sanayi (ORS), established in 1982 by Hasan ASLAN in Polatlı, Ankara, has established itself as Turkey's first and largest bearing manufacturer. Initially operating on a 26,000 square meter production area, ORS expanded its facilities to 300,000 square meters through significant investments. Since starting mass production in 1986 and initiating exports in 1988, the company has specialized in the production of high-quality bearings for various industrial applications.

ORS manufactures various types of bearings, including deep groove ball bearings, tapered roller bearings, and special-purpose models, using advanced technology and automation to improve production efficiency and precision.

Serving automotive, machinery, agriculture, and energy industries, ORS expanded its international presence by establishing a machine factory, ORS KOREA, in South Korea in 2019 to strengthen its position in the machine industry globally. Furthermore, ORS has opened sales & distribution centers in the USA (ORS USA), as well as expanded to Italy and Germany by opening sales representatives.

As of 2024, ORS ranks among Turkey's top 500 industrial companies, with an annual production capacity of over 100 million units. The company operates on a 120,000-square-meter closed facility in Ankara, employs around 1,500 worker, and exports around 80% of its total product to markets in Western Europe and North America.

22.2 System Analysis and Problem

22.2.1 System Analysis

Ortadoğu Rulman Sanayi (ORS) performs its production planning through a two-stage process: macro and operational planning. Macro planning is carried out biannually using historical averages and open orders to forecast annual sales volumes. Forecasting affects macro planning by shaping the overall production plan. If the forecast is inaccurate, capacity planning and resource allocation will also be incorrect. Operationally, an inaccurate forecast leads to an incorrect MPS (Master Production Schedule), which causes either overproduction or stockouts due to poor material purchasing and scheduling decisions. These forecasts are finalized through internal reviews and customer feedback, forming the basis for inventory policy and resource planning(capacity and labor). Operational planning is conducted monthly using SAP/MPS with a 12-month rolling horizon.

Forecasting has a direct impact on both macro and operational planning. At the macro level, inaccurate sales forecasts can lead to incorrect resource planning and capacity allocation. At the operational level, a flawed forecast affects the Master Production Schedule (MPS), resulting in either overproduction or underproduction, which can cause excess inventory or unmet customer demand.

Material requirements are calculated through MRP, and customer orders are matched with availability through system checks. If demand exceeds capacity, revisions are made to the production schedule. Despite having structured planning processes and ERP integration, the current system is limited in terms of automation, predictive accuracy, and responsiveness to unexpected demand changes.

22.2.2 Problem Definition

The existing planning system at ORS relies heavily on static, average-based forecasting and cannot detect anomalies in incoming sales data. This limitation makes it difficult to anticipate sudden demand shifts, leading to inefficiencies such as stockouts, overproduction, and misallocated resources. The absence of a dynamic, automated forecasting and anomaly detection system prevents planners from making timely, data-driven decisions. Therefore, there is a critical need for a decision support system that generates monthly sales forecasts using historical data and automatically identifies irregularities in sales patterns. Such a system would enhance forecast reliability, improve responsiveness, and support more efficient production and inventory planning.

22.3 Proposed Solution Strategy

This project proposes a two-part solution approach that integrates time series forecasting and anomaly detection to improve production planning at Ortadoğu Rulman Sanayi. Forecasting models are constructed based on time series analysis, while anomaly detection methods are employed to identify unusual sales behavior and generate real-time alerts. Several assumptions are made to ensure effectiveness, such as treating forecasts as unaffected by external factors and relying solely on time series models. The system operates under specific constraints: forecasts are limited to a 12-month horizon; anomaly detection begins in 2022 and receives monthly updates; the dataset covers the period from January 2022 to present, with 2020 and 2021 data excluded to avoid the influence on COVID-19 supply chain fluctuations; confidentiality restrictions limit data sharing; each product has predefined production capacity bounds; and anomalies are tested against the statistical distribution of the training data (Song and Yao, 2013). All data are imported from Excel and processed in R. The system enhances forecast accuracy, accelerates response to market changes, reduces excess inventory, and supports efficient, flexible, and customer-focused production planning.

22.3.1 Solution Approach

Solution Method of Forecasting

To generate accurate sales forecasts for 250 products, the time series data for each product was initially divided into a training set (first 45 months) and a validation set (last 12 months). Various forecasting models library—such as SES (Simple Exponential Smoothing) , Holt-Winters, ARIMA, and STL (Seasonal and Trend decomposition using LOESS) were applied, with parameter optimization performed during training. Forecast accuracy was evaluated using MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and RMSSE (Root Mean Squared Scaled Error) to ensure a balanced assessment across scale-sensitive and scale-free metrics.

For each metric, the best-performing models were identified, and the average of their forecast values are taken to form a hybrid model. Hybrid model is constructed by combining the results of multiple estimation methods to enhance forecasting accuracy and robustness. This approach leverages the strengths of top-performing models while minimizing the individual weaknesses of each method. Hybrid models are assessed using, RMSE, and RMSSE to balance performance across diverse data structures to ensure a

