Bilkent Üniversitesi
Mühendislik Fakültesi
Endüstri Mühendisliği Bölümü

Üniversite-Sanayi İşbirliği Öğrenci Projeleri 2022

Derleyenler

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Endüstri Mühendisliği Bölümü
Sistem Tasarımı Ders Koordinatörleri

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Bilkent University

Faculty of Engineering

Department of Industrial Engineering

University-Industry Collaboration Student Projects 2022

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Önsöz

Bu kitap, 2021-2022 öğretim yılında Bilkent Üniversitesi Endüstri Mühendisliği Bölümü tarafından gerçekleştirilen *Üniversite-Sanayi İşbirliği Bitirme Projeleri* özetlerini kapsamaktadır. Programımız 28 yıl önce sistem tasarımı derslerinin sanayi projelerine dönüştürülmesi ile başlamıştır. Bu süre içerisinde farklı sektör ve büyüklükte 119 iş, sanayi, ve kâr amacı gütmeyen kuruluşlarla toplam 513 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 Evren Cantürk (Akbank), Orhan Dağlıoğlugil (A101), Mustafa Bora Dilik (Nevzat Ecza), Erdinç Mert (BeNova Danışmanlık) ve Doç. Dr. A. Selin Kocaman'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 2021-2022 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 28 years ago. Since then, 513 projects have been completed, with 119 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 Evren Cantürk (Akbank), Orhan Dağlıoğlugil (A101), Mustafa Bora Dilik (Nevzat Ecza), Erdinç Mert (BeNova Consulting) and Assoc. Prof. A. Selin Kocaman (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

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The organizing committee thanks Bilkent University members named below for their invaluable help to run 2021-2022 program.

Bilkent Üniversitesi Endüstri Mühendisliği Bölümü Öğretim Üyeleri

Bilkent University Industrial Engineering Faculty Members

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University & Industry Cooperation Student Projects Coordinator

Yeşim Gülseren

Bilkent Üniversitesi Endüstri Mühendisliği Bölümü Sekreteri

Bilkent University Industrial Engineering Department Secretary

Ayşe Oran

Düzenleme kurulu, 2021-2022 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 2021-2022 program.

Arçelik Buzdolabı İşletmesi
Levent Çakır
Burcu Çelebioğlu
Hasan Tugay Çiftçi
Özlem Deviren
Hasan Karakum
Ali Kırıcı
Esra Öztürk
Fatma Paşa
Necmi Süloğlu
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Aslı Türkay

Arçelik Elektronik İşletmesi
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Aselsan
Cansu Ulukaya

Bakioğlu Holding
Sabahattin Bilgen
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Cenk Güreş
Yeliz Narlı
Beste Yıldız

Demir Export
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Supply Chain Wizard
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Yunus Emre Yurdagül

Türk Patent ve Marka Kurumu
Mustafa Kubilay Güzel
Mustafa Serin
Tuğba Yılmaz

UNDP
Gökhan Dikmener

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 28 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, *20. Endüstri Mühendisliği Proje Fuarı ve Yarışması*'nda 22 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, Tolunay Alankaya, Ömer Ekmekçioğlu, Aslı Eroğlu, İsmail Burak Taş'a ve emeği geçen herkese çok teşekkür ediyorum.

Prof. Dr. Bahar Y. 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 28 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-two projects are present at the *20th 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 Tolunay Alankaya, Ömer Ekmekçioğlu, Aslı Eroğlu, İsmail Burak Taş for their relentless efforts to ensure that the program succeeds.

Prof. Dr. Bahar Y. Kara
Industrial Engineering Department Chairperson

Teşekkür Mektupları

Appreciation Letters

Arçelik

Dayanıklı tüketim ve tüketici elektroniği sektörlerinde üretim, pazarlama ve satış sonrası destek hizmetleri ile faaliyet gösteren Arçelik, 1955 yılında kurulmuş bir şirkettir. Arçelik bugün; dünya çapında 40.000'in üzerinde çalışanı, Türkiye, Romanya, Rusya, Çin, Güney Afrika, Tayland, Pakistan, Hindistan ve Bangladeş'de olmak üzere 9 ülkede, 28 üretim tesisi, 49 ülkede 74 iştirak ile global bir organizasyon ağı inşa etmiştir.

Ar-Ge birimini 1991 yılında oluşturan Arçelik bugün Türkiye ve dünyada 28 Ar-Ge merkezinde 2000'in üzerinde Ar-Ge personeli ile kendi patentli teknolojilerini geliştirerek global pazarlarda rekabet edebilir bir güce ulaşmıştır. Kaynağı üniversitelerde olan bilimsel bilginin sanayinin Teknoloji geliştirme çalışmalarına aktarılması çok kritik öneme sahiptir. Bu önemin farkında olarak Arçelik'te üniversiteler ile farklı işbirliği süreçleri işletilmektedir. Lisans tez çalışmaları ile ile sanayinin tecrübe ettiği gerçek sorunlara çözümler bulunabilmekte, yenilikçi ürün ve süreçler geliştirilmesine katkı sağlanabilmektedir. Bununla birlikte mühendis adaylarımızın sanayi tecrübesi elde ederek mezun olmalarına da katkı sağlamaktadır. Başarı ile yürütülen ve tamamlanan bu projeler ile edinilen bilgi ve tecrübenin mühendis adaylarına ileride yapacakları çalışmalarda yol gösterici nitelikte faydalar sağlayacağını öngörüyor ve Bilkent Üniversitesi'nin Sanayi Odaklı Bitirme Projeleri kapsamında yürütülen çalışmaları çok katma değerli buluyoruz.

Bilkent Üniversitesi Rektörlüğü ve Mühendislik Fakültesi yönetici ve akademisyenlerimize, Teknoloji Transfer Ofisi'ne, ÜSİ Mezuniyet Projeleri Koordinatörü Sn. Yeşim Gülseren Hanım'a üniversite – sanayi işbirliği yürütüğümüz projelerde hedeflenen çıktı ve kazanımlara ulaşmamızda bizlere destek olan değerli mühendis adaylarımıza ve süreç içerisinde değerli katkıları ile projelerin uygulanabilirliğine yönelik geri bildirimleri sağlayarak proje ekibimizi başarılı sonuçlara yönlendiren Makina Mühendisliği, Endüstri Mühendisliği ve Elektrik – Elektronik Mühendisliği Departmanlarındaki değerli akademisyenlerimize teşekkür ederiz.

Evrim ÖZGÜL
Arçelik A.Ş.
Global Ar-Ge Teşvikleri ve Üniversite-Sanayi İlişkileri Yöneticisi

Arçelik

1955 yılında Sütlüce'de kurulan Arçelik A.Ş. Türk beyaz eşya sektörüne ilk adımı çamaşır makinesi ile atmıştır. 1970'li ve 80'li yıllarda ürün gamı genişletilerek buzdolabı, bulaşık makinesi, pişirici cihazlar, elektronik ve küçük ev aletleri segmentlerinde tüketicilere ürünler sunmaktadır.

Arçelik, 40.000'i aşkın çalışanı, 12 markasıyla (Arçelik, Beko, Grundig, Blomberg, ElektraBregenz, Arctic, Leisure, Flavel, Defy, Altus, Dawlance, Voltas Beko), 9 ülkede, 28 üretim tesisi, 30 ARGE merkezi, 49 ülkede iştirakleriyle global olarak faaliyet göstermektedir.

Bilkent Üniversitesi Endüstri Mühendisliği Akademisyenleri, Üniversite-Sanayi İşbirliği Koordinatörleri ve öğrencilerinin katkıları ile Eskişehir Buzdolabı İşletmesi'nde iki adet proje yürütmekteyiz.

"Yardımcı Sanayilerde Kalıp Atama Optimizasyonu ve Karar Destek Sistemi" projesinde tedarikçi firmalara kalıp atama prosesi çok amaçlı matematiksel model ile bir algoritma oluşturulmuştur. Çalışmada atanmayan kalıpların sayısının, fazla mesai kullanımının ve kademeli yardımcı sanayi hareketinin en aza indirilmesi ve öncelikli yardımcı sanayilere yapılan atamaların en çoklanması amaçlanmıştır.

"Karma Modelli Montaj Hatlarında Operasyon Planını Eniyileyen Karar Destek Sistemi" projesinde montaj hatları için bir algoritma tasarlanmış ve bu algoritma kullanıcı arayüzü ile kullanıma sunulmuştur. Bu algoritmada üretim hatlarındaki kısıtlar dikkate alınarak en iyi operasyon planını bulmak amaçlanmıştır.

Her iki projede de manuel yürütülen süreçler oluşturulan algoritmalar sayesinde belirtilen kısıtlara göre optimum çözümü verecek şekilde tasarlanmıştır. Hazırlanmış olan kullanıcı ara yüzleri ile de kullanımda kolaylık ve esneklik sağlanmıştır.

Gerçekleştirdiğimiz iki projenin şirketimiz ve öğrencilerimiz için son derece yararlı olduğuna inanıyoruz. Proje kapsamında emek vermiş öğrencilerimize, görüşleriyle projeye yön veren Bilkent Üniversitesi Akademisyenleri'ne, süreç boyunca her zaman destek veren Üniversite-Sanayi İşbirliği Koordinatörleri'ne çok teşekkür ediyoruz. Söz konusu projelerde beraber çalıştığımız mühendis adaylarına bundan sonraki iş ve akademik hayatlarında başarılar dileriz.

Özlem DEVİREN USLU
Arçelik A.Ş.
Metot Mühendisliği Yöneticisi

Sürekli yatırım ve gelişimle, yer aldığı tüm faaliyet alanlarında "en iyiye" ulaşarak ülkesine değer katan; dünya çapında saygın bir şirketler topluluğu olarak "baki" kalma misyonuyla faaliyetlerine yön veren Bakioğlu Holding; çekirdekten başlayarak 1973'ten günümüze entegre bir "Ambalaj Sanayi" geliştirmiş ve bunu uluslararası standartlara ulaştırmıştır ve bugün sürdürülebilirlik odağıyla, sosyal sorumluluk bilinci yüksek bir yaklaşımla, gelişime yeniliğe verdiği önemle yine faaliyetlerini sürdürmektedir.

2021 yıl sonu itibarıyla; 313.190 m^2 üretim alanında, 2000'i aşan çalışan gücüyle, yaklaşık 57 ülkeye gerçekleştirdiği ihracatla ülkemiz ekonomisine büyük katkı sağlayan Bakioğlu Holding ve Ambalaj Grubu Şirketleri, tüm faaliyetlerinde "önce insan" diyerek yola çıkmakta; güven esaslı ilişkilerle, hesap verilebilir, şeffaf ve adil bir kurum kültüründe, kalite ve çözüm odaklı yaklaşımla ilerlemektedir.

Bakioğlu Holding dikey entegrasyon yapılanmasının parçası olan ve Türkiye'nin lider esnek ambalaj üreticileri arasında yerini alan *Bak Ambalaj*; güçlü sermaye yapısı, tecrübeli ve dinamik çalışanları, müşteri odaklı yaklaşımı ve yenilikçi uygulamaları ile 1973'ten bu yana çeşitli sektörlerin önde gelen şirketlerine hizmet vermektedir.

İzmir Atatürk Organize Sanayi Bölgesi'nde bulunan ve 4 ayrı tesiste üretim faaliyetlerini yürüten Bak Ambalaj; 600'ü aşkın çalışanı ile çeşitli sektörlere baskılı, baskısız ve laminasyonlu olarak esnek ambalaj üretmektedir ve düzenli olarak gerçekleştirdiği yatırımlar sayesinde üretim portföyünü istikrarlı olarak genişletmektedir. Bak Ambalaj üretiminin %70'in üzerinde özellikle Batı Avrupa ülkelerine ihraç etmek suretiyle ülkemizin ihracatına önemli katkılarda bulunmaktadır.

Bak Ambalaj dünyanın her yerine İzmir'deki üretim tesislerinden ve gerektiğinde, Avrupa ve ABD'de deki depolama olanakları ile en hızlı şekilde teslimat sağlamaktadır.

Bak Ambalaj'ın verimlilik ve müşteri odaklılık ilkeleri doğrultusunda, müşteri taleplerini ön planda tutan yaklaşımına katkı sağlayacak projemizin gerçekleşmesini sağlayan Bilkent Üniversitesi yönetimi, Endüstri Mühendisliği Bölümü'nün değerli öğretim üyeleri, asistanları ve proje koordinatörümüze içtenlikle teşekkürü bir borç biliriz.

2021-2022 akademik yılında gerçekleştirdiğimiz projemizde; müşteri teslim süresi talepleri ile hammadde temini süresi arasında kalan karanlık periyodu en aza indirgeyecek şekilde müşteri siparişleri ve hammadde ihtiyaçları için, geçmiş müşteri/hammadde sipariş ve ürün ağacı verilerini kullanarak gelecek 12 aylık döneme dair müşteri talep tahmini ve hammadde ihtiyaç öngörüleri oluşturan, tahmin performans ölçüm raporlaması yapan ve tüm bunları kullanıcı dostu bir ara yüz üzerinden gerçekleştiren bir program ortaya çıkarılmıştır.

Kendi alanlarında geleceğin en iyi profesyonelleri arasında yerlerini alacağına inandığımız iyi yetişmiş mühendis arkadaşlarımızla bu projeyi hayata geçirmiş olmanın mutluluğunu yaşıyor; kendilerine en içten teşekkürlerimizi sunarak eğitim ve kariyer hayatlarında başarılar diliyoruz.

Sabahattin BİLGEN
Bakioğlu Holding Operasyonel Mükemmellik Direktörü
Bilkent Üniversitesi IE 2003 Mezunu

işbir yatak

İşbir Yatak, İşbir Sünger Sanayi A.Ş. bünyesinde yatak sektöründe faaliyet gösteren bir İşbir Holding kuruluşu olup, genelde hammadde üreticisi olan Holding'in Ergo Yatak ile birlikte son tüketici ile buluşan markalarından biridir.

İşbir Yatak, dünyada gelişen teknolojiyi sektöre adapte etme misyonu doğrultusunda 1997 yılından bugüne İşbir Sünger San. A.Ş.'nin sahip olduğu bilgi birikimi ve tecrübeyi; teknolojinin, sağlık ve uyku konforu için kullanımı felsefesi ile yatak sektörüne aktarmaktadır. Oldukça fazla oyuncusu olan ve son yıllarda çok dinamikleşen yatak pazarının oluşmasında söz sahibi olan İşbir Yatak; kalite ve müşteri odaklı marka ve ürün konumlandırılması doğrultusunda, kullandığı "açık hücreli visko teknolojisi," sadece İşbir için Türk mühendisleri tarafından üretilen "polimer yay teknolojisi", tüm yataklarda kullanılan lisanslı "Quallofil Allerban" teknolojisi, yatakların lavanta kokmasını ve anti-stress etkisine sahip olmasını sağlayan özel "nano teknoloji" ile üretilmiş yatak kumaşları, at saçı yatak, hindistan cevizi özlü yatak, sporcular için özel nem tutmayan yatak, doğaya ve çevreye duyarlı vizyonuyla geliştirdiği yeni ürün ve teknolojileri ile her anlamda ve her zaman sektöre yön vermiştir.

2021-2022 Öğretim Yılında Üniversite-Sanayi/İş Dünyası İşbirliği Projeleri kapsamında; Bilkent Üniversitesi Endüstri Mühendisliği Bölümü'nün saygıdeğer Akademisyenleri, Üniversite-Sanayi İşbirliğinin Değerli Koordinatörleri ve sevgili öğrencilerimiz ile iki projede birlikte çalıştık. Birinci projede; Yatak Fabrikamızdaki üretim hatlarımızın bir tanesinde toplam kârlılığı iyileştiren iki haftalık üretim planlama modeli ve toplam üretim süresini düşüren günlük çizelgeleme modeli önerilmiş, ayrıca fiyat ve talep arasındaki ilişkiyi göstermek için bir regresyon çözümlemesi geliştirilmiştir. İkinci projede ise hammadde satın almasının doğru zamanda ve doğru miktarlarda yapılmasını sağlayan bir Karar Destek Sistemi hazırlanarak daha verimli bir satın alma yöntemi önerilmiştir.

İki proje sonunda elde edilen Karar Destek Sistemlerinin İşbir Yatak'a karlılık ve verimlilik anlamında katkılar sağlayacağını değerlendirmekteyiz. Bu kapsamda; görüşleri ile projeye yön veren Bilkent Üniversitesi'nin Akademisyenleri'ne ve süreç boyunca her zaman destek olan Üniversite-Sanayi İşbirliği Koordinatörleri'ne ve projelerde beraber çalıştığımız mühendis adaylarına katkılarından dolayı teşekkür ediyor, öğrencilerimize bundan sonraki iş ve akademik hayatlarında başarılar diliyoruz.

H.Ünal AKMEŞE
İşbir Yatak İş Geliştirme Direktörü
Bilkent IE 2003 Yük. Lis. Mezunu

NORM FASTENERS

1973 yılında çift vuruşlu bir makine ile ilk üretimini gerçekleştiren Norm Holding, bugün 4'ü yurt dışında olmak üzere toplam 20 şirket, 12 üretim tesisi ve yıllık 160.000 ton üretim kapasitesi ile Türkiye ve Dünya'nın dört bir yanındaki müşterilerine hizmet veriyor.

Türkiye'nin ilk 500 şirketi arasında yer alan ve üretiminin yaklaşık %40'ını ihraç eden Norm Fasteners; güçlü Ar-Ge yapılanması, ihtiyaca yönelik tasarımları ve ürün kalitesi ile otomotiv başta olmak üzere faklı sektörlerde bağlantı elemanları tedarikinde global bir oyuncu olarak yer alıyor. Bu ilham veren dönüşümü kuşkusuz geçmişin tecrübesini geleceğe hizalayarak sürdürmeye devam ediyoruz. Aynı zamanda sürdürülebilirlik, eğitim ve sanat alanlarında yürütülen projeler ile sosyal sorumluluk bilincini ilke ediniyoruz. Sürdürülebilirlik Komitesi, Digiconnect Staj Programı ve Mesleki Eğitim Merkezi uygulamalarımız ile bu alanlarda da değer yaratmak önceliklerimiz arasında yer alıyor.

Değişen dünya koşullarına ayak uydururken global trendleri yakından takip etmenin şirketler için ne kadar kritik öneme sahip olduğunun farkındayız. Geçtiğimiz birkaç yıl boyunca çok yakından tecrübe ettiğimiz en önemli konulardan biri de global anlamda tedarik zincirlerinde yaşanan kırılmalar idi. Şirketler için güçlü ve esnek tedarik zinciri yapılanmalarının yarattığı fark göz ardı edilemeyecek öneme sahip. Bilkent Üniversitesi akademisyenleri ve öğrencileri ile yürüttüğümüz projede bu farkındalık ile yola çıktık. Orta ve uzun vadede stratejik düzeyde alacağımız kararları analitik olarak destekleyecek bir proje olan "Stratejik Seviyede Dağıtım Ağı Tasarımı" lojistik merkezlerimiz için alacağımız yatırım kararlarında bizleri yönlendirecek nitelikte. Proje bizlere Avrupa ve Türkiye'de kiralanacak veya satın alınacak depolarımız için dağıtım ağını hacim ve mesafe boyutunda analiz ederek lojistik maliyetlerini en aza indirecek bir yaklaşım sunuyor. Yeni merkezlerimiz için belirlenecek konumları optimize etmeyi amaçlayan bu karar destek sisteminden hem yatırım kararlarımız hem de mevcut durum analizlerimiz sırasında faydalanıyor olacağız. Proje süresince gerçekleştirdiğimiz çalışmaların hem firmamız hem de öğrencilerimize önemli katkıları olduğuna inanıyoruz. Değerli Bilkent Üniversitesi öğrencileri ve danışman akademisyenlerine özverili çalışmaları ve katkıları için gönülden teşekkür ederiz.

Dila NART
Norm Fasteners Lojistik Müdürü

All the best of success...

and all the best of luck!

PROJELER
PROJECTS

Bütüncül Kanal Perakendeciliği için Ağ Tasarımı | 1

Invent Analytics

Proje Ekibi

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Özet

Bu projede Invent Analytics'in bir müşterisi için çok kademeli bir bütüncül kanallı ağ tasarımı oluşturulmuştur. Hazırladığımız matematiksel model ile diğer mağazaların stoklarını yenileme ve risk havuzlama amaçlı kullanılan ara dağıtım merkezlerinin seçilmesi ve hangi mağazaların çevrimiçi satışa açılması gerektiği kararları, toplam maliyeti enazlayacak şekilde verilmiştir. Problemi çözmek için benzetimli tavlama algoritması geliştirilmiş ve bu algoritma farklı maliyet ve stok/hizmet seviyesi senaryoları için doğrulanmıştır. Algoritmamızın sunduğu sonuçlarla müşterimize istediği hizmet seviyesine göre optimal ağ konfigürasyonlarının raporlandığı bir karar destek sistemi hazırlanmıştır. Algoritma çözümlerimizin müşterinin eski sisteminden alınan baz senaryoyla karşılaştırıldığında, şirketin kayıp satışlarını ve envanter maliyetlerini azalttığı görülmüştür.

Anahtar Sözcükler: Bütüncül Kanal Perakendeciliği, Dağıtım Ağı Tasarımı, İkmal ve Yenileme, Sezgisel Yaklaşım

Network Design for Omnichannel Retailing

Abstract

In this project, a multi-echelon omni-channel network design was created on behalf of a client of Invent Analytics. A mathematical model is proposed to determine the locations of stores that will be used to fulfill online orders and the locations of mini distribution centers that will be utilized to replenish other other stores and benefit from risk pooling. To solve the problem, a simulated annealing is used and the algorithm is validated for different cost, inventory and service level scenarios. Utilizing the algorithm results, a decision support system has been developed in which optimal network configurations are reported according to the desired service level by the customer. When compared with the base scenario taken from the customer's current system, our algorithm is expected to lead to significant decrease in lost sales and inventory holding costs.

Keywords: Omni-Channel Retailing, Distribution Network Design, Replenishment, Fulfillment, Heuristic Approach

1.1 About the Company

Invent Analytics was founded in 2013 as a business analytics SaaS company operating across several locations including Philadelphia, Istanbul, London, and Dubai. It provides customizable and adaptive cloud-based solutions in retail merchandising and planning, supply chain management, and inventory management. Through AI-based algorithms with strong ties to scientific research and academia, the company provides retailers with integrated and optimized systems with increased sales and lower inventory. Using Omni-AI, which is an intelligent supply chain solution of the company, the company plans their customers' entire supply chain by combining network planning, inventory and pricing optimization, and store & DC replenishment decisions into a single framework. The company offers service to many companies operating in different fields which have a revenue of over $6B in total. Through their collaborations with Invent Analytics, these clients have observed gross margin increases in the range of 2-5%.

1.2 System Description

There is a radical change in customer behavior with the increasing prevalence of e-commerce technologies. Online sales have become more frequent as e-commerce penetrates the daily life of customers and changes the marketing trends. Retailing companies embrace various omni-channel (OC) strategies to adapt to the latest trends, retain customers, and enhance their market impact. OC networks are designs that ensure the integration of the customer experience in all channels including both online and offline platforms. However, OC networks come up with serious challenges for companies since they require a more complex supply chain planning that contains online/offline demands, and distribution center (DC) replenishments on a regular basis.

Invent Analytics reported to us that one of their retail customers has these kinds of difficulties due to the continuous rise in online sales and wants to benefit from OC management strategies to optimize their network design. Although more specific information and the details about the exact network operations of the retailer are anonymized to us for the sake of confidentiality, we were informed that the customer's main aim is to optimize their current network design by creating an OC structure that minimizes operational costs and lost sales.The current network of the retailer includes 516 facilities located in 74 cities in Turkey. There exists 513 stores and 3 distribution centers among the facilities. 408 stores could fulfill both online and offline demands, whereas all the stores except DCs are open to offline demands.

The online sales are made through e-commerce channels, and the desired product is shipped through online-available facilities via third-party logistics companies. In offline sales, customers examine and purchase the products by being physically present in a store. DCs are large warehouses that are responsible for fulfilling the online demand of the cities and replenishing the offline demand of the stores in the network. Stores, on the other hand, can replenish each other's internal orders and/or meet both online and offline demands. In the context of our problem, if a store is eligible to replenish the other stores, it is called a "mini distribution center (mini-DC)". If a store is available for online sales, it means that it can fulfill the online demand of the cities that are assigned to it.

Invent Analytics has already proposed different approaches for solving this complex network design problem. However, forecasting and fulfilling the online demands of 81 cities have become even more burdensome after every passing season. While this is the case, the lead time of the customer orders is steadily increasing due to capacity constraints of third-party logistics providers. Furthermore, many customers are still committed to offline, store-based shopping based on the given data. It leads to the problem being even more complex in inventory policies and network design. Therefore, the company wanted us to come up with a more detailed and responsive approach for designing this network.

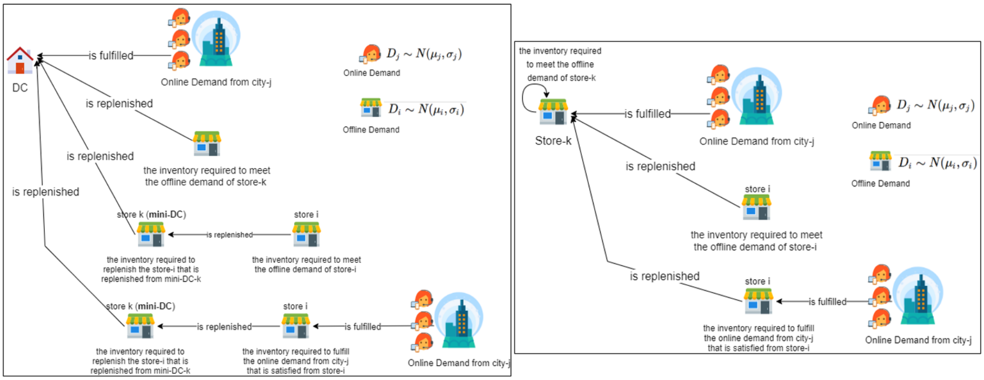

Figure 1.1: A sample distribution network with possible configurations of a DC (left) and a store (right)

1.3 Problem Definition

The main objectives of the firm was decreasing the total costs of inventory holding, transportation, and lost sales while benefiting from an OC network. To reduce these costs and meet the customer's targets, we decided to consider a supply chain network that consists of three echelons as DCs, mini-DCs, and stores as described above. Additionally, there will be stores that are open for online sales and responsible for fulfilling the online demand of the cities. With this consideration, we aimed to reduce the transportation lead times to stores and online demand points and reduce the inventory holding costs by pooling the demands around mini-DCs. Thus, the decisions we needed to take are determining the locations of the mini-DCs, assigning stores that will be replenished by DCs or mini-DCs, and the locations of facilities open for online sales and the cities to be fulfilled by them. A representative network with possible demand configurations of DCs and stores is shown in Figure 1.3.

1.4 Proposed Solution Approach

Due to the complexity of the given network, we framed the problem by introducing fundamental assumptions about the system as the first step of our solution approach. The critical assumptions we made are: i) The online and offline demands are distributed normally; ii) There will be one representative product that our model considers; iii) Each store is replenished by the same DC or mini-DC throughout the season; iv) All of the facilities are considered to have an unlimited capacity; v) Mini-DCs could not replenish each other; vi) DCs could only fulfill online demands along with their replenishment operations; vii) There will be an input for the service

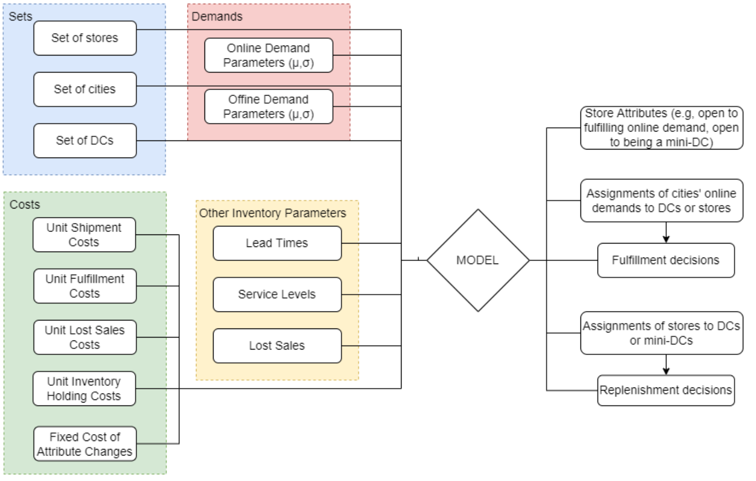

Figure 1.2: Flowchart representing the inputs and outputs of the model

levels for facilities not less than 95%; viii) All the facility-replenishment and fulfillment assignments are considered *strategic decisions*, meaning that the model is implemented only once and its results will be valid throughout the season.

The parameters utilized in the mathematical model were obtained from the past sales data provided by the company. We also prepared the data regarding the fixed cost of changing facility attributes, unit shipment costs between facilities, unit fulfillment costs, unit lost sales costs, lead times, and service levels. The performance measures for evaluating the model have been determined as the computation time and the proximity to optimality. Figure 1.2 shows the input and output flowchart of the model.

While solving our problem, we first developed mathematical models considering the assumptions and coded them via Python 3.9.7. As a powerful solver, Gurobi Optimizer has proven to be efficient in dealing with quadratic formulations so we used this software to find the optimal configuration in the shortest possible time. However, due to the complexity of the problem (which is known to be NP-hard), we were not able to obtain optimal solutions using Gurobi Optimizer, so we needed to develop heuristic approaches to accelerate the solution process while obtaining satisfactory solutions. We came up with two heuristic approaches and decided that the simulated annealing algorithm is a perfect fit for our problem to obtain satisfactory solutions in a reasonable amount of time. We implemented the algorithm in Google Compute Engine since our computers' hardware was not sufficient enough to run the full-sized problem and we benefited from the multiprocessing method for our code to use different CPUs simultaneously to reduce the overall computation time.

1.4.1 Mathematical Model(s)

First, as a base formulation, we benefited from the two-echelon model presented in Daskin et al. (2002) and Shen et al. (2003). The mathematical model we constructed under the assumptions is a mixed-integer quadratic program (MIQP) and can be seen in Figure 1.3. Objective function includes the fixed cost of opening a store for replenishment and online sales, the expected safety stock and lost sales costs, the cost of fulfilling the online demand, and outbound shipment cost of the cities. Additionally, inbound transportation costs are considered. Regarding the constraints, the first one ensures that each city's online demand must be fulfilled from either a DC or a store. The second one guarantees that if a city's online demand is fulfilled from a store, that store must be open to online orders. The third one defines that each store must be replenished from a DC or a mini-DC. The fourth one ensures that if a store is replenished from another store, then the latter must be a mini-DC. The fifth one defines that if a store is used to replenish other stores, then a DC must replenish that store. The sixth and seventh constraints are related to t_{kij} variable and the former one ensures that if a city's online demand is fulfilled from a store, and if that store is replenished by a mini-DC, then the city's online demand must be indirectly satisfied from that mini-DC. The seventh one states that if there is no replenishment between a city and a store or between the store and a mini-DC, then there must not be any indirect relation between the city and the mini-DC. Constraints from eight to eleven have been constructed for variables u_{lki} and s_{lkij} within the same logic of constraints six and seven. Finally, the last constraint defines the domain of decision variables.

Since this MIQP formulation includes non-linear expressions in the objective function which increases the complexity of optimization, it seemed impossible to achieve results with the commercial solvers for the real-sized problem. Therefore, we decided to benefit from CQMIP formulation in our solution methodology and reformulated the MIQP model as the CQMIP form as Atamtürk et al. (2012) suggested. For the transition to the CQMIP formulation, we introduced six auxiliary variables for each square-root terms in the objective function, namely $T_{1l}, T_{2k}, T_{3i}, T_{4l}, T_{5k}, T_{6i} \geq 0$. Then, by using the fact that $z_{ij} = z_{ij}^2, w_{ik} = w_{ik}^2 ...$ (and so on) for all of our binary network variables, we reformulated our model in the CQMIP form as it can be seen in Figure 1.3.

Although there was an improvement in computation time, the real-sized problem seemed still impossible to solve with the CQMIP formulation. To find optimal solutions within a reasonable solution time, we added the following restrictions to CQMIP formulation as the third approach: i) Mini-

Sets:
S : Set of stores $S = \{1, 2..., 513\}$
C : Set of cities $C = \{1, 2..., 81\}$
D : Set of distribution centers $D = \{1, 2, 3\}$

Parameters:
Demand Parameters:
μ_i : Expected weekly offline demand of the representative product on store i, $\forall i \in S$
$\hat{\mu}_j$: Expected weekly online demand of the representative product for city j, $\forall j \in C$
σ_i : Standard deviation of weekly offline demand of the representative product on facility i, $\forall i \in S$
$\hat{\sigma}_j$: Standard deviation of weekly online demand of the representative product for city j, $\forall j \in C$

Shipment Cost Parameters:
δ_{ik} : Unit shipment cost between store i and k, $\forall i, k \in S$ & $i \neq k$
β_{li} : Unit shipment cost between DC l and store i, $\forall l \in D, \forall i \in S$
h_{ij} : Unit fulfillment costs between store i and city j, $\forall i \in S, \forall j \in C$
h_{lj} : Unit fulfillment cost between DC l and city j, $\forall l \in D, \forall j \in C$

Lost Sales and Inventory Parameters:
g_i : Unit lost sales cost of the representative product for store i, $\forall i \in S$
L_l : Lead time of shipment from supplier to DC l, $\forall l \in D$
L_{lk} : Lead time of shipment from DC l to store k, $\forall l \in D, \forall k \in S$
L_{ki} : Lead time of shipment from store k to store i, $\forall i, k \in S$ & $i \neq k$
α_l : Service level for DC l, $\forall l \in D$
α_k : Service level for store k, $\forall k \in S$
z_α : Standard normal value associated with service level α
q_i : Unit inventory holding cost per week at facility i, $\forall i \in S \cup D$
$L(z)$: Standardized loss function

Attribute Change Parameters:
f_i : Fixed weekly cost of opening store i to online sales, $\forall i \in S$
c_i : Fixed weekly cost of converting store i to a mini-DC, $\forall i \in S$

$$
\begin{aligned}
\min \quad & \sum_{i\in S}(c_i y_i + f_i x_i) \\
& + \sum_{l\in D} q_l z_{\alpha_l} \sqrt{L_l(\sum_{j\in C} z_{lj}\hat{\sigma}_j{}^2 + \sum_{k\in S}(w_{lk}\sigma_k^2 + \sum_{j\in C} t_{lkj}\hat{\sigma}_j{}^2 + \sum_{i\in S/\{k\}}(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2)))} \\
& + \sum_{k\in S} q_k z_{\alpha_k} \sqrt{\sum_{l\in D}(L_{lk} + (1-\alpha_l)\,L_l)(w_{lk}\sigma_k^2 + \sum_{j\in C} t_{lkj}\hat{\sigma}_j{}^2 + \sum_{i\in S/\{k\}}(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2))} \\
& + \sum_{i\in S} q_i z_{\alpha_i} \sqrt{\sum_{l\in D}\sum_{k\in S/\{i\}}(L_{ki} + (1-\alpha_k)(L_{lk} + (1-\alpha_l)L_l))(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2)} \\
& + \sum_{l\in D} g_l L\left(z_{\alpha_l}\right) \sqrt{L_l \sum_{j\in C} z_{lj}\hat{\sigma}_j{}^2} \\
& + \sum_{k\in S} g_k L\left(z_{\alpha_k}\right) \sqrt{\sum_{l\in D}(L_{lk} + (1-\alpha_l)\,L_l)(w_{lk}\sigma_k^2 + \sum_{j\in C} t_{lkj}\hat{\sigma}_j{}^2)} \\
& + \sum_{i\in S} g_i L\left(z_{\alpha_i}\right) \sqrt{\sum_{l\in D}\sum_{k\in S/\{i\}}(L_{ki} + (1-\alpha_k)(L_{lk} + (1-\alpha_l)L_l))\,(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2)} \\
& + \sum_{j\in C}\hat{\mu}_j(\sum_{i\in S} h_{ij} z_{ij} + \sum_{l\in D} h_{lj} z_{lj}) \\
& + \sum_{k\in S}\sum_{i\in S/\{k\}} \delta_{ki}(w_{ki}\mu_i + \sum_{j\in C} t_{kij}\hat{\mu}_j) \\
& + \sum_{l\in D}\sum_{k\in S} \beta_{lk}(w_{lk}\mu_k + \sum_{j\in C} t_{lkj}\hat{\mu}_j + \sum_{i\in S/\{k\}}(u_{lki}\mu_i + \sum_{j\in C} s_{lkij}\hat{\mu}_j))
\end{aligned}
$$

$$
\begin{aligned}
\text{s.t.} \quad & \sum_{i\in S} z_{ij} + \sum_{l\in D} z_{lj} = 1, \quad \forall j \in C && (1) \\
& z_{ij} \leq x_i, \quad \forall i \in S \quad \forall j \in C && (2) \\
& \sum_{i\in S} w_{ik} + \sum_{l\in D} w_{lk} = 1, \quad \forall k \in S \quad i \neq k && (3) \\
& w_{ik} \leq y_i, \quad \forall i \in S \quad \forall k \in S \quad i \neq k && (4) \\
& \sum_{l\in D} w_{lk} \geq y_k, \quad \forall k \in S && (5) \\
& t_{kij} \geq w_{ki} + z_{ij} - 1, \quad \forall k \in S \cup D \quad \forall i \in S \quad \forall j \in C, \quad i \neq k && (6) \\
& t_{kij} \leq \frac{w_{ki} + z_{ij}}{2}, \quad \forall k \in S \cup D \quad \forall i \in S \quad \forall j \in C, \quad i \neq k && (7) \\
& u_{lki} \geq w_{lk} + w_{ki} - 1, \quad \forall l \in D \quad \forall k \in S \quad \forall i \in S \quad i \neq k && (8) \\
& u_{lki} \leq \frac{w_{lk} + w_{ki}}{2}, \quad \forall l \in D \quad \forall k \in S \quad \forall i \in S \quad i \neq k && (9) \\
& s_{lkij} \geq w_{lk} + t_{kij} - 1, \quad \forall l \in D \quad \forall i, k \in S \quad \forall j \in C \quad i \neq k && (10) \\
& s_{lkij} \leq \frac{w_{lk} + t_{kij}}{2}, \quad \forall l \in D \quad \forall i, k \in S \quad \forall j \in C \quad i \neq k && (11) \\
& x_i, y_i, z_{ij}, w_{ij}, t_{kij}, u_{lki}, s_{lkij}, \in \{0, 1\} \quad \forall i, k \in S \quad \forall j \in C \quad \forall l \in D && (12)
\end{aligned}
$$