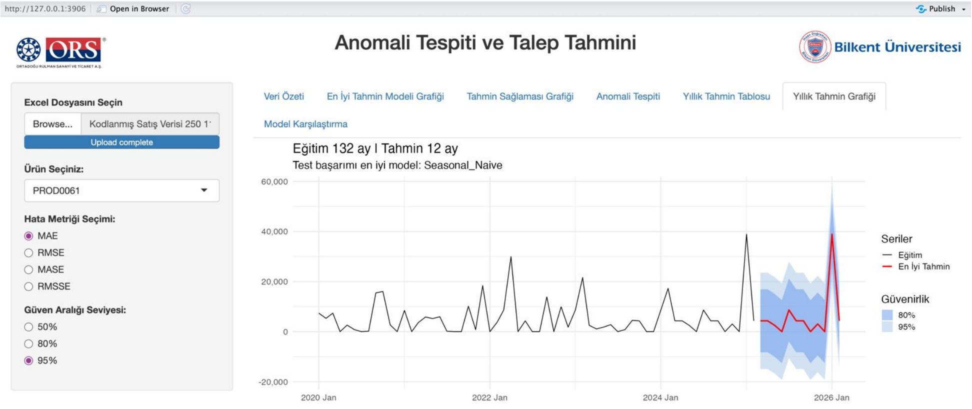


Figure 22.1: Yearly Forecast Graph of the Selected Product

well-rounded evaluation. Furthermore, all candidate forecasting methods are evaluated using these metrics, and the results are averaged to give equal weight to each method's contribution. In addition, an Average-ORS model was developed by taking the simple mean of the forecasts from all models without any selection, serving as a performance baseline. The hybrid model and the Average-ORS model were both evaluated using the same set of metrics, and the final model for each product was selected based on the one yielding the lowest MAE. Figure 22.1 gives a glimpse of the implementation of forecasting methods.

Solution Method of Anomaly Detection

Anomaly detection in time-series forecasting is essential for identifying unexpected deviations between actual and predicted sales values. The methodology is based on measuring forecast errors and evaluating their statistical significance through standardization and probabilistic scoring.

The mathematical formulation of this approach has been detailed in the appendix. This includes the computation of forecast errors, standardization across datasets, and the derivation of anomaly scores using properties of the standard normal distribution. The system triggers an alert when the computed anomaly score falls below a predefined threshold.

This method allows for consistent detection of both high and low outliers, providing critical support for early warning mechanisms in production planning.

22.3.2 Conceptual Model

The proposed conceptual model consists of two integrated components: demand forecasting and anomaly detection. Forecasting is performed using time series models from the `fpp3` library, applied to historical sales data. The last 12 months of data are used as a test set, and the remaining data is

Figure 22.2: Conceptual Model

used to train various models. Forecast accuracy is evaluated using RMSE, MAE, and RMSSE. The top three models based on these metrics are combined equally in a hybrid model. The hybrid forecast is then compared with the best-performing individual model using MAE. If the hybrid underperforms, the superior single model is chosen. This adaptive process helps reduce forecasting errors, especially in high-volume products, minimizing risks of over- or underproduction.

Anomaly detection is based on comparing actual and predicted sales values from the most recent month. Forecast errors are standardized using the standard deviation of predictions to normalize the deviations. These standardized errors are evaluated using the cumulative distribution function of the normal distribution. Anomalies are flagged when the resulting probability falls below a predefined threshold, which is set to 5% by default. However, it can be adjusted based on the company's sensitivity requirements. The model integrates Excel-based data with R language to support continuous monitoring and decision-making.

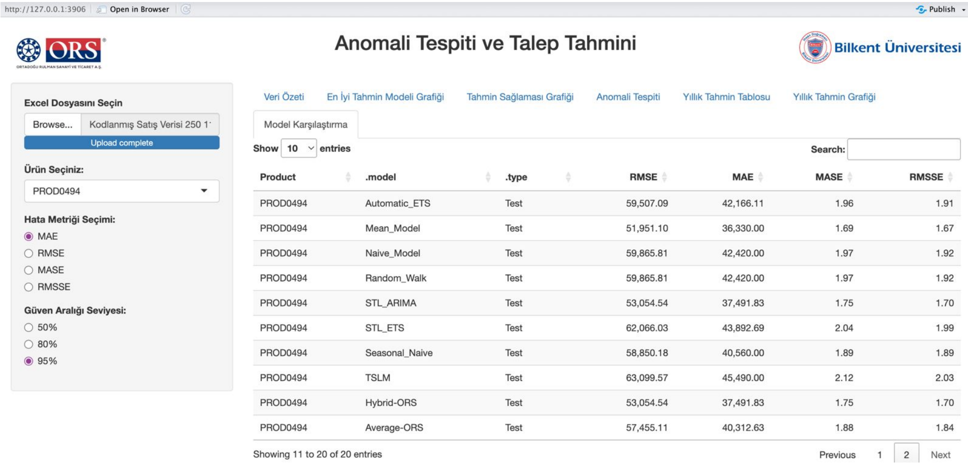
22.4 Validation

To make sure the system works reliably in real-life scenarios, validation is made for both the forecasting and anomaly detection components.

22.4.1 Forecast Validation

To ensure the applicability of the forecasting code to real-world data, its alignment with the company's requirements is evaluated. The evaluation begins by merging the forecasted and actual sales datasets using the month variable for the first two forecasted periods. The absolute error is then calculated as the difference between the forecasted and actual sales values.

To establish a performance benchmark, a naïve forecasting method is also implemented. This approach uses the previous month's actual sales as the forecast for the current month, obtained via the lag function. The corresponding naive error is computed in a similar manner. Observations lacking a value from the previous period are excluded from the analysis.



Product	.model	.type	RMSE	MAE	MASE	RMSSE
PROD0494	Automatic_ETS	Test	59,507.09	42,166.11	1.96	1.91
PROD0494	Mean_Model	Test	51,951.10	36,330.00	1.69	1.67
PROD0494	Naive_Model	Test	59,865.81	42,420.00	1.97	1.92
PROD0494	Random_Walk	Test	59,865.81	42,420.00	1.97	1.92
PROD0494	STL_ARIMA	Test	53,054.54	37,491.83	1.75	1.70
PROD0494	STL_ETS	Test	62,066.03	43,892.69	2.04	1.99
PROD0494	Seasonal_Naive	Test	58,850.18	40,560.00	1.89	1.89
PROD0494	TSLM	Test	63,099.57	45,490.00	2.12	2.03
PROD0494	Hybrid-ORS	Test	53,054.54	37,491.83	1.75	1.70
PROD0494	Average-ORS	Test	57,455.11	40,312.63	1.88	1.84

Figure 22.3: Method Comparison

The naïve approach's effectiveness is assessed by calculating the Mean Absolute Naive Error. This benchmark error is then used to compute the MASE(Mean Absolute Scaled Error), which is obtained by dividing the model's absolute error by the naïve error.A MASE value below 1 indicates that the forecasting model performs better than the naive benchmark, whereas a value above 1 suggests inferior performance. Figure 22.3 shows an example model performance comparison.