Decision Variables:

Store Attributes:

$$x_i = \begin{cases} 1 & \text{store } i \text{ can be used to fulfill online orders} \\ 0 & \text{otherwise.} \end{cases}$$

$$y_i = \begin{cases} 1 & \text{if store } i \text{ can be used to replenish other stores (i.e., if it is a mini-DC),} \\ 0 & \text{otherwise.} \end{cases}$$

Assignment (Allocation) Variables:

$$z_{ij} = \begin{cases} 1 & \text{if city } j\text{'s online demand is fulfilled from store } i \\ 0 & \text{otherwise.} \end{cases}$$

$$z_{lj} = \begin{cases} 1 & \text{if city } j\text{'s online demand is fulfilled from DC } l \\ 0 & \text{otherwise.} \end{cases}$$

$$w_{ik} = \begin{cases} 1 & \text{if store } k \text{ is replenished from store } i \\ 0 & \text{otherwise.} \end{cases}$$

$$w_{lk} = \begin{cases} 1 & \text{if store } k \text{ is replenished from DC } l \\ 0 & \text{otherwise.} \end{cases}$$

$$t_{kij} = \begin{cases} 1 & \text{if city } j\text{'s demand is satisfied from store } i \text{ that is replenished by facility } k \\ 0 & \text{otherwise.} \end{cases}$$

$$u_{lki} = \begin{cases} 1 & \text{if store } i \text{ is replenished from store } k \text{ that is replenished from DC } l \\ 0 & \text{otherwise.} \end{cases}$$

$$s_{lkij} = \begin{cases} 1 & \text{if city } j\text{'s online demand is fulfilled from store } i \text{ that is replenished from store} \\ & k \text{ that is replenished from DC } l \\ 0 & \text{otherwise.} \end{cases}$$

$$
\begin{aligned}
\min \quad & \sum_{i\in S}(c_i y_i + f_i x_i) + \sum_{l\in D} q_l z_{\alpha_l} T_{1l} + \sum_{k\in S} q_k z_{\alpha_k} T_{2k} + \sum_{i\in S} q_i z_{\alpha_i} T_{3i} \\
& + \sum_{l\in D} g_l L\left(z_{\alpha_l}\right) T_{4l} + \sum_{k\in S} g_k L\left(z_{\alpha_k}\right) T_{5k} + \sum_{i\in S} g_i L\left(z_{\alpha_i}\right) T_{6i} \\
& + \sum_{j\in C}\hat{\mu}_j(\sum_{i\in S} h_{ij} z_{ij} + \sum_{l\in D} h_{lj} z_{lj}) \\
& + \sum_{k\in S}\sum_{i\in S/\{k\}} \delta_{ki}(w_{ki}\mu_i + \sum_{j\in C} t_{kij}\hat{\mu}_j) \\
& + \sum_{l\in D}\sum_{k\in S} \beta_{lk}(w_{lk}\mu_k + \sum_{j\in C} t_{lkj}\hat{\mu}_j + \sum_{i\in S/\{k\}}(u_{lki}\mu_i + \sum_{j\in C} s_{lkij}\hat{\mu}_j))
\end{aligned}
$$

$$
\begin{aligned}
\text{s.t.} \quad & L_l(\sum_{j\in C} z_{lj}\hat{\sigma}_j{}^2 + \sum_{k\in S}(w_{lk}\sigma_k^2 + \sum_{j\in C} t_{lkj}\hat{\sigma}_j{}^2 + \sum_{i\in S/\{k\}}(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2))) \leq T_{1l}^2, \forall l \in D && (13) \\
& \sum_{l\in D}(L_{lk} + (1-\alpha_l)\,L_l)(w_{lk}\sigma_k^2 + \sum_{j\in C} t_{lkj}\hat{\sigma}_j{}^2 + \sum_{i\in S/\{k\}}(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2)) \leq T_{2k}^2, \forall k \in S && (14) \\
& \sum_{l\in D}\sum_{k\in S/\{i\}}(L_{ki} + (1-\alpha_k)(L_{lk} + (1-\alpha_l)L_l))(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2) \leq T_{3i}^2, \quad \forall i \in S && (15) \\
& (L_l \sum_{j\in C} z_{lj}\hat{\sigma}_j{}^2) \leq T_{4l}^2, \quad \forall l \in D && (16) \\
& \sum_{l\in D}(L_{lk} + (1-\alpha_l)\,L_l)(w_{lk}\sigma_k^2 + \sum_{j\in C} t_{lkj}\hat{\sigma}_j{}^2) \leq T_{5k}^2, \quad \forall k \in S && (17) \\
& \sum_{l\in D}\sum_{k\in S/\{i\}}(L_{ki} + (1-\alpha_k)(L_{lk} + (1-\alpha_l)L_l))(u_{lki}\sigma_i^2 + \sum_{j\in C} s_{lkij}\hat{\sigma}_j{}^2) \leq T_{6i}^2, \quad \forall i \in S && (18) \\
& T_{1l}, T_{2k}, T_{3i}, T_{4l}, T_{5k}, T_{6i} \geq 0, \quad \forall l \in D, \forall k \in S, \forall i \in S && (19)
\end{aligned}
$$

Figure 1.3: Sets, parameters, decision variables along with formulation of MIQP (left) and CQMIP models

DCs are selected from a set of stores that satisfy certain requirements; ii) each mini-DC's coverage span is limited to a certain distance (such as 250 km); iii) and the online demand of each city is fulfilled only by a store within the range of that city (such as 150 km). Even with these assumptions, it was not possible to solve the real-sized problem using Gurobi. Eventually, to cope with this model complexity and find a reasonable solution for a real problem size, we attempted to handle this problem with a metaheuristic approach.

1.4.2 Heuristic Development

We acknowledged that the simulated annealing algorithm is a good fit for this combinatorial optimization problem since it is suitable for exploring binary variable sets and finding close-to-optimal solutions (Rutenbar, 1989). It iteratively calculates the cost function given decision variables defined with binary strings. It generates a neighbor solution by switching some bits of these binary strings in each step. Then, it compares the cost of the neighbor solution with the cost of the previous solution. If the neighbor solution is less costly, the algorithm proceeds to the next step with the neighbor solution. Otherwise, the algorithm does the process called "annealing." It prefers continuing with the neighbor solution only with some transition probability. This probability depends on the number of steps taken, the difference between the neighbor and the original solution, and a normalizing parameter named "alpha." The following pseudo-code further explains the simulated annealing algorithm.

Algorithm 1: Pseudo-code for Simulated Annealing Algorithm

begin
$M \leftarrow$ total number of steps
$T \leftarrow$ current temperature
$S_0 \leftarrow$ initial solution
$S \leftarrow S_0$
$m = 0$
while $m < M$ do
Update the temperature: $T \leftarrow 1 - (m+1)/M$
Pick a random neighbor: $S_{new} \leftarrow neighbor(S)$
if $S_{new} < S$ then
$S \leftarrow S_{new}$
else
Calculate the probability of transition from S to S_{new} under T:
$P(C(S), C(S_{new}), T) \leftarrow e^{-\frac{\alpha(C(S_{new})-C(S))}{T}}$
if $P(C(S), C(S_{new}), T) \geq UNIF(0,1)$ then
$S \leftarrow S_{new}$
end if

```
end if
m ← m + 1
end while
```

Using the k-means clustering method, we created sub-regions in the map. We converted a store near the centroid of the sub-region to a mini-DC. Then, we clustered cities and stores in that sub-region under the mini-DC. Next, we finalized the network by connecting these mini-DCs to the DC. The initial solution S_0 is generated by a local search applied to that configuration. The random neighbor S_{new} is generated by switching an arbitrary bit in one of the store attributes. $C(S)$ denotes the cost incurred from the solution set S. If the cost value of $C(S_{new})$ is less than $C(S)$, then S will be the new best solution. Otherwise, we need to check the probability of transition $P(C(S), C(S_{new}), T)$.

The algorithm operates with some pre-defined parameters. The number of steps M is a parameter that is changed based on the size of the problem. Users may set a time limit parameter to terminate the algorithm as well. We propose defining a parameter α between 0 and 1 to control the change in cost. We decided on the reasonable value of α by doing various numerical tests and sensitivity analyses. Yet, the decision-maker is free to change the value of α. One can increase α to focus more on local search to find practical solutions. Decreasing α would increase the probability of transition and the chance to reach global optima. If the transition probability is as high as some randomly generated number between 0 and 1, we proceed to the next step with S_{new}. This simulation procedure helps us escape from local minimum points and find satisfactory solutions.

1.5 Verification and Validation

The verification process involved checking if the implemented mathematical models and the heuristic algorithm represent the conceptual model accurately. In this case, the correctness of these models was tested by checking if the connections between facilities obey the constraints, limitations, and assumptions provided within the conceptual framework. Utilizing the facility network graphs, we have ensured that all variants of the mathematical models satisfy the constraints accurately. Subsequently, we have manipulated the parameters of the algorithm to observe how the extreme changes in parameters correspond to a change in the network by using synthetic data. Testing these extreme scenarios such as increasing holding costs in DC or Mini-DC, we have observed that the algorithm responds to risk pooling. Thereby, we have verified the compatibility of the mathematical model.

Integrating the real data into both the algorithm and mathematical

α_l	α_k	μ	σ	$\hat{\mu}$
0.95	0.95	2.24-3.35	1.80-2.21	0-1570.23
$\hat{\sigma}$	h_{ij}	h_{lj}	L	g_i
0-27.67	5	10	10	112.68
g_l	q_i	q_l	c	f
112.68	14.08	14.08	1000	300

Table 1.1: Initial parameters of the base model

model for validation, we have identified the boundaries and constraints of the algorithm and tested its consistency by comparing it with the mathematical model. In other words, we have tested if the algorithm obtained similar results in a real system under the same set of conditions as the mathematical model. As the mathematical model would provide the optimal solution, the closeness of the objective function value of the algorithm to the optimal objective function value emphasized the consistency of our alternative solution.

Solving these models in smaller sizes with the same parameters, we have observed that the algorithm gave the same or significantly close results obtained through the mathematical programming model. Extending the study for the base problem setting with 7 stores and 10 cities, we changed the problem parameters both in the algorithm and the mathematical model under different scenarios. In this case, the outputs of the algorithm regarding objective function value were significantly close to the optimal objective function value which can be observed in Tables 1.1 & 1.2. Thereby, we have ensured the applicability and acceptability of the algorithm in the real system by ensuring the consistency of the outputs to the results that the mathematical model proposes.

1.6 Project Outcome and Deliverables

In our project, our focus was on creating a simulated annealing heuristic that provides us with decisions about the network design, namely the facility configurations. Our objective was to minimize the operational cost while finding the optimal configuration of the decision variables regarding the constraints. As a result, we have achieved a complete network configuration that minimizes the existing costs. The company can implement this model to reconfigure and restructure their supply chain system so that they could have an improved network design by making educated decisions using our

	Parameter Changes	Algorithm Step Size	Objective Value of Algorithm	Objective Value of Mathematical Model
Base: 7x10		8000	2767.6097	2767.61
Ins1	$\alpha_l \to 0.99$	8000	2829.5459	2829.55
Ins2	$\alpha_k \to 0.90$	8000	2711.6750	2711.68
Ins3	$\mu \to 10$	8000	4409.8347	4409.83
Ins4	$\sigma \to 5$	8000	4078.3883	4078.39
Ins5	$\hat{\mu} \to 2000$	8000	201255.5333	201256
Ins6	$\hat{\sigma} \to 100$	8000	16272.4744	16272.5
Ins7	$h_{ij} \to 20$	8000	2767.6097	2767.61
Ins8	$h_{lj} \to 2$	8000	1557.9486	1557.95
Ins9	$L \to 2$	8000	2495.7653	2495.77
Ins10	$g_i \to 300$	8000	2870.2016	2870.2
Ins11	$g_l \to 1000$	8000	3270.7025	3270.7
Ins12	$q_i \to 50$	8000	4316.4962	4316.5
Ins13	$q_l \to 2$	8000	2507.0700	2507.07
Ins14	$c \to 300$	8000	2767.6097	2767.61
Ins15	$f \to 900$	8000	2767.6097	2767.61

Table 1.2: Investigation of the objective functions of the mathematical model and the algorithm under different parameter scenarios

approach. The main output of our approach is the store and city maps that show the network design for both online and offline demand fulfillment.

1.6.1 Results and Improvements

Our algorithm outputs an interactive map integrated with Google Maps and a summary of results by showing how much the new design improved the existing supply chain system. By considering risk pooling, mini DCs, lost sales, and other crucial aspects, we are able to improve the OC network design and help the company make educated decisions. In addition to the retailer's current facility configurations, Invent Analytics's solution approach and related facility configurations were shared with us. For benchmark, we have compared our model's solution with the cost of these two structures and reported the improvements. Comparing the former structure, we observed a decrease in lost sales and holding costs with the integration of risk pooling and mini-DCs.

Graphical User Interface

As the last phase of implementation of our project, we built a user interface (UI) on a third-party platform, Anvil, a Python-integrated platform for building and hosting full-stack web apps. Since Anvil has open-sourced web server, we could build a connection between Anvil and our code. In this way, each platform can feed the other. Over the UI, we provide some

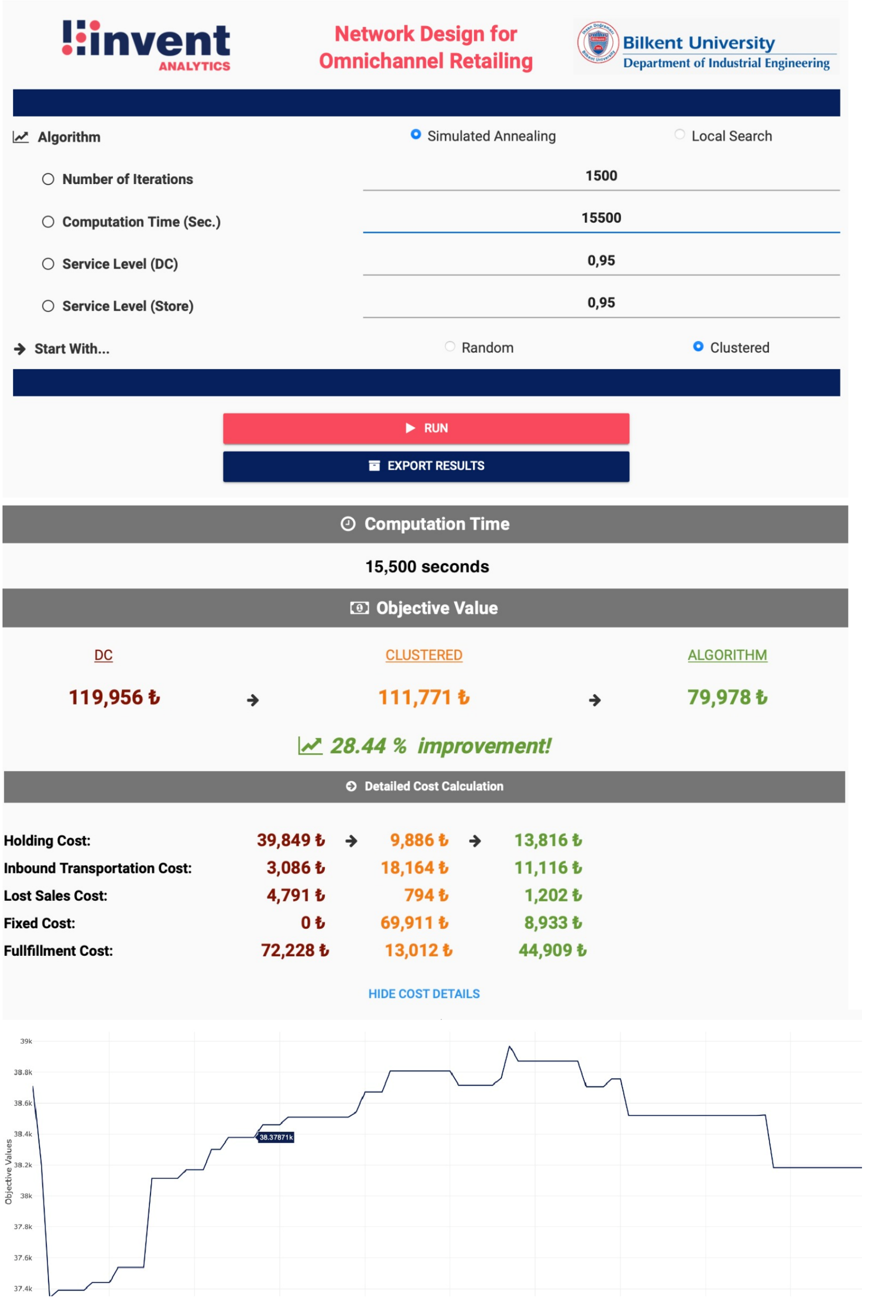

Figure 1.4: The results and improvements of our solution implemented on the user interface

options regarding our algorithm. Users may choose the type of algorithms (Simulated Annealing or Local Search) or select the first solution that initializes the algorithm. Moreover, users can enter the number of iterations and maximum computation time of the algorithm. Additionally, service lev-

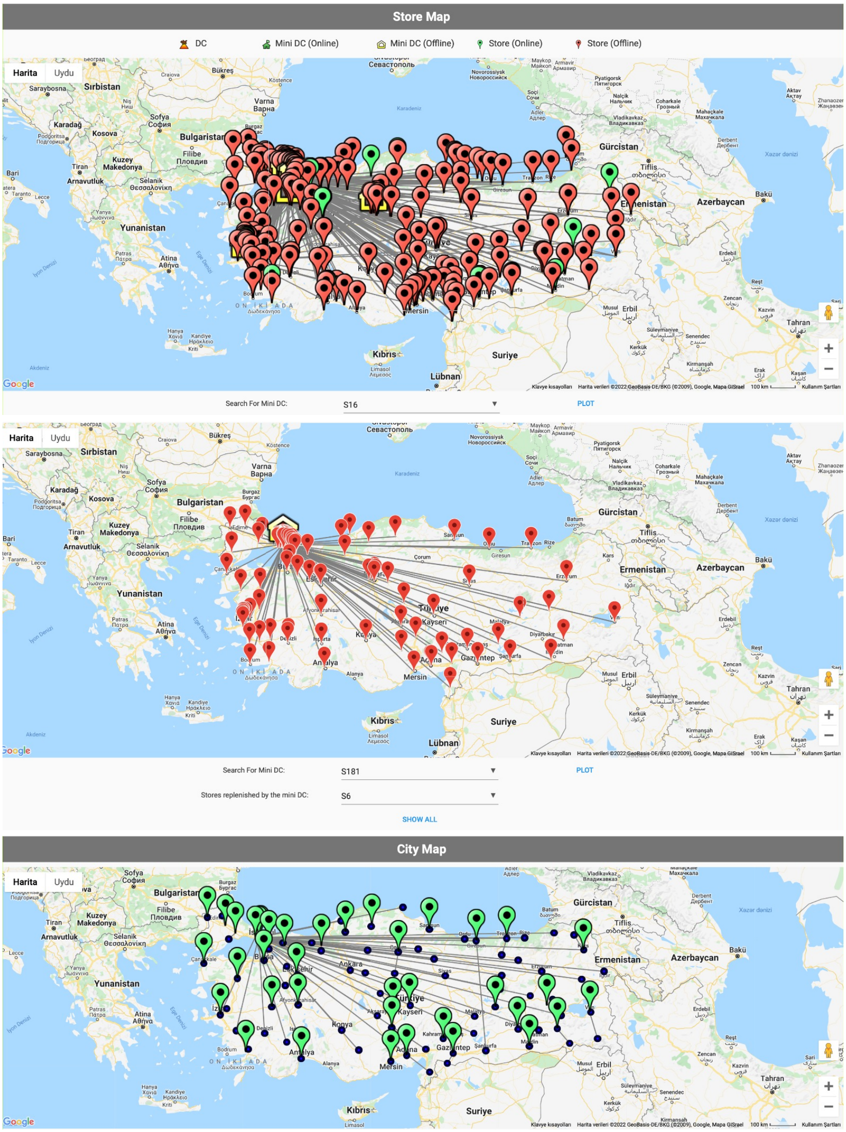

Figure 1.5: The resulting maps of our algorithm on the user interface

els for stores and DC can be input via the UI. As the run button is clicked on UI, our algorithm takes the inputs from Anvil and starts processing. As soon as the run completes over the server, the outputs are sent back to Anvil to display the results. The UI displays the algorithm's running time, a detailed cost calculation including the improvements made across different scenarios, and an improvement plot indicating objective values through iterations. Moreover, the network outputs are displayed on two different Google Maps separately: the one for stores and the other for cities, whose names are displayed as labels when clicked on them. Furthermore, users may narrow the network to a specific mini DC and its connections. Finally, we have an export button in our UI to download the final results and the executive summary of the overall changes made in the system. Figures 1.4 and 1.5 show two sample screens of the user interface.

1.7 Conclusion

Our proposed algorithm decreases the inventory holding and lost sales costs of the current network by pooling the online and offline demands. Utilizing the results of our project, the retailer will obtain more cost-efficient network configuration that can be integrated into their strategic planning. As a further step, the company may also run the algorithm for multiple products (by adjusting the necessary data and model parameters), and utilize our solution as a comprehensive approach.

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Conta Aralık Şikayetlerinin Temel Sebep Analizi | 2

Arçelik Buzdolabı İşletmesi

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Özet

Bu çalışma Arçelik Buzdolabı Fabrikası'na gelen buzdolabı conta aralığı hatası şikayetlerinin temel sebep tespiti için yapılmıştır. Olası temel sebepler farklı etkileşim koşullarında istatistiksel modellerle test edilmiştir. Veri girişi yapıldığında temel sebebi ve uygun algoritmayı gösteren bir karar destek sistemi tasarlanmıştır. Bu sistem sayesinde hem mevcut conta aralığı hatası hem de gelecekte oluşabilecek şikayetler için temel sebep analizi yapılabilecektir.

Anahtar Sözcükler: Buzdolabı, conta, kalite kontrol, temel sebep analizi, karar destek sistemi

Root Cause Analysis of Gasket Gap Complaints

Abstract

This study was carried out to determine the root cause of refrigerator gasket gap error complaints received from Arçelik Refrigerator Factory. Possible root causes were tested with statistical models under different interaction conditions. A decision support system has been designed to show the root cause and the appropriate algorithm when data is entered. By using this system, root cause analysis will be possible for both the current gasket gap error and the complaints that may occur in the future.

Keywords: refrigerator, gasket, quality control, root cause analysis, decision support system.

2.1 Company Information

Arçelik is the second largest white goods company in the market of Europe and it ranks first in the Turkish white goods market. Arçelik refrigerator factory is one of the Koç group brands, and it was established in 1975. The refrigerator plant is Arçelik's largest and most profitable business. The product capability portfolio of the company consists of no-frost refrigerator, wardrobe type refrigerator, mini refrigerator, double door refrigerator, fridges with freezer on the bottom and freezer on top, refrigerators 70 cm in width and smaller, refrigerators between 70 cm or 80 cm in width, fridges with a width of 80 cm and above.

2.2 System Analysis

2.2.1 System Description

Arçelik refrigerator plant in Eskişehir produces refrigerators for Arçelik, Grundig, and Beko brand names. One of the facilities in the plant produces door thermoforming, the other has assembly lines, painting division, pressing machine sections to give shape to doors and bodies of the refrigerator. Although some of the raw materials are produced in the company's thermoforming facility, a lot of them come from the suppliers. One of the materials that comes from the two different suppliers is the rubber gasket.

2.2.2 Problem Definition and the Scope of the Project

The concern of this project is the customer dissatisfaction due to rubber gaskets in the refrigerators which are below 70 cm length. The refrigerator types "D70540" and "D70465" are the company's main focus on the rubber gasket problem. The problem frame is the gasket which cannot fit into the door or get loose when it is used and creates complaints such as "Not-closing","deformed","dislocated", "torn","other". The problem can be caused by many reasons such as temperature, supplier of the gasket, operator, plastic sheet of the refrigerator door, and the door type.

The company carries out mass production to meet the high demand. The production takes place in three shifts, and approximately 400 products are produced in each shift, but there is a lack of inspection due to this serial production and inspection with template is performed for about 3 out of 1200 products. As a temporary solution, the company tried to put a small piece of iron inside the lid and prevent the gasket from coming apart, but while this increases the cost, it is not an engineering solution, either and will not provide a lasting effect.

2.3 Solution Approach and Proposed Model

To identify the root cause of gasket gap errors, interaction effects are decided to be observed. The combinations of the effects of plastic sheet of the refrigerator door, temperature, supplier of the gasket, operator, or the door type are examined.

2.3.1 Possible Root Causes

Plastic Sheets (Thermoform Type)

Plastic is used as a raw material for doors. These plastic sheets are produced by the company itself. The shape of the plastic is given by two molding machines to obtain the shape of that sheet. One of the molding machines is named "inline" and the other one is "rotary". In the inline molding machine, 1.1 mm plastic sheets are being produced where in rotary machine the plastic door thickness is 1.4 mm. Since these two molding machines produce different plastics according to thickness, this situation affects the quality of door. Due to the fineness of the inline plastics, the production cost of the door plastic is cheaper than the rotary plastics. The reason why the company uses inline production of plastics is retrenching.

Plastic sheets have a rectangular well around it where the gasket is fixed. As the thickness of the plastic sheet decreases, its durability decreases, too. Therefore, gasket can be dislocated easily from the well. In the process where the gasket is put into it, there is only one inspection done in each shift with a template. Therefore, out of approximately 1200 refrigerators produced, only three of the plastic sheets are inspected. Of course, there is a time limit that the company might face everyday so they cannot give efficient time to inspect that process. Hence, the quality of the plastic sheets cannot be maintained. With that quality issue, any gasket put on that area might get loose with the small changes in the temperature. Also in a FRZ door, the air can get into due to the fact that the gasket cannot fit firmly into the well. To test the error rate of plastic sheets, their confidence interval levels should be calculated by conducting linear regression.

Temperature (Weather Condition)

The plastic gaskets that are used in the refrigerator are sensitive to heat. Air infiltration is highly related with the conservation conditions of the seal (Afonso and Castro, 2010). Hence, it can be said that the gasket can be affected by the heat coming from outer surface. Also, the study indicates that air condensation which can lead to the icing in the freezer is driven from both humidity and the temperature of the environment. The air comes from outside and goes through inside with the gap in the gasket (Gulmez and Yılmaz, 2020). In our case, air also comes from outside and turns to the condensation and lead icing. Therefore, the conservation circumstances have great importance. Also, the installment place of the refrigerator is significantly important in terms of temperature. To understand behaviour of the PVC material in exposure to heat, we can apply a thermogravimetric test and differential thermal analysis can be used. If the material cannot have the endurance that it must have, we should discard that material. If these materials are produced in the mass production in supplier companies, with the use of quality control techniques, some specimens can be used to check.

Supplier

Suppliers are responsible for the production and delivery of the gaskets. This gasket problem may be caused by supplier change because although the material sizes are the same, each supplier produces gaskets with different chemical structures. Therefore, the hardness, flexibility and durability value ranges of gaskets produced with different chemical structures may vary. Such physical properties affect the durability ratio between the gasket and the threads on which the gasket is attached. In addition to possible physical differences, the transportation and storage conditions of the newly agreed supplier may differ from the previous one. Gaskets can be damaged, crushed or compressed during storage and transportation, and their efficiency rates may vary depending on storage temperatures. All these reasons that may occur depending on the supplier may cause the fact that the gasket cannot fit into the well good enough. To differentiate which supplier sends problematic gaskets, data should be collected that is separated according to suppliers, then we compare the results by conducting Anova test. In the Anova test, a hypothesis test is conducted to decide which suppliers' seal is out of the specified range, which is the confidence intervals. By doing this, we will analyze possible correlations between suppliers. Then, confidence intervals can be used to interpret the significance level.

Arcelik works with two different gasket suppliers. Ilpea and Rehau supply gasket to the company with batches of 80 and 120 units. The company has an agreement with Rehau for a longer time than Ilpea. When Rehau monopolized as a gasket supplier, Arcelik decided to add a new supplier since the gasket is a crucial part in the refrigerator door. Lately, Arcelik quality engineers claim that Rehau became imprecise on supplying gaskets in terms of quality and delivery times. The late arrivals and quality problems of gaskets have an impact on the customer complaints. Therefore, it is aimed to test the supplier effect, focusing on which company is the supplier. Regarding the problems of Rehau, a new design of technical drawing of gaskets which has more precise measurements in gasket wingspan can be submitted to the supplier company.

2.3.2 Data Analysis

The company provided us data from 2021 January. In addition, as a recent study and observation, customer and dealer visits (for both Beko and Arçelik dealers) were made by the company for gasket problems in Urfa was given to us. The current technical drawing and acceptance interval data of the rubber gaskets are used to gain insight about quality test approaches. To ensure whether there is seasonality effect, customer complaints data are evaluated by considering the forecasting methods. The information regarding the operator is received to evaluate the operator effect in rubber gasket gap problem. Air inflation problem is researched and discussed with the quality assurance manager of the company to understand the possible impacts on the main problem. The information about plastic sheets is also important to analyze the deviation between gaskets by applying linear regression. Moreover, supplier data are provided to understand the possible correlation between gasket problems and supplier selections.

2.4 Validation

The method and mathematical models we used were selected in accordance with problem definitions that we did and the data that we have received. The data used in the created model are close to reality and estimated values are given. The estimated values given are the product of a combination of the data we have and a deep analysis. If the mathematical models and methods used give effective results which have been proven with scientific methods will emerge in the determination of the root cause. At this point, we evaluated whether the data used are correct and give the desired result with the data type validation, range and constraint validation, code and cross-reference validation, structured validation and consistency validation.

To validate our analysis, we use expert opinion from the quality control department of company. Company representatives evaluated the analysis in the light of their experiences. In this validation method we separated data as train and test groups. The train data were used to create the method, and the test data were used to predict the variances from train data.

2.4.1 The Result of Dynamometer Test

2^k Full Factorial Experiments is proposed to investigate the association between factors and detect the possible root causes of the rubber gasket problem. By considering the Lenth Plot results, the most effective predictors are the door and combinations of region-door-thermaform, door-thermoform and region-door. According to the dynamometer data that are received from the company, there are 160 combinations for the D70 refrigerators with 5 factors which are region type, door type, supplier, thermoform type, mold type. The response of this model is assumed to be the value of the tensile test. It is assumed that as strength of the applied force is higher, the yield of the combination is also higher and it implies that it is hard to get the gasket output errors. Therefore, in order to test the accuracy of the dynamometer measurements and find the relations between the predictors and response we used R. Since these test results contain replications for some of the combinations, it is possible to fit the model.

First of all, we applied power transformation to normalize the distribution of the predictor values. To find the relation between the predictors and response, we used scatter and correlation plots. We observed that gasket is related to both tensile test and thermoform.

In the interaction plot, two clusters were apparent. The density of the left upper side cluster is higher which implies that the gasket received from the Rehau comes off when higher forces are applied compared to the gasket received from the Ilpea. Through our analysis, it can be claimed that there should be some relationship between the change in magnitude of tensile strength and supplier selection.

The data accumulation between the tensile strength and door type is demonstrated. It is observed that approximately two clusters are apparent. The density of the right upper side cluster is higher than the left side cluster. It can be stated that it is more likely to have more density if the value increases on the x axis. Moreover, having tensile strength between 4.5 and 5 increases the density of the cluster. In addition to this, the left side cluster has less density but it spreads over more areas, so it is more comprehensive.

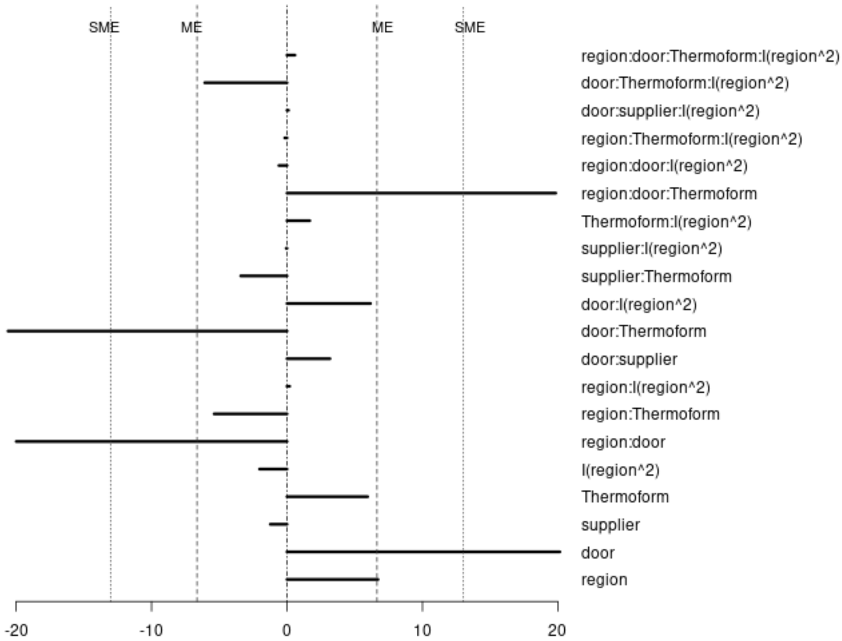


Figure 2.1: Lenth effect plot: important variables have long spikes

After that, we checked the adjusted R-square to test the accuracy of the data. In the initial version the adjusted R-square value was 21.34%. This ratio was low and we needed to increase it by applying some statistical methods. As the ratio was low, we took the interactions of the predictors and applied a step function to find the best AIC value. The smaller AIC gives the best result. When we checked the adjusted R-square value, it was 41.44%. So in some way we increased the accuracy of the model.

When we examined the diagnostic plots, it can be said that the residual vs. fitted graph almost satisfies the condition of a straight line. Also, most of the Q-Q plot points are placed on the dashed line. Scale-location graph gives information about the standard deviation and in these plots, it can be claimed that the standard deviation is less. To improve our model another method is used and we checked the interactions of all predictors with all of them. The adjusted R-square then became 51.57%.

We also interpret the normal Q-Q plot to evaluate the effect of the main and interaction factors on the model. According to the normal Q-Q plot, it is proposed that thermoform, door, interaction of region and door, interaction of region, door and thermoform have a significant influence on the fitted model since they are located below or above the straight line. When the door ratio is less than or equal to zero, the percent conversion rate decreases from 4.9 to 4.1, in the 0-0.307 interval for the supplier and door interaction. If the door ratio is equal to 1.098 then the percent conversion rate decreases from 4.65 to 4.5. The interaction of the thermoform vs. door type shows both increase and decrease depending on the door ratio. If the door ratio is at its low level of 0, then the line shows a decrease from 4.66 to 4.65, whereas the ratio is 1.096 level then the line increases from 4.61 to 4.69.

In the beginning of the model, it can be claimed that supplier type and thermoform type have a high influence on the magnitude of the tensile test as considering the scatter plots and correlation plots. However, it is investigated from the final fitted model, the rubber gasket error can be resulted from some main and interaction effects mostly. The magnitude of each effect is found and some of the predictors' effect on the model which can be seen in Figure 2.1 is highly important. These are thermoform, door, interaction of region and door, interaction of region, door and thermoform. Therefore, we can state that these are the root causes of our analysis.

2.4.2 Clustering Algorithm

The purpose of the *clustering* is to partition the data into K clusters. The aim is to ensure that the clusters obtained at the end of the partition process have maximum similarities within clusters and minimum similarities between clusters. It is important to support the root cause analysis process by dividing our data into two clusters. The number of clusters can be achieved by drawing cluster plot on R. There is only one sharp decrease and some smooth decreases. Sharp decrease makes this data have two clusters.

When the misclassification rates of each cluster without including low, mid, and high temperature predictors, the lowest misclassification rate is obtained as 0,2608. From all clustering predictors, the best clustering predictors are respectively pull point 1, pull point 2 and gasket variables. R prepares predictors table which gives information about the situations where at least one of the three predictors we found in the best cluster is absent. These predictors may cause another root cause when they come together. When these data applied on R, without temperature regressors, the train misclassification rate is 0,4239. When the misclassification rate table is considered, the best subset is on the red row whose cross validated misclassification rate is 0,25.

2.4.3 K Nearest Neighbour

The KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other. By obtaining the real data, we moved on to make analysis with KNN.