22.4.2 Anomaly Detection Validation

In the validation phase of the anomaly detection process, the alarm status for the last three months of each product's sales data is recorded. These results were shared with the company to verify whether the detected anomalies correspond to actual irregularities observed in real-life operations.

The effectiveness of the anomaly detection model is evaluated based on the percentage of correctly identified anomalies. A high match rate between the detected anomalies and real-world deviations indicates a successful validation phase. Conversely, if discrepancies are significant, further refinements and improvements were made to enhance the accuracy and reliability of the anomaly detection system.

22.5 Outcome and Deliverables

22.5.1 Outcome

Twelve-month demand forecasts are generated for 250 products using 57 months of historical sales data. Time series models such as ARIMA, SARIMA and Holt-Winters are applied with model performance evaluated using error metrics such as RMSE, RMSSE, and MAE. Specifically, MAE is preferred

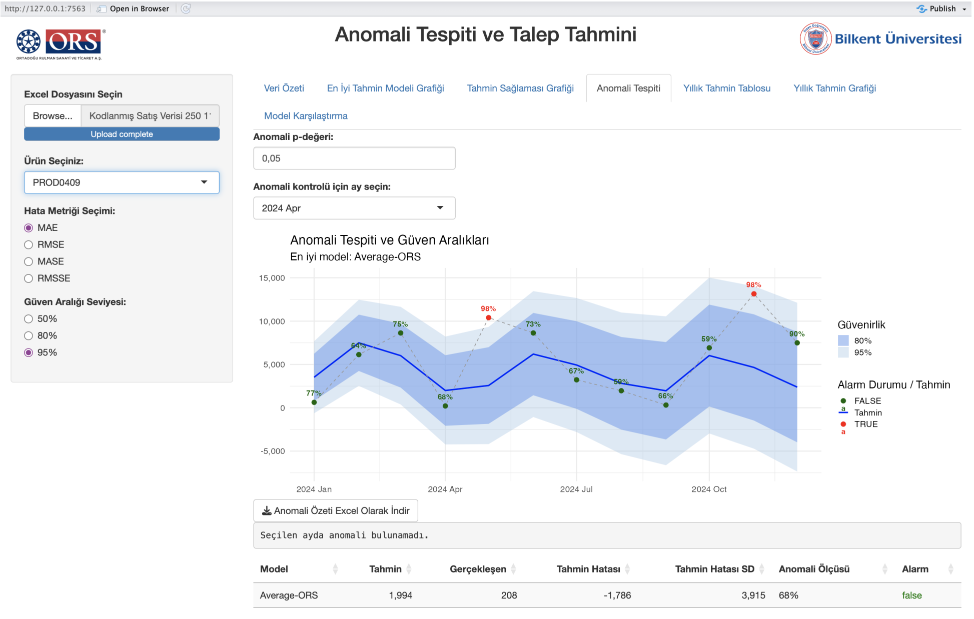


Figure 22.4: Anomaly Detection Graph

due to its interpretability, robustness to outliers, and scale-independence, making it suitable for comparing model performance across different product categories. If the hybrid model yields lower error values, it is selected as the final forecasting approach. All error scores are made accessible through a user-friendly interface.

An integrated anomaly detection system is also developed and validated using MASE with actual company data; see Figure 22.4. The interface, built with R Shiny, allows users to access forecast results, view anomaly alerts, and generate detailed reports with visualizations. This decision support system enables more effective production and inventory decisions by identifying unusual patterns and improving forecast reliability.

22.5.2 Deliverables

A Decision Support System is developed to generate 12-month demand forecasts and detect anomalies for each product using time series analysis. Forecasts are updated based on historical data and open orders and reviewed by the planning team. Anomaly detection mechanisms are designed to identify unusual changes, particularly in the post-pandemic period.

The system is built using the R programming language with a user interface developed in R Shiny. The interface allows users to view forecasts, monitor anomalies, and receive alerts when new data shows irregular patterns. Designed for speed and accessibility, the UI can be flexibly used by employees in the Production Planning and Information Systems Depart-

	A	B	C	D	E
1	Product	Month_3	Month_2	Month_1	Total_TRUE
2	PROD3891	TRUE	TRUE	TRUE	3
3	PROD5201	TRUE	TRUE	TRUE	3
4	PROD5541	TRUE	TRUE	TRUE	3
5	PROD5905	TRUE	TRUE	TRUE	3
6	PROD6734	TRUE	TRUE	TRUE	3
7	PROD6774	TRUE	TRUE	TRUE	3
8	PROD7204	TRUE	TRUE	TRUE	3
9	PROD0393	FALSE	TRUE	TRUE	2
10	PROD0565	FALSE	TRUE	TRUE	2
11	PROD2044	FALSE	TRUE	TRUE	2
12	PROD2195	TRUE	FALSE	TRUE	2
13	PROD2360	FALSE	TRUE	TRUE	2
14	PROD2639	FALSE	TRUE	TRUE	2
15	PROD3999	TRUE	TRUE	FALSE	2
16	PROD4902	FALSE	TRUE	TRUE	2
17	PROD4931	TRUE	FALSE	TRUE	2
18	PROD4940	FALSE	TRUE	TRUE	2
19	PROD4943	FALSE	TRUE	TRUE	2
20	PROD4953	FALSE	TRUE	TRUE	2
21	PROD4957	TRUE	TRUE	FALSE	2
22	PROD5434	TRUE	FALSE	TRUE	2
23	PROD5519	TRUE	FALSE	TRUE	2
24	PROD5520	TRUE	FALSE	TRUE	2
25	PROD5641	FALSE	TRUE	TRUE	2
26	PROD6080	TRUE	FALSE	TRUE	2
27	PROD6322	TRUE	TRUE	FALSE	2
28	PROD6510	FALSE	TRUE	TRUE	2
29	PROD6664	TRUE	TRUE	FALSE	2
30	PROD7316	FALSE	TRUE	TRUE	2
31	PROD0485	FALSE	FALSE	TRUE	1
32	PROD0519	TRUE	FALSE	FALSE	1
33	PROD0520	TRUE	FALSE	FALSE	1
34	PROD0546	TRUE	FALSE	FALSE	1
35	PROD0713	FALSE	FALSE	TRUE	1

Anomaly Summary

Figure 22.5: Sorted (Critical) Anomaly Summary

ment. A user guide is also provided to support effective use of the system.