We try to get K value that gives lowest error while we get K values for all subsets of the dataset. To do this, we store the misclassification rates of the all 16383 subsets. When the temperatures are included, the perfect

KNN prediction can be obtained. As a result, the the dimensions of well measured in the area 1 of the seal, door type (whether inline or rotary) and low temperature directly affect the accuracy of the grouping the data.

To select the K that is right for our data, we run the KNN algorithm several times with different values of K and choose the K that reduces the number of errors we encounter while maintaining the algorithm's ability to accurately make predictions when it is given data it has not seen before.

As we know that the loop we made gives us the lower misclassification rate, we can hypothesize that these three predictors have more importance and one can conclude that these can be the real reasons why we faced such problem. According to the information we acquired from the industrial advisor, they also suspect from the temperature and door type and they decided to change the inline door type. Low temperature should not be understood that lower temperature gives defective item. It should be understood that we can divide the group in terms of whether these variables are 1 or 0.

It can be seen that the dimensions of well measured in the area 2, 3 and 4 of the seal, directly affect the accuracy of the grouping the data. As we know that the loop we made gives us the lower misclassification rate, we can hypothesize that these three predictors have more importance and one can conclude that these can be the real reasons why we faced such problem.

2.4.4 Random Forest Classification

Another algorithm we used to determine which variables are affected by our dependent variable "error" is the Random Forrest classification algorithm. We also used this algorithm to confirm the results we found as a result of KNN and obtain more accurate results. Random forest is a Supervised Learning algorithm that uses ensemble learning methods for classification and regression.

Due to the effect of temperature on the accuracy rate of the data prevents the algorithm from working correctly. The temperature factor independently generated data were converted to CSV format and were run in Random Forest algorithm. The importance scores were calculated with an accuracy rate of 92.85%. As a result, it was determined that the importance scores of the 2^{nd} and 3^{rd} seal well measures were the highest.

Overall error rates of the methods that we have used can be seen in Table 2.1.

2.4.5 Kernel Support Vector Machines

Another method that we used to determine which variables have the most significant effect is the SVM Kernel method. By using the real data, we

Methods	Best Output	Method Accuracy Rate
K-nearest Neighbors Algorithm	Seal well Measure 2, 3, 4	%97
Random Forest Algorithm	Seal well Measure 3, 2	%92
Clustering Algorithm	Seal well Measure 1, 2 and gasket type	%73
Bayesian Logistic Regression	Pull Point 1, Seal well 4	-
Kernel Support Vector Machine	Seal well 3,4, gasket and door type	%87,6

Table 2.1: Method accuracy rates

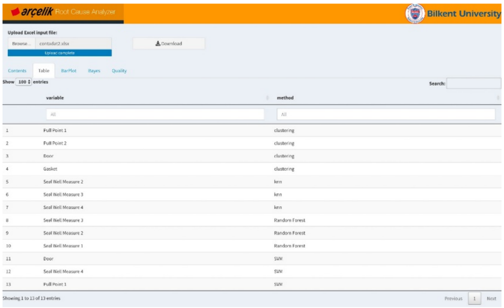
made analysis with Kernel which takes the data as an input and transform it into the required form. We tried to reach the Kernel matrix to summarize the similarity measurements. When we applied the Kernel function to the made up data, the important variables are seal well 2,3 and 4 are obtained. Unlike that when the real data are used some extra variables are found significant. Additionally to the seal well 2,3 and 4 gasket, door, thermoform and pull point 1 have a significant effect.

2.5 Decision Support and Implementation

An important output of this project is a user interface (UI) accessible for company engineers. Detecting similar problems from data set with our machine learning algorithms is our motivation. An engineer can upload an Excel file to UI, which is generated by Shiny and can obtain the most significant subsets as the possible root causes from each ML method with their accuracy rates. Until the solution of this root causes are found, the engineer can add the specific dimensions of the material and see how probably an error occurs due to this material. It provides both frequentist statistical models and Bayesian logistic regression. Decision support system screens can be seen in Figure 2.2.

2.6 Benefits to the Company

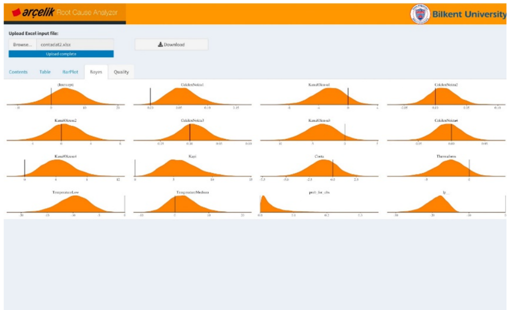
By implementing our test approaches to the possible root causes, the main reason for the gasket gap problem can be found. After the main cause is determined, the test methods, algorithms and problem solving approaches can be applied to get the solution. In this way, positive progress can be achieved in terms of minimizing customer complaints and reducing the cost



Screen 2: Table screen

Screen 3: Bar plot screen

Screen 3: Rar plot screen



Screen 4: Bayes screen

Figure 2.2: User interfase to decision support system

of defective products.

2.7 Conclusion

Throughout the project, we aimed to decrease the customer complaints due to gasket gap error. We analysed complaints and company processes to understand the root causes. Due to our analyses that we did by using Excel, Python and R, we represented the interactions between possible root causes to get the accurate root cause. With the decision support system, we aimed to serve a user interface that gives the root cause of complaints by the given data to the company representatives.

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3 Depo Alanının Verimli Kullanımını Sağlayacak Karar Destek Sistemi

Aselsan

Proje Ekibi
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Özet

Bu proje Aselsan Rehis ambarının hazırladığı kit sayısını arttıracak bir karar destek sisteminin geliştirilmesi üstünedir. Temin edilen veriler ışığında hazırlanan karar destek sistemi, her iş emrinde sık kullanılan malzemeleri belirleyerek, aynı iş emirlerine ait ürün kümelerine erişim hızını artırarak kit hazırlama işlemini hızlandırmayı hedeflemektedir. Karar verme süreci, en iyi malzeme eşleştirmelerini apriori algoritması ve hiyerarşik kümeleme algoritması kullanarak, depo içinde en uygun yerleri bulmaya odaklanır ve hazırlanan kitlerin sayısını artırmayı hedefler. Böylelikle sistemin performans ölçüsü olan zaman açısından şirkete fayda sağlayacaktır.

Anahtar Sözcükler: Kümeleme, İlişik Malzemeler, Kitler, Karar Destek Sistemi, Depo, Kardex.

Decision Support System for the Efficient Usage of Storage Yard

Abstract

This project is primarily about the development of a decision support system that will increase the number of kits that are prepared according to received work orders from Research and Development department in Aselsan Rehis. Based on the data provided by the warehouse manager, Bill of Materials (BOM) of each work order is analyzed to maximize the number of kits prepared. By determining the frequently used material pairs in each work order, the provided decision support system aims to maximize the number of kits by finding clusters based on products belonging to the same work orders in a shorter amount of time. The decision-making process focuses on finding the best material pairings based on the appropriate clustering methods which are apriori algortihm and hierarchical clustering algorithm to achieve a faster allocation system of materials. Feasible material pairings will provide optimal locations inside the warehouse which will increase the number of prepared kits that will eventually benefit the company in terms of time, which is the performance measure of the system.

Keywords: Clustering, Material Pairs, Kits, Decision Support System, Warehouse, Kardex.

3.1 Company and problem description

ASELSAN is the biggest defense company in Turkey, which meets the communication needs of the Turkish Armed Forces Foundation. It was established in 1975 and has been functioning to provide a wide product portfolio including communication and information technologies, radar and electronic warfare, electro-optics, avionics, unmanned systems, land, naval and weapon systems, air defense and missile systems, command and control systems, transportation, security, traffic, automation, and medical systems. In the ASELSAN depot, there are a variety of materials that are stored in shelves and Kardexes, waiting to be prepared into kits to serve the work orders of System Application and Product in Processing (SAP) system and Material Requirements (MR) form coming from employees of various departments. The warehouse has a project-based system and the orders are prepared after the production plan is revised. Due to uncertainty of the requirements of a project, there exist materials supplied but not used yet. This uncertainty results in some overload problems and possible bottlenecks inside the warehouse.

Currently, the kit preparation staff can prepare 1200 kits daily. The

lhs		rhs	support	confidence	coverage	lift	count
{AC-7759-0018}	=>	{5865-7759-3110}	0.003459201	1.0000000	0.003459	287.7395	214
{5865-7759-3110}	=>	{AC-7759-0018}	0.003459201	0.9953488	0.003475	287.7395	214
{5840-7914-0013}	=>	{5840-7914-2000}	0.002537825	1.0000000	0.002537	394.0382	157
{5840-7914-2000}	=>	{5840-7914-0013}	0.002537825	1.0000000	0.002537	394.0382	157
{5840-7914-0013}	=>	{AB-7914-0011}	0.002537825	1.0000000	0.002537	341.7901	157
{5840-7914-2000}	=>	{AB-7914-0011}	0.002537825	1.0000000	0.002537	341.7901	157
{MJ-0000-6099}	=>	{MK-0000-2141}	0.002570154	1.0000000	0.002570	334.4000	159
{MM-7770-0023}	=>	{MM-7770-0024}	0.002893444	1.0000000	0.002893	317.2513	179
{MM-7770-0023}	=>	{MM-0000-1044}	0.002844950	0.9832402	0.002893	169.4350	176
{MM-7770-0024}	=>	{MM-0000-1044}	0.003103582	0.9846154	0.003152	169.6720	192

Figure 3.1: Summary of some rules of subset size two

problem of the kit preparation process is that only SAP suggestions are considered rather than following a complex analysis particularly focuses on material allocation inside the warehouse. Since those grouped materials are feeding the production lines of the factory, it is essential to optimize the preparation time by making the necessary items ready at planned times with the least tardiness. The efficiency of the system outcomes is directly correlated with the material grouping pace, which is affected by the location of the materials in the warehouse. The performance measure of the problem is the number of kits prepared daily which is affected by the adequacy of the material allocation plan of the warehouse. This project will serve a Decision Support System to dynamically allocate the materials into appropriate places to avoid time inefficiency. This way, the production line will be enhanced and fastened. Within the scope of this project, the storing units, namely the Kardexes and the shelves in the warehouse will be organized in accordance with the relationships between frequently used materials.

3.2 Proposed model and system

To locate a material, its size and the availability of the storage units are essential. Every work order includes a BOM list which indicates the materials and necessary quantity to prepare the associated kit. After various aspects and approaches are investigated and the data given by the company is analyzed, the methodology is determined to be using the Apriori algorithm in R to reveal the relationships between frequently used materials. The material groups are clustered by using the feasible Apriori clustering algorithm. From the data set that we evaluated, we sorted the materials in the BOM lists of all the work orders and clustered them according to the outcome of the Apriori algorithm. By using those sorted BOM lists, we evaluated all the lists and tried to find how frequently the specific materials are used together under different work orders. After the investigation of the material lists and their relationship (Figure 3.1), we determined the conve-

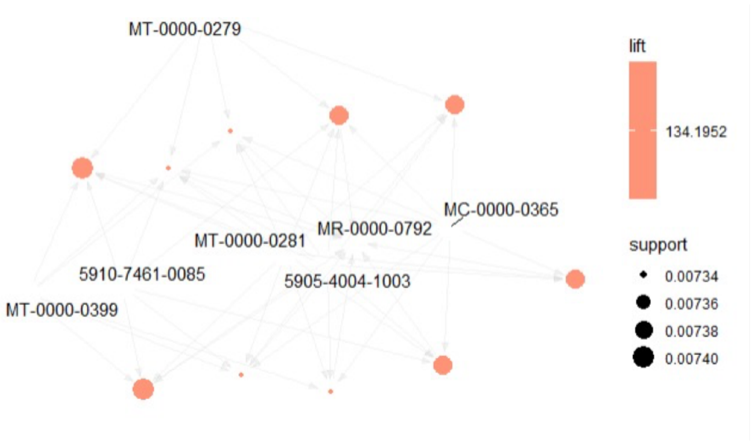

Figure 3.2: A visualization of materials relation

nient allocations to place the materials into the Kardex systems and shelves. Frequently used materials will be stored together and the total time for the preparation of a kit will be minimized by crosswise Kardexing which will allow the project to achieve the objective of constructing the most efficient allocations.

Once the relationships were revealed (Figure 3.2), we planned to make an interface for the company in which they will be able to see the candidate possible locations for materials. This system works with taking into account the possible locations in which the materials are used during production. The major constraints in this process were the immobile materials and materials that can only change locations within a range. Some materials could move only inside the Kardex or shelf that they were already being stored. We created a new Excel file containing 42381 distinct materials that are currently stored, taking into account the probable addresses and material categories that are not available to changing position in the warehouse. There are approximately 39000 transactions within 2.5 years. It is interpreted that the warehouse turnover rate is nearly two years. In this file, there are only materials which we can determine the exact sizes (storage unit types). We also indicated possible locations as shelves and Kardexes and specified each of their compartments that will store the materials. The candidate locations are Kardexes with various types and there are 53 main addresses in total. The number of floors of these main addresses differ. Moreover, the materials that required special storage units like chemicals and humidity cabinets were taken out of the system.

For temporary acceptance areas, microwave and humidity cabinets, material allocations can only be changed among themselves. Our aim is to locate materials that have a relation at the same main address and at the

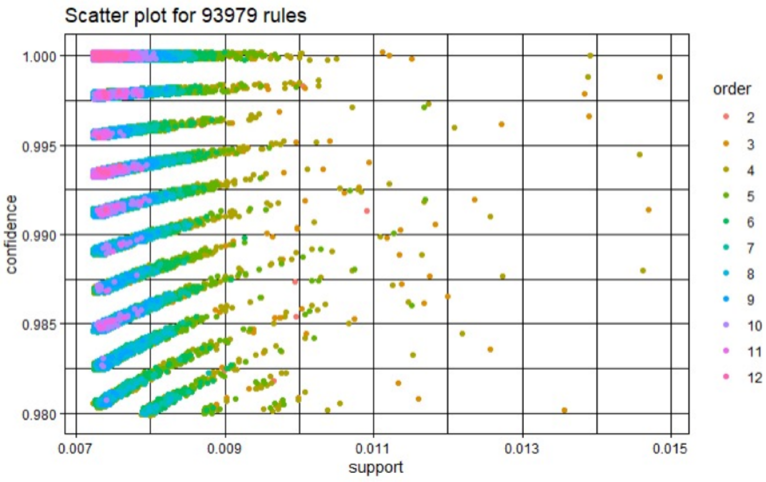

Figure 3.3: Visualization of strength of the rules

same floor or alternatively, to locate them in different main addresses. The benefit of putting them in different main addresses will be the reduced time it will take to gather the materials for a kit. In other words, it is planned that the materials that have a relation will not be placed to the various floors of the same main address (cross-Kardexing). To keep track of the remaining capacity of locations, we will be subtracting the material that is already placed in location X from the total capacity of that location. The system will then take into account the capacity constraints, too. For this purpose, we considered the sizes of materials and calculated how many materials will fit into a specific location. According to material size, association rules and capacity constraints, the decision-support system will provide suggestions of possible locations for any material. When the algorithm is run once more and adapts the allocations to the recent work order data, first our tests in R will be run to reveal the association rules with recent work orders. The association rules will be exported to an Excel file. Considering these rules, we will suggest candidate locations of recent data.

3.3 Validation of the approach

The strength of association rules between materials are indicated with the support and confidence levels of the Apriori algorithm (Figure 3.3). Measures that are used in apriori algorithm are support, confidence and lift. The frequency of occurrence of items is the support value. The confidence measures how often A and B occur together based on the number of A occurring. Lift is one of the correlation measures of the relation between items.

The validity and significance of the association rules stem from the fact

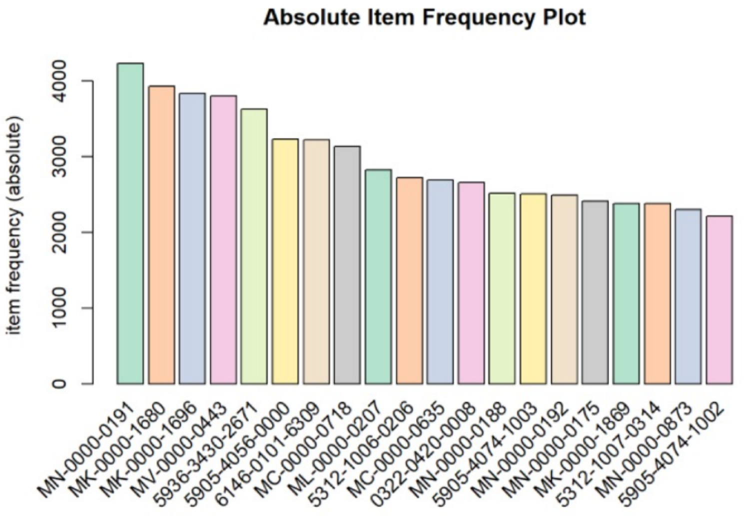

Figure 3.4: Histogram of materials frequency in data

that the investigated rules include materials that have the highest frequencies in the analyzed work orders. The frequency of the most frequent materials are shown in the histogram in Figure 3.4. After investigating the association rules we tested in R, we confirmed that the effect of these rules will be in correlation with the show up values of materials. Validation was done in three different ways. The first way followed was using Excel manually to check whether the association rules obtained from the code in R were meaningful. The support, confidence and lift values were double-checked. By using handwritten formulas of support, lift and the confidence values are recalculated. These values are also consistent with the R results. In addition to these findings, we sorted the lift values in ascending order, we ended up with the same sorting with R. The second validation we made was using a simulation in Arena to check whether the proposed system would decrease the kit preparation time. Analyzing randomly picked association rules, we recorded the real (under the existing allocation plan) and proposed (under the new allocation plan we propose) times inside the Arena Simulation and observed that the average increase in efficiency for all rules is 13.47%. In other words, the new proposed allocation of the warehouse will enable an increase in the number of kits prepared. The third way of validation was by using Python and checking the accurateness of the association rules. It was again observed that the rules were as strong as the system required, with aimed support and confidence levels.

With the current application of the algorithm, the minimum confidence level is taken as 0.98 and the support value under this confidence is taken as 0.00073. The confidence values vary between 0.98 (min) and 1 (max).

The mean is observed as 1 and the median is observed as 0.9968. For the minimum support value of 0.0073; lift values varied between 14.33 (min) and 134.2 (max). The mean and median are 49.56 and 48.24, respectively; see Figure 3.5 (Amiry, 2015).

3.4 Integration and implementation

We have received distinct dimensions of every material, the available warehouse locations and the Warehouse Size Type (WST) dimensions from the given Excel file. The WST dimensions have been compared with the sizes of materials. A macro code that converts bill of materials in each work order has been written and the output of macro code is applicable for R or Python to give an output. Apriori algorithm is worked in R and Python and gives the association rules according to predetermined support and confidence level. The program is able to extend the number of association rules by changing the support and confidence values. After the comparison, the identified relations (association rules) have been applied to the system of material size and location comparisons.