Finally, the system generates dynamic Excel outputs, including the detection of anomalies in the last three months of sales data. These outputs provide a detailed list of products ranked by the number of detected anomalies. In addition, 1-year forecasts for all products can be exported to Excel, offering valuable information for long-term planning and decision making.

22.6 Benefits to the Company

The Decision Support System developed in this project significantly enhances demand forecasting accuracy and anomaly detection capabilities. With rolling 12-month forecasts based on time series models, the system enables better production and inventory planning by dynamically adapting to changing market conditions using historical sales data. For benchmarking purposes, our forecasts were compared against internal company estimates. Out of 206 products evaluated (after excluding exceptional cases), the system outperformed internal forecasts for approximately 56% of the products when considering March 2025 results. Additionally, considering longer periods such as six-month aggregates, the system showed successful performance for around 60% of the products, demonstrating robustness against temporary volatility.

The integrated anomaly detection module successfully identified unusual sales behaviors across 250 products, flagging potential anomalies with a color-coded severity scale (red, orange, yellow, green) as in Figure 22.5. Several detected anomalies were confirmed to signal actual trend changes, supporting proactive planning actions. The system operates on a decision support basis, highlighting critical points for planner review without making automatic decisions.

Developed using R Shiny and Excel, the system provides an intuitive interface for forecast visualization, anomaly monitoring, and report generation. It enables the Production Planning Department to act faster and more precisely, offering a scalable tool for strategic and operational decision-making.

22.7 Integration and Implementation

A structured implementation process ensured the seamless integration of the forecasting and anomaly detection models into the company's operations. Initial refinements addressed minor issues, enabling the system to process real-time data efficiently.

Meetings with industry advisors were held to present the validated models, gather feedback, and demonstrate the user interface and reporting features. A comprehensive user manual was presented, detailing the system's functionalities, data requirements, model execution steps, and output interpretation.

The pilot study was launched using historical sales data from a selected product group to evaluate forecasting accuracy and operational impact. The anomaly detection component effectively flagged irregularities, particularly during the post-pandemic period, contributing to proactive decision-making.

Feedback from company personnel guided final adjustments, benchmarks and informed updates to the documentation. After the pilot, the necessary improvements were made, and the system was fully deployed. The integration process aligned well with existing decision-making procedures, proving the system to be both accurate and operationally valuable.

22.8 Conclusion

A flexible and user-centric Decision Support System (DSS) was developed and deployed at Ortadoğu Rulman Sanayi to support production planning through data-driven insights. The system combines 12-month sales forecasting with anomaly detection, using 57 months of historical data and time series models to anticipate demand patterns while flagging unexpected sales behaviors. This integrated approach allows decision-makers not only to plan ahead but also to respond proactively to irregularities—something that forecasting or anomaly detection alone could not achieve as effectively. Built entirely in R and delivered via an intuitive R Shiny interface, the solution emphasizes usability and adaptability, enabling engineers and planners to interpret results with ease, make timely adjustments, and ensure continuous operational alignment.

Bibliography

Song, J. and D. Yao (2013). *Supply Chain Structures: Coordination, Information and Optimization.* International Series in Operations Research & Management Science. Springer US.

Appendix: Anomaly Detection

The anomaly detection mechanism relies on a series of mathematical steps as follows:

- **Forecast Error Calculation:**

  $$\text{Forecast Error} = \text{Sales} - \text{Average Forecast}$$

  where Sales is the observed value, and Average Forecast is the predicted value from the model.

- **Standardization of Forecast Error:**

  $$\text{Standardized Forecast Error} = \frac{\text{Forecast Error}}{\text{Average Forecast SD}}$$

  where Average Forecast SD is the standard deviation of the forecast values.

- **Anomaly Score Calculation:**

  $$\text{Anomaly Meas} = \min(1 - P(Z \leq x), P(Z \leq x))$$

  where $P(Z \leq x)$ is the cumulative distribution function (CDF) of the standard normal distribution for standardized error x.

- **Anomaly Alarm Condition:**

  $$\text{Alarm} = \text{Anomaly Meas} < \text{anomaly\_thresh}$$

  A typical threshold value is $\text{anomaly\_thresh} = 0.05$.

23 | İşgücünü Dengeleyen Vardiya Atamaları için Karar Destek Sistemi

Memorial Sağlık Grubu

Proje Ekibi

Selin Aksoy, Mürsel Oğuzhan Çalışkanoğlu, Zeynep Eyiyol, Osmancan Naycı, Arda Polatkan, Emrecan Serin, Mehmet Tonguç

Şirket Danışmanı
Berna Dursun
Süreç ve Verimlilik Grup Müdürü

Akademik Danışman
Doç. Dr. Özlem Karsu
Endüstri Mühendisliği Bölümü

Özet

Memorial Sağlık Grubu, hemşireler ve hasta danışmanları için vardiya planlamasında çeşitli sorunlarla karşı karşıya kalmaktadır. Şu anda, vardiyalar amirler tarafından düzenlenmektedir. Mevcut proje, çalışan tercihlerini dikkate alarak ve Türk İş Kanunu'na uyumlu eşit iş yükü dağılımı yapan dinamik, iyileştirilmiş bir vardiya atama modelini ele almaktadır. Önerilen çözüm, matematiksel bir model kullanarak ani personel eksiklikleri veya talep değişiklikleri gibi durumlarda gerçek zamanlı ayarlamalar yapabilen esnek bir planlama sistemi sunmayı hedeflemektedir.