In the first part of our implementation plan,material sizes are compared to dimensions of possible warehouse locations –if it is applicable to empty the convenient locations inside the warehouse– that are suitable for reallocation, the materials will be reallocated on Kardexes and shelves considering the relations amongst them (association rules). After the first step, we will be providing the company with a DSS which will be practical to use as a dynamic algorithm. Aselsan is a defense industry company and therefore the company has strict restrictions considering security procedures such as the inability to connect to the internet from the warehouse. Thus, Aselsan

```
```{r}
summary(association.rules)
```

set of 93999 rules

rule length distribution (lhs + rhs):sizes
    2   3   4   5   6   7   8   9   10   11   12
   38   748 4278 11994 20630 23637 18492 9881 3489   740   72

   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
  2.000   6.000   7.000   6.909   8.000 12.000

summary of quality measures:
    support   confidence   coverage   lift   count
 Min.   :0.007306   Min.   :0.9800   Min.   :0.007306   Min.   : 14.33   Min.   : 452.
 1st Qu.:0.007355   1st Qu.:0.9937   1st Qu.:0.007371   1st Qu.: 36.54   1st Qu.: 455.
 Median :0.007452   Median :1.0000   Median :0.007484   Median : 48.24   Median : 461.
 Mean   :0.007560   Mean   :0.9968   Mean   :0.007585   Mean   : 49.56   Mean   : 467.
 3rd Qu.:0.007662   3rd Qu.:1.0000   3rd Qu.:0.007678   3rd Qu.: 63.03   3rd Qu.: 474.
 Max.   :0.028854   Max.   :1.0000   Max.   :0.029436   Max.   :134.20   Max.   :1785.
```

Figure 3.5: Apriori's output summary in R

generally uses Excel. To implement this algorithm, a company should have access to either R and Python. However, due to the easier implementation opportunities of R, it is highly recommended to use this software. Python was used to double-check the accurateness of the outcome. Based on the past data and statistical parameters that we determined, the algorithms find the relationships of some frequently used itemsets. These materials' relationships are either not considered by the company or there has been no action taken to replace them according to their relationships. The analysis is aimed to reveal these material relationships. As an output of the implementation of Apriori algorithm, the relationships between the materials are discovered. Similarly, with the VBA code, it is observed whether the current addresses in the warehouse are ideal or not. In the first part of our implementation plan, material sizes are compared to the dimensions of possible warehouse locations that are suitable for reallocation, and the materials will be suggested to be reallocated on Kardexes and shelves considering the relations that has been found by R.

3.5 Benefits to the company

The main motivation of the project is to decrease the cycle time of the kit preparation process. Therefore, an increase in the number of kits that are prepared is aimed. For this purpose, the Decision Support System is developed in a way that is specialized to ASELSAN. It is specified according to the ASELSAN Rehis facility. The expectation of the company is to reallocate a desired small number of materials which will make it possible for material handling, due to the fact that changing locations of more materials would cause harder tracking and a less applicable reallocation plan. The provided plan should be feasible and easily handled by the company for implementation to avoid interrupting the daily routine of the warehouse operations. The tracking of materials will also be easier. We tried to obtain maximum effect with minimum handling inside the warehouse. It can be emphasized that we have reached more than 23% of the transactions by handling 0.5% of all materials which corresponds to 214 frequent and related materials.

With a more efficient allocation plan for the materials in the warehouse, the number of kits prepared daily would gradually increase in time. Furthermore, finding out the relationship of the materials eliminates the system's current problem of bottlenecks. The candidate locations for the materials that we have provided will be applied for reallocation of related materials. The existing materials are going to be used for the production while the new arriving materials are being placed to the empty addresses. The objective is to locate the materials that have a relation at the same main address and at

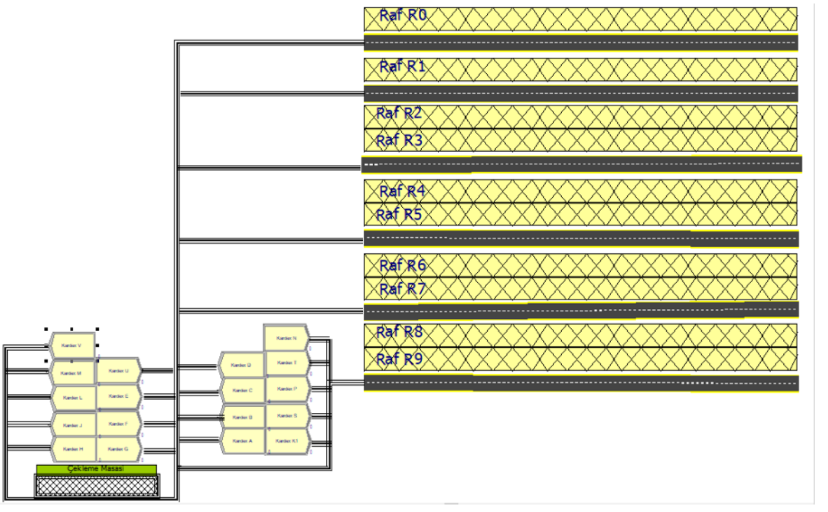

Figure 3.6: Representation of current replacement of the warehouse

the same floor or, alternatively, to locate them in different main addresses. The benefit of putting them in different main addresses will be the reduced time of preparing a kit because of the elimination of shelf changing time of Kardex's. The main aim is to reallocate the materials to their proposed places as the optimal storage areas are emptied in time. The effect of the new designed plan is expected to benefit in a longer run as the production is based on the projects and that the turnover rate of the warehouse is short, therefore, to observe the effect of the decision-support system is hard, but the effect will be beneficial in the long run. When the new system is applied, it is not quantitatively possible to compare the current and the new system because the new suggested plan cannot be physically seen and analyzed before changing the allocations in the warehouse. This is the main reason behind the simulation analysis we conducted.

Though,our industry advisor stated that they can be implemented, the performance of the plan cannot be measured in the short term inside the warehouse. In order to measure the improvement, we selected work orders randomly. Simulation is used for quantifying the selected representative subset of forecasted work orders which are the association rules we obtained. The simulation takes into account not only the placement of the Kardexes, but also the time elapsed during the walking period (Figure 3.6). As a result of our analysis, we can say that there can be approximately 13.47% improvement, and this number will gradually increase as the Decision Support System progresses.

3.6 Conclusion

Throughout the project, we tried to satisfy the company's expectations as much as the system allowed us to do so. By using Apriori algorithm, relevant statistical inferences are obtained to reveal the relationship between the materials that are frequently used together in the work orders. This way, the company will be provided with a more efficient layout plan to reallocate Kardex and shelf placement. As a result of these changes, the process of placing the newly arrived materials in the warehouse will be faster and more efficient. We will be maximizing the number of prepared kits, thus eliminating the current system's problem of bottlenecks.

With this project, a Decision Support System for the company to allocate the materials with regard to constraints regarding mobility activities, the sizes of materials and the association rules between the materials will be provided within the scope of their project-based working discipline. A further improvement to increase efficiency could be enabled if the warehouse could be totally emptied. However, under the current circumstances, the allocations could be re-organized to some extent as the materials are used in manufacturing processes. A gradual increase in efficiency is expected, which serves the purpose of the project and meets the constraints of the mobility in the warehouse.

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4 Depremden Sonra: En "Güvenli" Rota

United Nations Development Programme

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Özet

Deprem bölgesindeki şehirlerde, depreme karşı cevap verilebilirliği artırmak önemlidir. Proje, İstanbul'da beklenen depremden sonra Fatih'te herhangi iki nokta arasındaki kısa ve güvenli yolları bulmayı amaçlamaktadır. Problem, iki amaç fonksiyonlu en kısa yol bulma problemidir. Fatih bölgesi, her ayrıt üzerinde risk ve mesafe olmak üzere iki ağırlık parametresi bulunan bir ağla temsil edilmiştir. Risk parametreleri belirlenirken o ayrıt üzerinde bulunan binaların özellikleri ve depremle ilgili parametreler dikkate alınmıştır. Veriye bağımlılığı azaltarak genellenebilir kılmak için çaba harcanmıştır. Tamamlanan ağdaki herhangi iki düğüm arasındaki Pareto optimal yolları bulmak için ağırlıklı toplam skalarizasyonu uygulanmıştır.

Anahtar Sözcükler: Deprem, insani yardım operasyonları, afet yönetimi, afet cevap verilebilirliği, iki amaç fonksiyonlu en kısa yol bulma problemleri.

The Way: "Safest" Way Out

Abstract

In earthquake-prone cities, it is crucial to have a post-disaster plan to mitigate the disastrous effects of the earthquake and increase disaster responsiveness. This project aims to find the shortest and safest path between any two points in Istanbul, Fatih area after the realization of an earthquake scenario. Therefore, the problem is a bi-objective shortest path problem. To solve the problem, Fatih is represented as a network with two weights on each edge: risk and distance. While defining the risk parameter on edges, attributes of the buildings such as their heights, construction types, age, and various earthquake-related parameters are considered. A regression model is constructed, and the k-nearest neighbor algorithm is used to enable the application of this methodology outside Istanbul by reducing its data dependency. A Python code is used to build the network and assign arc parameters according to the earthquake scenario. Once the network is complete, weighted sum scalarization is used to find Pareto optimal paths between any two points in the network.

Keywords: Earthquake, humanitarian operations, disaster management, disaster responsiveness, bi-objective shortest path finding.

4.1 Problem Definition

Sustainable Development Goals Artificial Intelligence Lab (SDG AI Lab) is one of the initiatives hosted under the United Nations Development Programme's (UNDP) Istanbul International Center for Private Sector in Development (IICPSD) (SDG AI Lab, 2022b). Primary goal of the SDG AI Lab team is to research and provide advisory support on digital solutions like artificial intelligence and machine learning to achieve sustainable development goals. They also contribute to the inclusion of the private sector for resilience and crisis response by specializing in disaster preparedness with assistance from private sector stakeholders (SDG AI Lab, 2022a).

In Turkey, seismologists have been warning the government and citizens for a long time now about a major earthquake that will strike Istanbul in the near future. Therefore, having an immediate response plan right after the earthquake is crucial. One of SDG AI Lab's latest endeavors is to harness the potential of AI and machine learning technologies to unite families and loved ones after the disaster by providing them with safe and quick paths to travel. For this problem, SDG AI Lab proposed a solution statement inspired by the solution developed by a collaborative platform focused on solving problems with AI, called Omdena. (Mercian, 2021). This study is the starting point of our project.

Our project aims to find shortest and safest paths in Fatih, Istanbul, after an earthquake, by solving a bi-objective optimization problem. The previous solution methodology of SDG AI Lab inspired by Omdena is limited as their definition of safeness considers only the density of surrounding buildings and the width of the roads, but no parameters related to the ground structure, earthquake, and properties of the buildings. Therefore, our goal is to develop a risk measure that incorporates this information and to come up with a model that can find the safest and shortest Pareto optimal paths between any two locations using the network representation of Fatih with two weights defined on each arc (distance and risk). The total distance and risk score for each alternative path proposed is also provided.

4.2 Proposed Solution Strategy

To propose a solid solution strategy, we defined our assumptions about the system and the restrictions we would face. Accordingly, we mapped out a solution approach that we have built upon throughout the project.

4.2.1 Critical assumptions

While representing Fatih as a network, roads and streets were denoted as arcs, and the starting and ending points of these arcs were denoted by nodes in the network.

We focused on safety hazard risks caused by the possibility of buildings collapsing or debris falling on the people passing by. However, we did not consider other safety hazard factors regarding utility systems such as water lines, gas pipes, oil pipelines, and electric power systems.

In line with the SDG AI Lab's aim, we provided the shortest and safest paths for pedestrians. We did not assign people to paths or consider effects like congestion but only offered alternative paths between two chosen points in the network.

4.2.2 Major constraints

We did not have real-time data on blocked roads while providing the paths, so we did not consider the effects of any possible aftershocks on the path. Therefore, the methodology we constructed simply offered the safest and shortest paths right after the earthquake. This is a significant constraint for the precision of the solution; thus, to reduce the effect of this constraint, we worked with probabilistic models.

Moreover, roads blocked by a collapsed building restrict the feasibility of following the path. In other words, if a building collapses and blocks a road, according to the extent of the blockage, we were not able to use that road while constructing paths.

4.2.3 Objectives

Our objective was to provide the safest and shortest paths between two locations in Fatih, Istanbul after an earthquake.

We had two main objectives in our solution approach: minimizing risk and distance in order to construct a path between any two given points.

4.2.4 Solution approach

The first step in our solution approach was data collection. This step included collecting data about buildings in Fatih, like building heights, construction types, ages, and the geological parameters, together with the collapse probabilities of buildings. The gathered data were reliable as we obtained them from İstanbul Municipality Earthquake Directorship's research.

After the data collection, we developed a regression model for obtaining the building collapse probabilities if such sophisticated data are absent. We aimed to make sure that the methodology that we are presenting applies to other cities in the world. Our work on such customization will be explained in detail in Section 4.3.

To obtain the road blockage probabilities from the building collapse probability data, we considered the event that collapse of a building may cause a road to be blocked. We coded a model in Python which calculates the road blockage probabilities considering the positions of the buildings. As a result, we computed road blockage probabilities from the collapse probabilities of the buildings in our network.

After calculating the road blockage probabilities, we assigned the distance values of the roads in the network. Consequently, we obtained a network representing Fatih, with two parameters on each arc: distance and risk. We used weighted sum scalarization by Ehrgott (2000) to solve this bi-objective shortest path problem to obtain the Pareto optimal paths between any two points. A flow chart that explains our conceptual solution model is provided in Figure 4.1.

Arc Blockage Model

Our arc blockage model aims to obtain road blockage probabilities using building collapse probabilities gathered in the data collection stage. We used the methodology from Yamamoto and Li (2017) in this model.

To calculate arc blockage probabilities, we initially assigned buildings to arcs by determining a threshold distance for each building. Then buildings whose distances to roads are below threshold were assigned to the closest arc. We assumed threshold value to be 3 meters multiplied by the number of floors of the building of interest. To obtain road blockage probabilities, we considered the event that blocks a road, which is the collapse of a building.

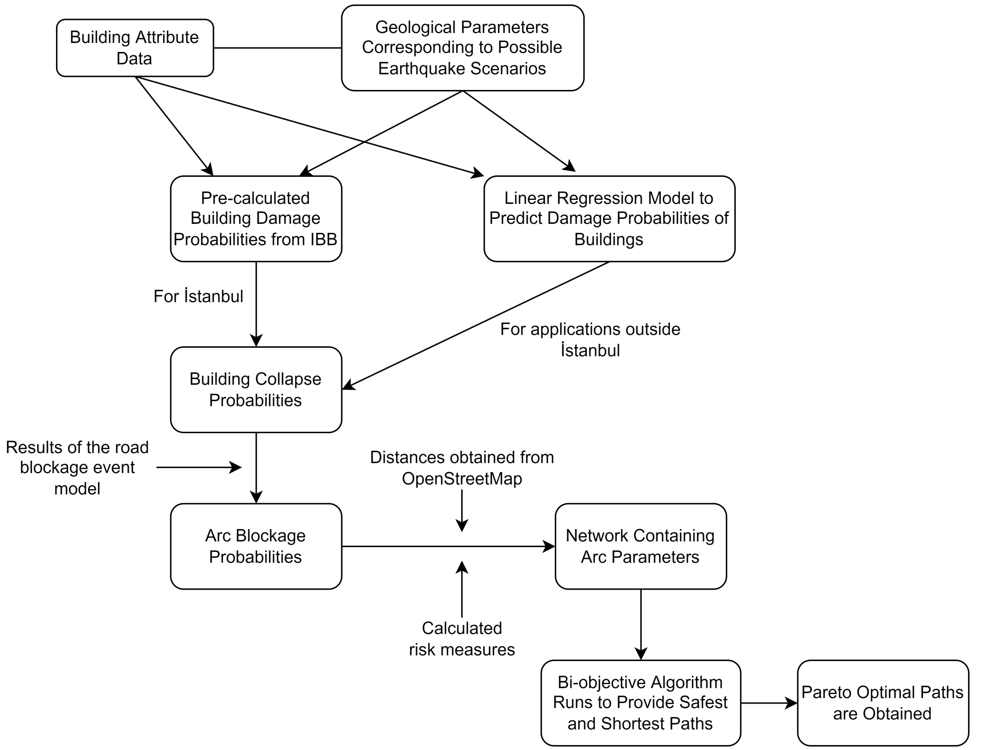

Figure 4.1: Flow chart of our conceptual solution model

Bi-objective Shortest Path Algorithm

In the weighted sum scalarization,we defined weights for our risk and distance objectives, and minimized a single objective function. We denoted the objective function for distance as $f_1(x)$ and risk as $f_2(x)$. The risk score of a path was calculated as multiplying the probabilities that each of the arcs on that path will not be closed, and taking the negative of its base 2 logarithm of this multiplication. Therefore, the objective was to minimize $\alpha f_1(x) + (1 - \alpha) f_2(x)$.

In the algorithm, we increased the weight for risk objective with an increment of 0.002, and decreased the weight for the distance with the same increment. As a result, we obtained 500 Pareto optimal points. We assume that, even if this method provides only a set of weakly non-dominated solutions, it will give a clear indication of the safest and shortest paths. The risk and distance values of the Pareto optimal paths between two sample points can be seen in Figure 4.2.

4.3 Customization

One of our aims in this project was to develop a framework that will help us accommodate our solution methodology in different cities worldwide. As

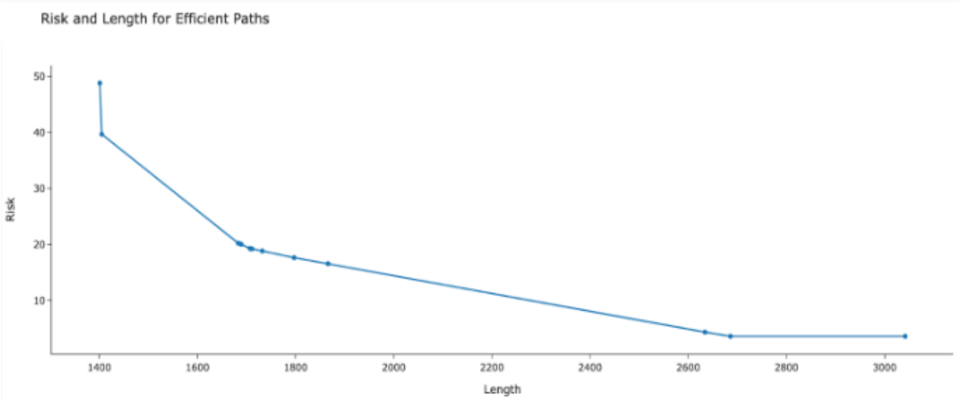

Figure 4.2: The graph shows the risk value and the length of each Pareto optimal path between two sample points

our solution requires some input data, we developed methods to overcome our model's dependence on specific and sophisticated data such as building heights. Therefore, we minimized the number of data required.

One of these methods that we have developed was a regression model to predict the buildings' complete and heavy damage probabilities as they are the reason for most road blockages and debris scattering after an earthquake. We constructed this model to predict the heavy and complete damage probabilities so that our solution applies to the other parts of the world where the damage probability data are not readily available. While constructing the model, we have also minimized the number of metrics that the regression model would depend on for the ease of implementation in other locations.

To test the prediction performance of the regression model, we separated the data we had for Istanbul into two parts. We had a 50/50 split for test and training data, following a conservative approach. Our model predicted the complete and heavy damage probabilities with a minimal error. The final model captured more than 99% of the variation in the test complete damage probabilities, with a 0.00168 mean absolute error and a maximum absolute error of 0.108.

Next, we worked on the case where the data on building height are missing. We utilized a distance-weighted k-nearest neighbor algorithm with the value of $k = 5$ to predict building heights. We first used the median height value and then implemented the weighted kNN algorithm to replace the missing building height values.We observed that the algorithm led to a significant improvement and reduced the difference of risk scores between the full data model and the limited data model.

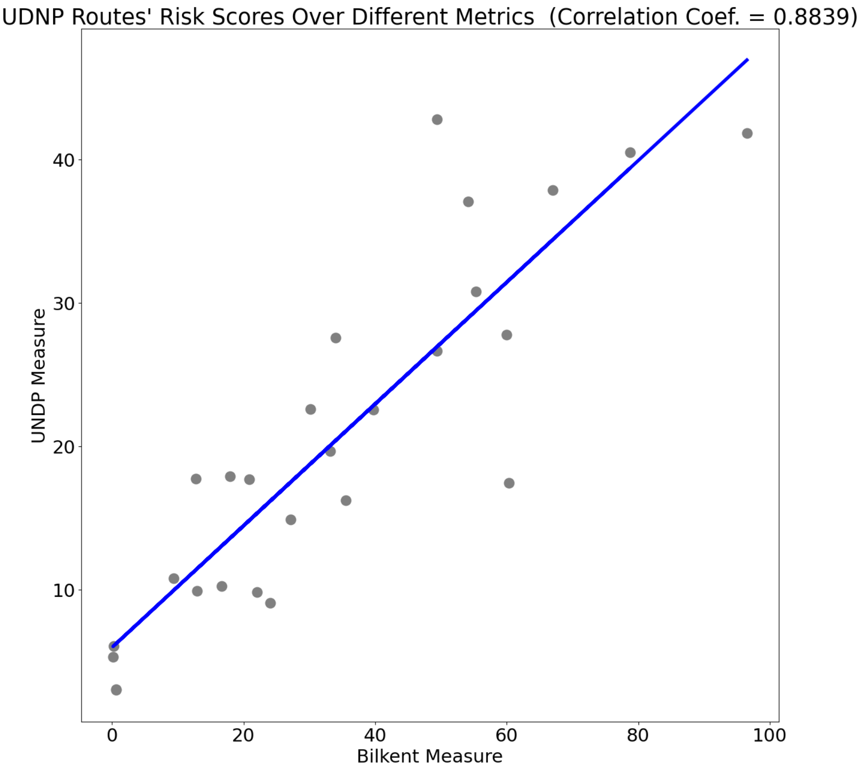

Figure 4.3: Comparison of the risk measures of trials paths provided by Bilkent and UNDP measures

4.4 Validation

Our aim with the validation process was to obtain logical results for both objectives when comparing our solution with the existing solution of SDG AI Lab. To do so, we received several paths along with their calculated risk scores and distances from SDG AI Lab. We ran the algorithm with these provided paths and compared the objectives. The shortest paths we obtained had the exact same distance values and followed the same roads as the current solution. This comparison showed us that the two solutions worked towards the same goal of minimizing the distance.

To compare the risk measures, we found the risk values of the paths provided to us using our methodology. After plotting the two risk values for the trial paths, we observed an evident increasing linear relationship. The comparison plot can be seen in Figure 4.3. While the risk values do not exactly mirror one another due to the different measures used, the positive correlation between the two risk calculations shows that our methodology is in line with theirs. 4.4 and 4.5, respectively.

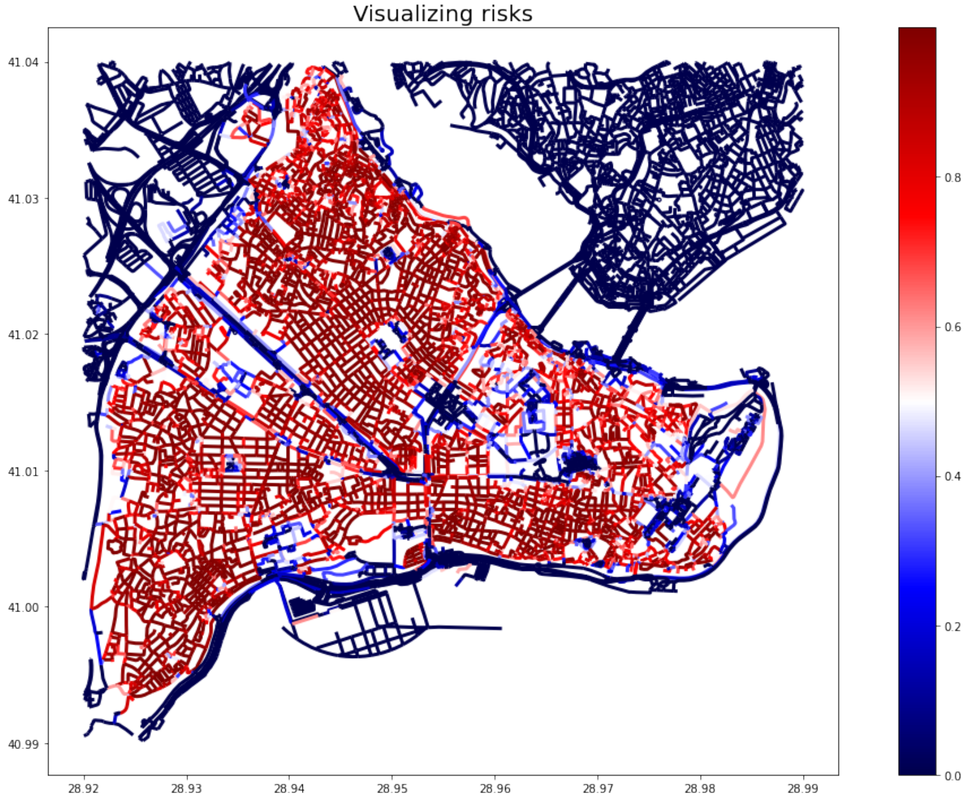

Figure 4.4: The map conveys the risks of the roads in Fatih district where the color red shows high risk and blue shows low risk

4.5 Benefits to the Organization

The current solution of SDG AI Lab utilizes a single, deterministic network where all the arcs are available. Whereas in our solution, some arcs can be excluded from the network if required. The risk scores of the arcs are only based on the road width and the building densities in the current solution. However, in the case of an earthquake, those measures may not be adequate to define the risk. While defining the risk, our solution considers the probability that a building can collapse and block an arc.

Moreover, since the current solution methodology of SDG AI Lab is deterministic, risk scores assigned to arcs remain the same regardless of the earthquake scenario. However, in reality, damages to the buildings change according to an earthquake scenario; thus, road blockage probabilities are subject to change. Our solution assigns risk scores to the roads according to the earthquake scenario studied by experts in this field, making our solution methodology more sensitive for direct effects of road blockage caused by the realization of the earthquake scenario. The current solution of SDG AI

Figure 4.5: The blue line conveys one of the paths between two sample points found with our solution

Lab provides the shortest route, while keeping the sum of risks per edge as small as possible. They use a version of a A*-PO algorithm which provides multiple Pareto optimal solutions per step (Lavin, 2015). A cost-normalized point is then chosen by the A* algorithm from the Pareto front.

With the help of the expanded risk measure, and consideration of an earthquake scenario, our solution is more realistic and appropriate for the problem at hand than the existing solution.

Sample risk map of Fatih and an alternative path found according to our solution are presented in Figures

Additionally, we believe that network we have constructed will be beneficial in other areas of post-disaster management for planning a disaster response mechanism after an earthquake. For instance, network can help determine crucial roads in the district to get from one place to another, which is useful while deciding on the roads to clear out first to send help.

4.6 Implementation and Conclusions

Implementation process consists of sharing our Colab notebook with SDG AI Lab. They wrote a tool with Streamlit and chose to use our code as it is. Thus SDG AI Lab did not request us to construct a user interface. They will add our solution to their coding environment. In our Colab notebook, we converted our method into flexible functions for ease of use.

To conclude, our solution provides a more composite risk measure than the solution by SDG AI Lab as it incorporates different attributes. We can provide Pareto optimal paths between any two points, which gives flexibility to the user when deciding on a path to take. Moreover, in case of a blockage in the chosen path, the algorithm can be re-run to find another path to the destination point. Our solution also gives a framework to follow when the input data are insufficient or missing, allowing the solution methodology to be generalized to other locations.

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5 Dış Lojistik
Milk Run Sistemi Tasarımı

Arçelik Kurutma Makinesi İşletmesi

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Özet

Arçelik Kurutma Makinesi İşletmesi tedarik sürecinde Tam Zamanında Methodu'na geçiş yapmıştır. Fabrikaya parçaların erken ve fazla miktarda gelmesi tam olarak bu metoda uymamaktadır. Ek olarak, sevkiyat programlarında çakışmalarla, kampüs içi araç trafiğiyle ve yükleme/bindirme bölgerinde aşırı stoklamayla karşı karşıya kalınmaktadır. Bu projede, olası çözüm yaklaşımlarından Milk Run sistemi endüstri mühendisliği perspektifiyle tartışılmakta ve etkin bir karar destek sistemi kurularak şirketin dış lojistik operasyonlarındaki verimliliğini artırmak amaçlanmaktadır.

Anahtar Sözcükler: Ulaştırma Bilimi, Yöneylem Araştırması, Performans İyileştirme, Süreç Analizi, Nakliye Programı, Tedarik Zinciri, Milk Run

Design of Outbound Milk Run System

Abstract

Arçelik Dryer Factory recently initiated a transition to the Just-in-Time Method in the supply chain process. Parts coming to the facility early and in large quantities do not comply with the Just-in-Time method. In addition, the factory faces conflicts in the shipment schedules, vehicle traffic in the campus entrance and excessive inventory in the loading and unloading zones. This project intends to improve the outbound logistics operations of the company by discussing one of the probable solution approaches, Milk Run system, through an industrial engineering perspective and constructing an effective decision support system.

Keywords: Transportation science, operations research, performance improvement, process analysis, transportation schedule, supply chain, milk run.

5.1 System Analysis and Problem Definition

Arçelik was founded in 1955 by Vehbi Koç and Lütfi Doruk in İstanbul. Initially, Arçelik produced white appliances such as washing machines, dishwashers, freezers, and air conditioners. However, they diversified their product types in time. The Consumer Confidence Index of Arçelik in Turkey increased by 5.6% in September 2020 compared to the same period of the previous year and its wholesale white goods sales grew by 4.5% in Turkey, maintaining its leadership in the white goods market. Furthermore, Arçelik's Beko brand is in second place in terms of total market share in the European market. The total number of white goods production in domestic and foreign factories reached 14,325 units in 2020.

In 2007, Arçelik entered the dryer sector. Arçelik currently produces 3 types of drying machines. These are the air vented filter dryer, condenser dryer, and heat pump dryer. However, as the air compressor filter dryer is not preferred by customers the majority of the production in the Tekirdağ plant is dedicated to the latter two. Moreover, these two are more useful as they do not need a rearrangement in the houses' pipe system. Production of these aforementioned drying machines includes many service and manufacturing processes that are interrelated with each other. Furthermore, each process has a range of different sub-tasks in itself, and end products are obtained by combining these different processes. In particular, the front and back interfaces of dryers are produced with die casting in the plant while the metal cylindrical part in the dryers is purchased in the form of thin metal plates in rolls. These plates are cut into rectangular dimensions and their shapes are converted to cylinders with a press machine and the two ends are riveted together with heat in the reshaping process. In other words, while some of the byproducts are produced in the factory from raw materials, some parts such as compressors are supplied directly as end products for drying machine production. The supply system is the most crucial of these operations as it determines the production schedule. Electronic supplies are mostly provided by suppliers in the Far East and Europe whereas essential, plastic and sheet metal supplies are provided by domestic suppliers most of which are located around Çorlu or Çerkezköy, Tekirdağ.

The Tekirdağ factory has 38 suppliers and 11 of them are managed in line with the Just-In-Time (JIT) method. These 11 suppliers located in Tekirdağ are focused on in this project. Moreover, among those suppliers, 2 of them use Arçelik's vehicles to send the ordered materials whereas the rest use their own vehicles. Shipments from sub-industries to the factory are continuous every day in different time periods.

Current system operations in Arçelik Dryer Plant generate several driving forces to the problem at hand. Firstly, suppliers using their own trucks for delivery tend to load trucks although not all of them are scheduled in that particular time slot in order to maintain low inventory level. Therefore, unloading time increases and stock space decreases rapidly at Arçelik. This creates congestion in the layout and disturbs the production line.

Lastly, as previously mentioned, the main facility has one gate for vehicles to enter. In the facility, there are 5 unload/load zones and only one forklift is assigned to the unload/load process per vehicle. Although up to 5 vehicles can be loaded and unloaded simultaneously, shipment schedules may coincide for several suppliers, causing more than 5 vehicles to arrive at the same time. Consequently, vehicles wait for each other, unload/load times take longer than planned, and in some cases production lines need to be stopped if a part is delayed due to traffic in the facility entrance. In short, asynchronous shipment schedules entail the risk of interruption of production rate and filling up the limited inventory space in the facility.

Although there seems to be a flow in this system, JIT is not conducted properly. JIT components should be transferred to production lines upon arriving. However, materials are stored in three stages due to capacity limitation. Therefore, unnecessarily loaded trucks and bottlenecks in the campus entrance generate costs that can be prevented with systematic planning.

5.2 Solution Approach and Model

In the context of our project, a milk run system could be useful as it gathers deliveries among suppliers and reduces the length of the overall routes. Instead of multiple vehicles setting off from each supplier, Arçelik might send out vehicles that travels between suppliers and picks up deliveries according to the order of unloading. For instance, normally three different trucks are required for three different suppliers. By constructing a route for the suppliers that are close to each other, Arçelik could use less than three vehicles. That way, reduction on the number of vehicles and consequently, the utilization of loading and unloading spaces may be achieved.

A mathematical model is formed to optimize routes for the trucks (see Appendix). Milk Run system might be applied to outbound logistics operations of the company to reduce the downtime in the manufacturing system. For the delivery system, we apply Milk Run only to the sub-industries working for 24 hours. The sub-industries that are working for 16 hours are not included to project's scope. In particular, at certain time intervals Arçelik and suppliers' trucks filled with predetermined lot sizes will arrive. Therefore, Arçelik could omit unloading excessive lots that will not be required in the next planning horizon, and follow JIT's basic standards. As our solution method, we coded our mathematical model in CPLEX Optimization Studio. We constructed decision variables, parameters and constraints that address the problem definition above and we verified that our model gives logical results. However, since the licence fees of these programs are significantly high, we moved to heuristics, in particular Genetic Algorithm (GA). Since we coded the algorithm in Python, it does not involve extra expenses. GA adopts genetic operators, selection, and crossover operations over many populations as Tan et al. (2001) assert.

To construct the algorithm, we generated the initial population by creating random routes. Each route is treated as a gene while all of the routes as a whole construct a chromosome. Then, we checked our solutions', the chromosomes', feasibility with respect to the conditions that are equivalent to the constraints in our model. Also, we constructed a fitness function to evaluate the solutions. A score is assigned to each resulting chromosome via a fitness function. This function considers three different scenarios to calculate scores according to user input. These scenarios are prioritizing the scores that have less total waiting time of the products, ones have less number of vehicles used per run in addition to total waiting time of the products, and ones that has less tour duration.

Initial population members are various length artificial chromosomes which are subjected to a selection mechanism, namely tournaments, that determines parent chromosomes. In order to create offspring, we constructed a tournament between solutions. The scores of randomly chosen solutions are assessed and the one that has the best score is chosen as the winner and added to the parent list. This procedure is repeated to choose the next parent. To ensure a solution is not matched with itself in the crossover, a solution that is added to the parent list is excluded from the population before the next iteration. In crossover, random positions in two parent chromosomes are selected. The genes in these positions of chromosomes are placed into a new chromosome and offsprings are obtained as a result. Additionally, offsprings go through a mutation process which is swapping inside the random genes in an offspring chromosome with a small probability, to explore the influence of crossover, whether the offspring is an improved version of the parents. In genetic algorithm, Chen et al. (2010) argue that various crossover and mutation operators may be used to solve the Simultaneous Delivery and Pickup Problem with Time Windows. Therefore, we applied mutations to newly generated offsprings to help crossovers to stray from the local optima and to possibly achieve a better performance Puljic and Manger (2013). Then, the algorithm decides on the preferable solutions among the population based on the best 20 score which constitutes elites as Miller and Goldberg (1995) state. After offsprings are obtained, we merged them with the elites to construct the next population. The same procedures, starting with the creation of elites and the tournament until the mutation of offsprings, are applied to the next population until a termination condition is met. We set the terminating condition as 512 iteration limit, but it can be changed by the user. Figure 5.1 shows the conceptual model of GA.

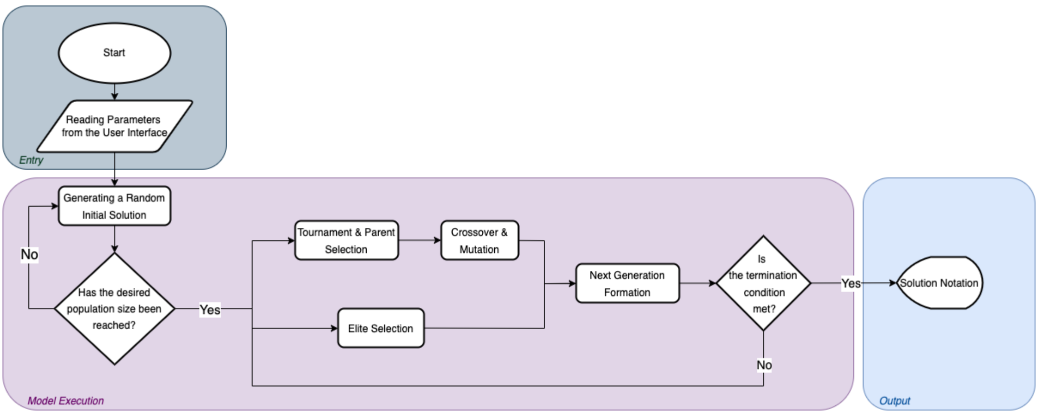

Figure 5.1: Conceptual model of Genetic Algorithm

5.3 Validation

To determine how one solution dominates another, we specified Key Performance Indicators (KPI). We selected KPIs such that they address the inefficiencies that were described in the system analysis. In this sense, the number of trucks used in a run period is the first KPI. Accordingly, the number of vehicles present in the facility at a given time is another KPI since one of the essential aims of our solution approach is to reduce the campus traffic. The closeness between the arrival time of the vehicles may indicate the intensity of the traffic in the facility. That is, the further the arrival times apart the more the traffic in the facility is reduced. Therefore, the waiting time, i.e., the difference between a part's arrival time and the time that it goes into the manufacturing line, should be minimized. In particular, the materials should not wait longer than desired in the warehouse so that the warehouse occupancy is not increased. The compatibility of the system to JIT can be addressed using the waiting time as another KPI since the time difference is minimized as a result of its improvement.