Anahtar Sözcükler: Hemşire planlaması, iş gücü eniyilemesi, dinamik vardiya ataması, sağlık sektörü personel yönetimi, iş kanunu uyumu.

Decision Support System for Shift Assignments Balancing the Workforce

Abstract

Memorial Healthcare Group faces various problems in planning shift schedules for nurses and hospital receptionists. Currently, the supervisors schedule it manually. The present project deals with a dynamic, optimized shift assignment model for equal workload distribution concerning employees' preferences and full observance of the Turkish Labor Law. The proposed solution will be able to provide a flexible scheduling system that can make real-time adjustments for sudden staff absences or changes in demand using a mathematical model.

Keywords: Nurse scheduling, workforce optimization, dynamic shift assignment, healthcare staffing, labor law compliance.

23.1 Company and System Description

Memorial Health Group is one of Turkey's premier healthcare organizations, operating a nationwide network of hospitals and centers celebrated for high-quality, patient-driven services. Founded in Istanbul in 2000, the organization has enjoyed steady growth while investing significantly in cutting-edge technology and streamlined operational processes to meet the evolving demands of modern healthcare (Memorial Healthcare Group, 2024). Historically, the group relied on manual scheduling methods that, although effective in its early years, have become inadequate amid rising patient care demands and growing scheduling complexity. Recognizing the limitations of manual scheduling, Memorial Health Group wanted to adopt an advanced, data-driven system designed to optimize shift assignments, balance workforce needs more effectively, and enhance overall service quality. This new approach aims to minimize errors and inefficiencies by integrating historical data with real-time inputs, ensuring staffing levels are accurately aligned with patient care requirements while enabling a more responsive and sustainable work environment.

23.2 Problem Definition

The current manual scheduling system at Memorial Health Group has become insufficient with growing patient admissions and service requirements. Relying primarily on manual entries, the system bred frequent errors such as misplaced shifts, causing staffing imbalances. All these created unnecessary overtime and boosted operating costs. The unnecessary overtime and staffing imbalances can be seen in Figures 23.1 and 23.2.

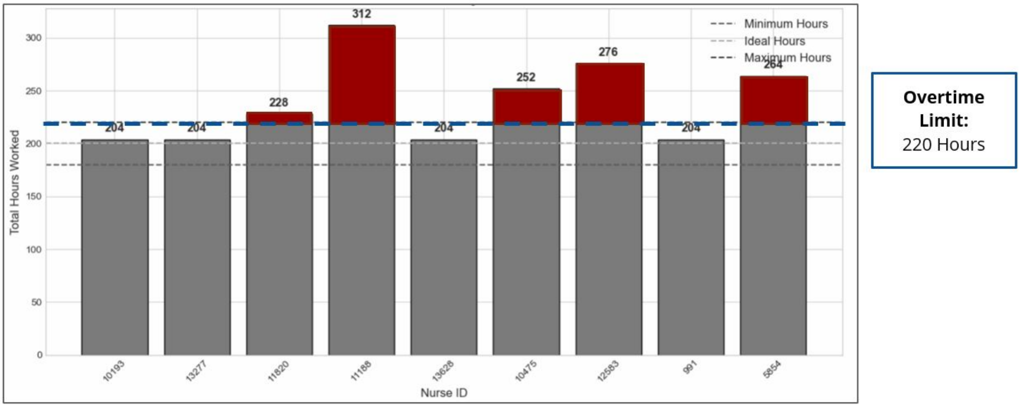


Figure 23.1: Total Hours Worked by Nurses, 15th Floor, September 2024

Memorial Health Group wanted to implement a data-driven scheduling system to address these challenges. Designed to generate balanced and anticipatory shift schedules, the system can quickly adapt to changes in patient demand, reduce scheduling errors, optimize resource allocation and overtime, cultivate a more resilient and efficient work setting for nurses and hospital receptionists.

23.3 Proposed Solution Strategy

The project presents an optimized scheduling framework for Memorial Healthcare Group that uses a data-driven mathematical model to address nurse and hospital receptionist shift assignments. By employing Mixed-Integer Linear Programming (MILP) techniques, the model minimizes overtime costs, balances workload distribution, and complies with staff preferences and regulatory limits. It integrates advanced optimization methods —combining Mixed-Integer Linear Programming (MILP) with a re-scheduling strategy— to manage real-time demand variability and uncertainty in shift

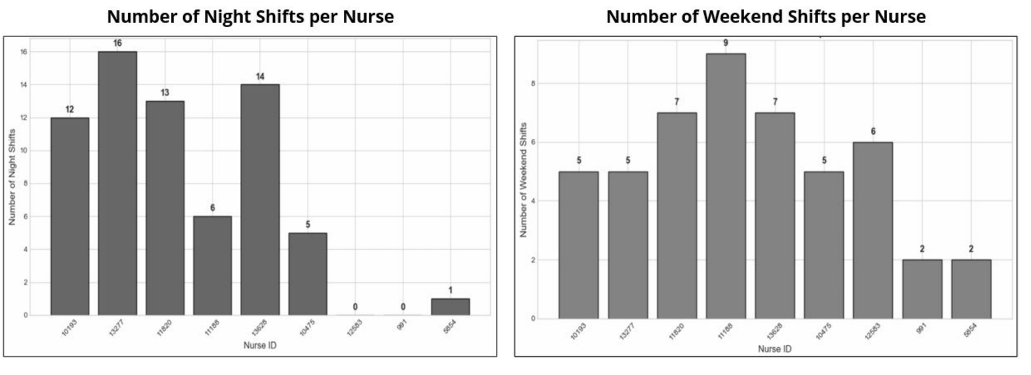


Figure 23.2: Shift Distributions, 15th Floor, September 2024

planning.

23.3.1 Critical Assumptions

Nurses

The following assumptions are made regarding nurses:

- The scheduling environment is entirely predictable; all input data —including staffing requirements, nurse availability, and shift preferences— are known and remain constant throughout the scheduling period.

- All nurses are available during the scheduling period except for predefined off days. If an unexpected absence occurs, it will be handled by the reassignment model.

- All nurses have the same workload capacity, but shift assignments vary based on skill level and individual shift preferences.

- Shifts have fixed durations and start times (e.g., 12-hour shifts), though flexible or partial shifts might be incorporated as operational needs evolve.

- Overtime is consistently calculated and penalized when hours worked exceed the predefined target (e.g., 200 hours), applied as a penalty without a strict cap.

Hospital Receptionists

The following assumptions apply to hospital receptionists:

- Each receptionist works fixed shift durations (12 hours for a full day, 6 hours for a half day), ensuring consistent and simplified scheduling.

- All receptionists are assumed to attend their assigned shifts reliably except on pre-approved leave days.

- The model operates within an anticipated demand range, assuming that patient and visitor volumes remain within expected limits without accounting for rare or unexpected surges.

- All receptionists are assumed to have uniform skills and workload capacities, enabling shift assignments without requiring individual skill differentiation.

23.3.2 Major Constraints

Nurses

The nurse scheduling model adheres to the following major constraints:

- Nurses must have at least two consecutive days off each week, and no day shift should follow a night shift to ensure adequate rest.

- Nurses cannot work more than two consecutive night shifts and are restricted to a maximum of 12 night shifts per month to promote a balanced distribution.

- Each nurse is limited to a maximum of 5 weekly shifts to maintain a manageable workload.

- A nurse may be assigned to only one shift each day.

- Nurses are scheduled exclusively within their designated departments; inter-department shifts are prohibited.

- The model ensures that weekend shifts are distributed equitably among all nurses.

- Overtime hours, which incur higher pay rates than regular hours, are minimized through cost control measures in the objective function.

Hospital Receptionists

For hospital receptionists, the scheduling model enforces the following constraints:

- Receptionists work 6 days a week (with Sundays off) under fixed shifts (full day = 12 hours, half day = 6 hours). Daily (non-Sunday) coverage must meet the predetermined staffing requirement in full-day equivalents.

- Every receptionist must be assigned to exactly one half-day shift each week (weeks 1-4) to ensure predictable rest periods and balanced workload distribution.

- Each receptionist is assumed to attend all assigned shifts reliably, except on pre-approved leave days.

- An individual receptionist can only be scheduled for one shift daily, ensuring a clear and manageable work schedule.

- Since overtime hours are paid at a higher rate than regular hours, the model minimizes overtime by penalizing work hours exceeding a set normal threshold.

23.3.3 Objectives

The objectives of the scheduling models are as follows:

- The nurse scheduling model aims to generate a fair, balanced, and efficient monthly work schedule that meets hospital staffing requirements while respecting nurse preferences, legal constraints, and workload fairness. It minimizes a weighted sum of penalties associated with deviations from target working hours, excessive overtime, unequal distribution of night and weekend shifts, violation of shift preferences, and inadequate rest periods.

- The hospital receptionist scheduling model aims to minimize total overtime while meeting staffing requirements and ensuring consistent shift assignments. Using fixed shift durations (12-hour full days and 6-hour half days) and assigning one half-day per week to each receptionist promotes balanced workloads and controls costs, with overtime penalized due to its higher pay rate.

23.3.4 Solution Approach

Tools and Platforms

The scheduling models are implemented in Python, using the PuLP library for mathematical modeling and optimization. Excel served as both the input and output platform for the user interface, allowing hospital administrators to manage nurse data easily. Required data for scheduling models, including leave days, shift preferences, and skill levels, is imported using Pandas. After solving the model, the optimized schedules are exported back to Excel. Visual tools such as Matplotlib generate Gantt charts for schedules and bar plots for further analyses, enhancing interpretability.

Shift Count and Time Forecasting

A time-series analysis was performed to forecast patient arrival numbers at different hours of the day, leading to the design of an optimized shift system based on these projections. Patterns and seasonality were identified by examining historical hourly arrival data, and a SARIMA forecasting model was applied to predict future patient inflows. Based on these predictions, alternative shift structures —such as transitioning from two daily shifts to three— were evaluated to align staffing levels with demand better. Ultimately, this approach aims to minimize waiting times, optimize staff workloads, and ensure high-quality patient care by more accurately matching staffing needs to peak patient volumes.

Optimization Model

Rather than relying on heuristics or manually defined rules, a complete MILP approach is adopted. The CBC solver is used with a specified time limit and optimality gap, ensuring efficient, high-quality solutions. The model incorporates soft constraints with associated slack variables to handle infeasible or tight scheduling scenarios. These slack terms allow the solver to relax specific rules when necessary while penalizing any deviation through the objective function. This design ensures practical feasibility in the output. An example output of the model can be seen in Figure 23.3.

Reassignment Model

In practice, shift plans may need to be revised due to unexpected absences or other changes. To handle such cases, the planning horizon is divided into two sets: fixed days where assignments remain untouched, and optimizable days where reassignments can occur. The optimization aims to preserve as much of the original schedule as possible by minimizing deviation variables. Thus, stability is maintained while ensuring that staffing needs and constraints are still satisfied. An example output of the reassignment model

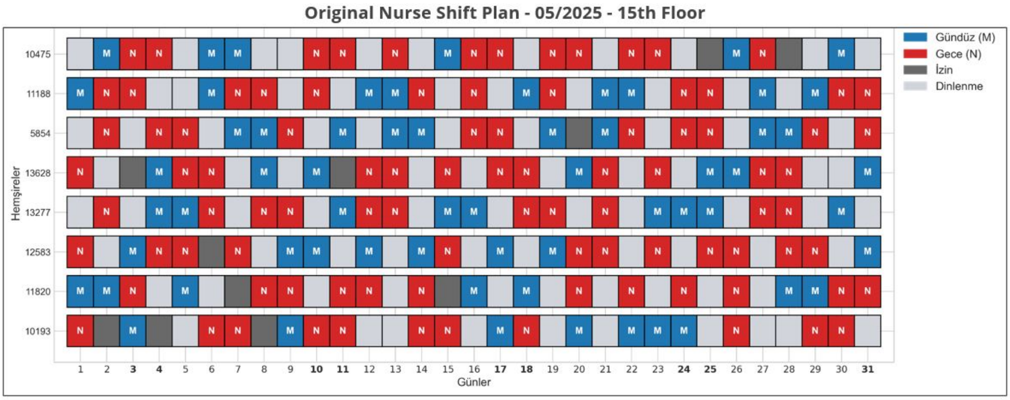


Figure 23.3: Nurse Shift Assignments

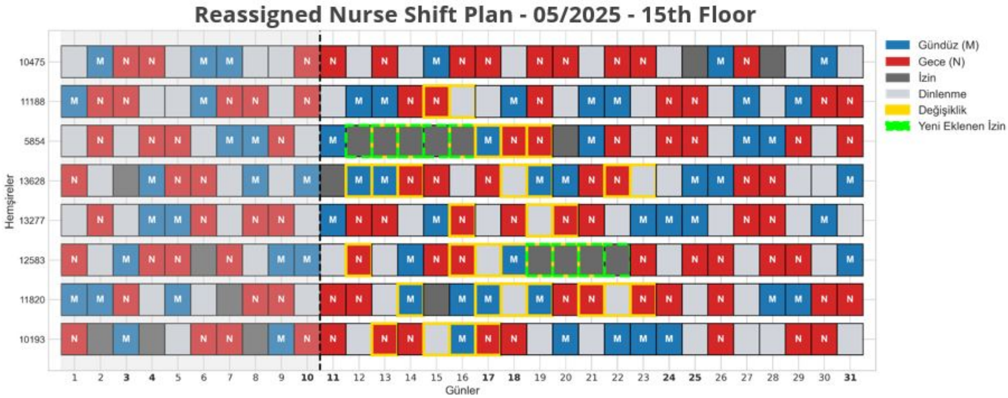


Figure 23.4: Adjusted Nurse Shift Assignments

can be seen in Figure 23.4.

23.4 Validation

23.4.1 Nurse Scheduling Validation

We conducted several tests and sensitivity analyses to validate our nurse scheduling optimization model. The primary objective of our model is to integrate multiple criteria —including deviations in night and weekend shifts, differences in working hours, overtime, rest violations, and nurses' preferences— into a single weighted objective function. By minimizing this composite measure, the model aims to achieve a schedule close to the ideal scenario. The model was solved using PuLP with the CBC solver, applying a 10-second time limit and a gap tolerance of 1% to ensure efficiency and quality. We executed iterative runs, halting after three consecutive iterations without improvement. We monitored key performance metrics in each cycle, such as slack variables representing unmet staffing requirements, to ensure the solution remained feasible and balanced.

23.4.2 Hospital Receptionist Scheduling Validation

Using real department operational data, we assessed validity by comparing the model's generated shift assignments to historical receptionist schedules. The model outputs closely matched past distributions in total hours worked and weekend shift counts. Comparative analysis of work-hour metrics and shift patterns reinforced the model's credibility by demonstrating alignment with actual records. In conclusion, validation confirms that the shift-assignment model effectively distributes receptionist workloads while adhering to staffing constraints and established patterns. These results demonstrate the model's reliability for hospital operations and its ability to produce balanced, practical schedules for receptionists.

23.4.3 Reassignment Model Validation

We validated the reassignment model by simulating real-world scheduling disruptions using actual nurse shift data. The model was tested under various scenarios, including unscheduled leave requests and unexpected changes in patient demand. The model reassigned affected shifts in each case while ensuring compliance with operational constraints. Without overloading nurses or violating staffing rules, the model successfully adjusted schedules in a balanced manner. These results demonstrated the reassignment model's ability to maintain stability and operational feasibility when responding to real-time disruptions.

23.4.4 Integration and Implementation

During the pilot phase, the following features were in place:

- The nurse-shift scheduling system is deployed on a secure internal workstation, ensuring controlled access and minimizing cybersecurity risks. After the review with the Information Technologies Department, the system entered pilot operation in April under the hospital's operational schedule.

- Nurse-specific data —leave days, shift preferences, and competency levels— is imported from standardized Excel templates, preserving compatibility with existing processes and reducing training requirements. Generated schedules were exported directly to Excel for archival and managerial review.

- A dedicated web interface provides an intuitive, browser-based environment for running the optimization engine, uploading input data, and reviewing results. Gantt charts and bar graphs were utilized to display total hours, night/weekend allocations, and constraint compliance, supporting informed decision-making. The user interface screen for selecting the employee type and department for which the assignments will be scheduled can be seen in Figure 23.5.

Figure 23.5: User Interface Screen to Initiate a Schedule

This integrated backend/frontend design combines technical robustness with practical usability, delivering a scalable, accessible solution for hospital-wide deployment.

23.5 Benchmarking

Benchmarking was conducted to assess the impact of the proposed scheduling solution on system performance, particularly by reducing deviations in night and weekend shift allocations and eliminating overtime. The analysis utilized three key performance indicators: the maximum deviation in night shifts, the maximum deviation in weekend shifts, and overtime —measured by hours exceeding a 220-hour threshold per nurse per month. Historical data gathered over a 6-month period showed that nurses experienced, on average per month, deviations of approximately 7.8 night shifts and 5.2 weekend shifts, alongside an average of 117 overtime hours per nurse. However, in July, night shifts under the proposed system varied by approximately 4 shifts and weekend shifts varied by approximately 2, resulting in improvements of roughly 50% in both categories. This consistency not only enables a more equitable distribution of shifts —thereby reducing administrative burdens and mitigating burnout risk— but also reduces labor costs and improves compliance with labor regulations. In summary, the mathematical analysis of the benchmarking process demonstrated that the revised scheduling model significantly enhances system efficiency, promotes fairness among nursing staff, and ultimately contributes to better patient care outcomes.

23.6 Benefits to the Company

The proposed scheduling system provides significant organizational, operational, and managerial benefits to Memorial Healthcare Group by addressing inefficiencies arising from manual scheduling. Through mathematical modeling, demand forecasting, dynamic reassignment, and an interactive user interface, the project improves scheduling quality, employee satisfaction, and resource utilization.

Operationally, the system replaces manual Excel-based scheduling, reducing preparation time, human error, and administrative burden while ensuring stable patient care. Equity-focused optimization promotes fairer distribution of shifts and hours, improving employee satisfaction, reducing fatigue, and enhancing well-being. The reassignment model enables quick adjustments to sudden leaves or demand changes without compromising fairness. An integrated forecasting module uses historical patient arrival data to generate short-term demand projections, optimizing staffing decisions and avoiding over —or under— staffing during different periods. Built on open-source platforms (Python, PuLP, Flask, Pandas), the system is cost-effective, scalable, and easy to adopt for hospital management and staff.

In summary, the new scheduling system advances Memorial Healthcare Group's goals by improving scheduling accuracy, reducing manual workload, promoting fairness, ensuring compliance, and enhancing workforce planning — eventually supporting better patient care delivery.

Bibliography

Memorial Healthcare Group (2024). About Us. Accessed: 2024-10-26.

Appendix: Mathematical Model

Table 23.1: Set Definitions

Symbol	**Description**
$\mathcal{N}$	Set of nurses, indexed by n.
$\mathcal{S}$	Set of shift types, e.g., $\{M, N\}$.
$\mathcal{D}$	Set of days in the planning horizon.
$\mathcal{D}_{\text{weekend}}$	Subset of weekend days.
$\mathcal{P}$	Set of competency levels.

Table 23.2: Parameter Definitions

Symbol	**Description**
$\omega_{n,s,d}$	Preference weight.
$a_{s,d}$	Staffing requirement.
t_s	Shift duration.
$H^{\min}, H^{\max}, H^{\text{target}}$	Min, max, target hours.
$\beta_{\text{night}}, \ldots$	Objective weights.
$\delta_{\text{night}}, \ldots$	Max deviations.
M	Penalty constant.
$N_{\text{night}}, \ldots$	Normalization factors.

Table 23.3: Decision Variables

Symbol	**Description**
$x_{n,s,d}$	Binary assignment.
h_n^{over}	Overtime hours.
$z_{n,s,d}$	Rest violation indicator.
dev_n^+, dev_n^-	Work-hour deviations.
$dev_{\text{night},n}^+, \ldots$	Night/weekend deviations.
$s_{s,d}$	Staffing slack.

Objective Function

$$\begin{aligned}\min f = {} & \beta_{\text{night}} \frac{\sum(\text{dev}^+_{\text{night},n} + \text{dev}^-_{\text{night},n})}{N_{\text{night}}} + \beta_{\text{weekend}} \frac{\sum(\text{dev}^+_{\text{weekend},n} + \text{dev}^-_{\text{weekend},n})}{N_{\text{weekend}}} \\ & + \beta_{\text{rest}} \frac{\sum(z_{n,s,d} - 1)}{N_{\text{rest}}} + \beta_{\text{pref}} \frac{\sum x_{n,s,d}(1 - \omega_{n,s,d})}{N_{\text{pref}}} \\ & + \beta_{\text{overtime}} \frac{\sum h_n^{\text{over}}}{N_{\text{overtime}}} + \beta_{\text{working}} \frac{\sum(\text{dev}_n^+ + \text{dev}_n^-)}{N_{\text{working}}} + M \sum s_{s,d}\,.\end{aligned}$$

Constraints

$$\sum_n x_{n,s,d} + s_{s,d} \geq a_{s,d} \qquad \forall s, d \qquad (1)$$

$$x_{n,s,d} = 0 \qquad \forall n, d, s \qquad (2)$$

$$\sum t_s\, x_{n,s,d} - H^{\text{target}} = dev_n^+ - dev_n^- \qquad \forall n \qquad (3)$$

$$\sum t_s\, x_{n,s,d} \geq H^{\min} \qquad \forall n \qquad (4)$$

$$\sum t_s\, x_{n,s,d} - H^{\text{target}} \leq h_n^{\text{over}} \leq \delta_{\text{overtime}} \qquad \forall n \qquad (5)$$

$$\sum_{d'=d}^{d+6} x_{n,s,d'} \leq K \qquad \forall n, d \tag{6}$$

$$\sum_{s} x_{n,s,d} \leq 1 \qquad \forall n, d \tag{7}$$

$$\sum_{d} x_{n,N,d} \leq L \qquad \forall n \tag{8}$$

$$x_{n,N,d} + x_{n,N,d+1} + \sum_{s} x_{n,s,d+2} \leq 2 \qquad \forall n, d \tag{9}$$

$$z_{n,s,d} \geq 1 - x_{n,s,d} \qquad \forall n, s,\ d < \max D \tag{10}$$

$$N_n - \bar{N} = dev^{+}_{\text{night},n} - dev^{-}_{\text{night},n},\ dev^{\pm} \leq \delta_{\text{night}} \tag{11}$$

$$W_n - \bar{W} = dev^{+}_{\text{weekend},n} - dev^{-}_{\text{weekend},n},\ dev^{\pm} \leq \delta_{\text{weekend}} \tag{12}$$

$$x_{n,N,d} + x_{n,M,d+1} \leq 1 \qquad \forall n,\ d < \max D \tag{13}$$

$$\sum_{n \in N_{D1}} x_{n,s,d} \leq 1 \qquad \forall s, d \tag{14}$$

Dizin

Index