These KPIs are used in calculating the improvement percentage of our solution approach. To validate our solution approach and to persuade Arçelik that the model we built is adequate and useful, we compared the values of the results of our mathematical model with their counterparts in Arçelik's current system operation. Comparison presented resembling outcomes with the real system under the same set of conditions. Accordingly, daily changes and small scaled real-life inconsistencies or extreme situations such as production disruptions were also considered as different scenarios. We used the same KPIs for both CPLEX and the GA coded in Python. A valid solution can be seen in Table 5.1.

Vehicles	Set-off/ Arrival	Routes (Letters Representing Suppliers)	Part Amount Picked Up From Each Supplier
T1	22:40 - 23:50	O-E-B-H-O	4 crates of Part 1 from E 6 crates of Part 2 from E 3 crates of Part 3 from B 3 crates of Part 4 from H 5 crates of Part 5 from H
T3	01:15 - 01:50	O-F-H-O	1 crates of Part 3 from F 2 crates of Part 7 from H
T5	23:30 - 23:50	O-J-O	16 crates of Part 8 from J

Table 5.1: Solution Instance

To provide evidence on how reliable the GA results are, we computed an approximation rate i.e., how far the solution obtained with GA is from the optimal solution obtained with CPLEX. To determine the approximation rate, we arbitrarily created 7 scenarios to test with CPLEX and GA. We diversified part demands and latest part arrivals in different scenarios. Overall, the average approximation rates indicate that GA is 35,91% far from the optimal number of vehicles that are used in a period and is

19,65% far from the optimal total waiting time at the facility in a period.

5.4 Deliverables

A user interface is developed for suppliers. This interface is to serve as a supply chain decision support tool for people responsible from suppliers to access the number of trucks used in the run period, route for each truck, and the amount of part that is picked up from each supplier in the route. Our decision support system consists of three important consecutive steps; accepting inputs from Excel, executing the heuristic by Python, and displaying the outputs to user by VBA in Excel, which can be seen in Figure 5.2. Inputs, i.e., the parameters of the algorithm are provided by the company.

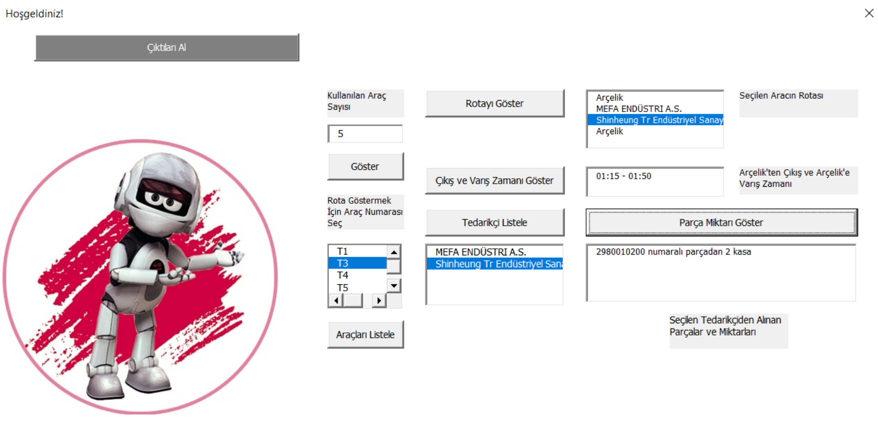

Figure 5.2: The userform developed for Arçelik

5.5 Benchmarking and Benefits

Our aim is to contribute to the company by arranging outbound logistics with Milk Run and thus, improving the practice of JIT and reducing the traffic in the facility. By the GA, material pick-up routes mostly consist of multiple suppliers rather than only one supplier. This way, vehicles are loaded based on the sequential demands in the required amount instead of larger amounts of specific parts. Additionally, vehicle set-off and arrival times are arranged such that the parts loaded to each truck arrives at the facility not too early than its scheduled production time but early enough to comply with the schedule. The duration which a part can arrive before its scheduled production time is called the "JIT Goal" in the GA and can be adjusted by the user before each run.

Our solution approach is preferable only if it presents improvement in comparison with the real system output. Concordantly, we aimed to analogize the KPI values presented by the output of our model with the KPI

KPI	Arçelik	Genetic Algorithm (GA)			Improvement			
		Objective 1	Objective 2	Objective 3	Objective 1	Objective 2	Objective 3	
Number of Vehicles Used **(per day)**	50	43	38	42	**14%**	**24%**	**16%**	↑
Number of Vehicles Present at the Facility **(per hour)**	4	3	2	2	**25%**	**50%**	**50%**	↑
Total Waiting Time of All Products Until Production **(in minutes)**	615038	9356	10182	9699	**98%**	**98%**	**98%**	↑

Figure 5.3: Number of Vehicles Present at the Facility per hour

values we obtained by observing the real system operations. As for the assessment of our GA through KPIs, we checked few things in our result. The number of trucks used in a run period was given to the algorithm as a parameter and meant to be increased if a feasible solution is not attained. However, since we found a valid solution by the GA with the same number of trucks that the optimal solution obtained from CPLEX gives, we made no changes in truck number.

When the objective is chosen as prioritizing the solutions that have smaller waiting time, the improvement is 14% in number of vehicles used, 25% in number of vehicles present in the facility. For the objective that prioritizes smaller number of trucks used in addition to waiting times, the improvements are 24% and 50% in the number of vehicles used and the number of vehicles present in the facility respectively. In the case of the objective that limits the route times of vehicles by the length of the planning horizon the improvements are 16% and 50% again in the number of vehicles used and the number of vehicles present in the facility respectively.

The improvement in total waiting time of whole products with respect to all three objectives are all 98%. In the old system at Arçelik, a significant amount of parts used to wait more than 20 hours before going into the manufacturing line, mainly because the suppliers prefer loading the trucks with parts that are required later in the production plan to minimize their stock levels. With GA, parts' latest time to arrive at Arçelik is determined solely by the time that they enter the manufacturing line. This leads to a

Time Interval		Number of Vehicles Used			Unload Amount (in crates per hour)				Waiting Time Until Production (in minutes)		
		Objective 1	Objective 2	Objective 3	Arçelik	Objective 1	Objective 2	Objective 3	Objective 1	Objective 2	Objective 3
JIT Goal is 2 hours!	00:00-06:00	9	9	9	273	200	200	200	1322	1322	1322
JIT Goal is 3 hours!	06:00-12:00	9	6	8	312	263	263	263	2968	3544	3052
JIT Goal is 3 hours!	12:00-16:00	8	8	8	134	169	169	169	500	750	750
	16:00-20:00	9	8	9	145	236	236	236	2748	2748	2757
	20:00-24:00	8	7	8	148	146	146	146	1818	1818	1818

Figure 5.4: Improvement Percentages Presented Based on KPIs

major improvement in total waiting time of all products until production.

When we consider these three objective results, choosing the second one gives the most preferable outcomes. However, we offer Arçelik the choice of objective in the GA in the case that they have a different goal. However, the different objectives are offered to Arçelik in case they have different goals.

The percentages of the improvements can be found in Figure 5.3. In addition, the objective values and their corresponding values in Arçelik with respect to different time intervals can be seen in Figure 5.4.

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Appendix: Model Development

Sets: i,j$\in \{0,1,2,...,w\}$where 0 denotes Arçelik;
p$\in \{1,2,...,n\}$; k$\in \{1,2,...,m\}$

Parameters:

Q^k : capacity of vehicle $k \in \{1,2,...,m\}$

q^p : demand for part p $\in \{1,2,...,n\}$

$$c_i^p = \begin{cases} 1, & \text{if part p} \in \{1,2,...,n\} \text{ is produced by supplier i} \in \{0,1,2,...,w\} \\ 0, & \text{otherwise} \end{cases}$$

t_{ij}: time it takes to got from supplier i $\in \{0,1,2,...,w\}$ to supplier j $\in \{0,1,2,...,w\}$

E^p: earliest arrival time of part p $\in \{1,2,...,n\}$

L^p: latest arrival time of part p $\in \{1,2,...,n\}$

b^p: unload time of 10 units of part p $\in \{1,2,...,n\}$

a^p: load time of 10 units of part p $\in \{1,2,...,n\}$

M: a very high value

Decision Variables:

$$z^{kp} = \begin{cases} 1, & \text{if vehicle k carries part p} \\ 0, & \text{otherwise} \end{cases}$$

T_{ij}^k: travel time of vehicle k from supplier i to j

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

$$\alpha_i^{kp} = \begin{cases} 1, & \text{if part p is loaded to vehicle k at supplier i} \\ 0, & \text{otherwise} \end{cases}$$

π_i^k: load amount of vehicle k after leaving supplier i

β_i^k: time that vehicle k arrives at supplier i

l_i^{kp}: amount of part p picked up from supplier i with vehicle k

v : number of vehicles used

Mathematical Model: $\min v$ s.t.

$$x_{ii}^k = 0 \qquad \forall i \in \{1, 2, ..., w\}, \forall k \in \{1, 2, ..., m\}$$

$$\sum_{j=1}^{w} x_{ij}^k - \sum_{j=1}^{w} x_{ji}^k = 0 \qquad \forall i \in \{1, 2, ..., w | i \neq j\}, \forall k \in \{1, 2, ..., m\}$$

$$\sum_{k=1}^{m} \sum_{j=1}^{w} x_{0j}^k = v, \quad \sum_{k=1}^{m} \sum_{j=1}^{w} x_{j0}^k = v$$

$$\pi_j^k \geq \pi_i^k + \sum_{p=1}^{n} l_j^{kp} - M(1 - x_{ij}^k)$$

$$\forall i \in \{1, 2, ..., w\}, \forall j \in \{1, 2, ..., w | i \neq j\}, \forall k \in \{1, 2, ...m\}$$

$$\pi_i^k \leq Q^k \qquad \forall i \in \{1, 2, ..., w\}, \forall k \in \{1, 2, ..., m\}$$

$$\sum_{i=1}^{w} l_i^{kp} \leq M z^{kp} \qquad \forall p \in \{1, 2, ..., n\}, \forall k \in \{1, 2, ..., m\}$$

$$\sum_{k=1}^{m} \sum_{i=1}^{w} l_i^{kp} c_i^p = q^p \qquad \forall p \in \{1, 2, ..., n\}$$

$$\pi_0^k = 0 \qquad \forall k \in \{1, 2, ..., m\}$$

$$T_{ij}^k \geq t_{ij} x_{ij}^k, \quad T_{ij}^k \leq M x_{ij}^k$$

$$\forall i \in \{0, 1, 2, ...w\}, \forall j \in \{0, 1, 2, ...w\}, \forall k \in \{1, 2, ...m\}$$

$$\beta_j^k \geq \beta_i^k + \sum_{p=1}^{n} a^p l_i^{kp} + T_{ij}^k - M(1 - x_{ij}^k)$$

$$\forall i \in \{1, 2, ..., w\}, \forall j \in \{1, 2, ..., w | i \neq j\}, k \in \{1, 2, ..., m\}$$

$$\beta_j^k \leq \beta_i^k + \sum_{p=1}^{n} a^p l_i^{kp} + T_{ij}^k + M(1 - x_{ij}^k)$$

$$\forall i \in \{1, 2, ..., w\}, \forall j \in \{1, 2, ..., w | i \neq j\}, \forall k \in \{1, 2, ..., m\}$$

$$\beta_i^k + T_{i0}^k + M(1 - x_{i0}^k) + \sum_{p_3=1}^{n} b^{p_3} l_i^{kp_3} + M(1 - z^{kp}) \geq E^p$$

$$\forall i \in \{1, 2, ..., w\}, \forall k \in \{1, 2, ..., m\}, \forall p \in \{1, 2, ..., n\}$$

$$\beta_i^k + \sum_{p_1=1}^{n} a^{p_1} l_i^{kp_1} + T_{i0}^k - M(1 - x_{i0}^k) + \sum_{p_2=1}^{n} b^{p_2} l_i^{kp_2} - M(1 - z^{kp}) \leq L^p$$

$$\forall i \in \{1, 2, ..., w\}, \forall k \in \{1, 2, ..., m\}, \forall p \in \{1, 2, ..., n\}$$

$$l_i^{kp} \leq M \alpha_i^{kp} c_i$$

$$\forall i \in \{0, 1, ..., w\}, \forall k \in \{1, 2, ..., m\}, \forall p \in \{1, 2, ..., n\}$$

$$M \sum_{i=0}^{w} x_{ij}^k \geq \sum_{p=1}^{n} \alpha_j^{kp}$$

$$\forall j \in \{1, 2, ..., w\}, \forall k \in \{1, 2, ..., m\}$$

$$\sum_{i=0}^{w} x_{ij}^k \leq \sum_{p=1}^{n} \alpha_j^{kp} \qquad \forall j \in \{1, 2, ..., w\}, \forall k \in \{1, 2, ..., m\}$$

$$M z^{kp} \geq \sum_{i=0}^{n} \alpha_i^{kp} \qquad \forall k \in \{1, 2, ..., m\}, \forall p \in \{1, 2, ..., n\}$$

$$z^{kp} \leq \sum_{i=0}^{n} \alpha_i^{kp} \qquad \forall k \in \{1, 2, ..., m\}, \forall p \in \{1, 2, ..., n\}$$

$$\alpha_0^{kp} = 0 \qquad \forall k \in \{1, 2, ..., m\}, \forall p \in \{1, 2, ..., n\}$$

$$M \sum_{j=1}^{w} x_{ji}^k \geq \sum_{p=1}^{n} l_i^{kp} \qquad \forall k \in \{1, 2, ..., m\}, \forall i \in \{1, 2, ..., w\}$$

$$\sum_{j=1}^{w} x_{ji}^k \leq \sum_{p=1}^{n} l_i^{kp} \qquad \forall k \in \{1, 2, ..., m\}, \forall i \in \{1, 2, ..., w\}$$

$$x_{ij}^k, z^{kp}, \alpha_i^{kp}, \in \{0, 1\}$$

$$\pi_i^k, \beta_i^k, l_i^{kp}, v \geq 0$$

6 Dijital Fabrika Çözümleriyle Üretilen Dinamik İş Emri Planlama Programı

Supply Chain Wizard

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Özet

Supply Chain Wizard şirketinin ‘Çizelgeleme‘ modülü kapsamında hızlı ve otomatize edilmiş bir algoritmik yaklaşım, projenin temel kapsamını oluşturmaktadır. Çözüm, makinenin işlem gücü ile insanın saha tecrübesini birleştirerek hem makinenin, hem de insan zekasının artı yönlerini kullanmaktadır. Performans ölçümlerine göre yeni sistem geciken iş emri sayısını azaltmıştır. Oluşturduğumuz gösterge paneli sayesinde ise kullanıcılar, çizelgede kolayca ve kısa sürede değişiklik yapabilmektedir.

Anahtar Sözcükler: Çizelgeleme, En Büyük Gecikmeyi Enküçükleme, Döngüdeki İnsan Mantığı, Google OR Tools, Hat Çizelgelemesi

Dynamic Work Order Scheduling Program with Digital Factory Solutions

Abstract

The scope of the project mainly lies in the micro-service program that is intended to be delivered as an add-on to Supply Chain Wizard's current 'Scheduler' module. The solution combines the processing power of the machine with the field experience of the human and uses the positive aspects of both the machine and the human intelligence. According to performance measurements, the new system reduced the number of delayed work orders. Thanks to the dashboard we have created, users can make changes to the chart easily and in a short time.

Keywords: Scheduling, Makespan Minimization, Maximum Tardiness Minimization, Human in the Loop Logic, OR Tools, Line Scheduling

6.1 Description of the Company

Supply Chain Wizard LLC, established in 2014, is a company providing consulting services and products to companies from variety of sectors. Their core operations are based on life sciences, supply chain, and digital transformation. There are more than 80 different clients, however, the main target group is in the pharmaceutical industry. Supply Chain Wizard LLC currently has "Digital Factory Journey - The 3D Concept" as their system. This system consists of three domains: Data - Dashboard - Decision(Supply Chain Wizard, 2021).

6.2 Current System and Problem Analysis

6.2.1 Current System Analysis

The main purpose is to come up with the best possible schedule that satisfies some Key Performance Indicators (KPIs) [1] as the final output in the scheduler tool. There are four different KPIs indicated in the scheduler tool by the company. The first one shows the number of jobs scheduled in the output. The second one indicates the lines' capacity utilization. The third one should be considered if the user is satisfied with the capacity utilization. If the user thinks that the capacity utilization is enough for their business, they can look at the performance matrix which is the cost. The last box indicates violations in the scheduling process. Although constraints seem satisfied, the output may not satisfy some of its constraints. The algorithm

[1] KPIs are measures that are quantifiable and indicate the performance of specific jobs.

takes part in this process and warns the user about the availability of these kinds of situations. Users can come up with different schedules according to their KPI preferences. In this way, different simulations are being made to see the variations of KPIs' values.

6.2.2 Problem and Its Scope

The main problem of the company is that its current scheduling solution needs an algorithm to semi-automate the scheduling process and improve the overall schedule quality in the end. They are manually scheduling work orders and changing them according to KPI values in the dashboard. Moreover, companies are aware that there are certain advantages and disadvantages of scheduling only manually or scheduling only via machines. For instance, manual scheduling is more adapted to changes but it cannot schedule relatively large systems. On the other hand, machines can work on larger systems but they are data-oriented, hence not as flexible as humans (manual). The key is to create an environment in which humans and machines can operate together with "Human in the Loop" logic, which enables them to neutralize their weaknesses.

All in all, this problem is a "Work Order Scheduling" problem. The goal is to schedule Work Orders to the appropriate lines with having minimum-maximum lateness possible. Due date is considered to be the most crucial aspect of schedules, hence the goal is to have work orders scheduled with the least amount of violated due dates. As stated previously, the complexity of scheduling problems and changing high setup and cleanup times are the main challenges against solution options. Therefore, the company desires to obtain "Human in the Loop" logic which enables humans to interact and make arrangements on the schedule. By implementing this logic, the company can remove the weaknesses of humans and machines by combining their strengths.

6.3 Proposed Solution Strategy

6.3.1 Critical Assumptions

For the model to be applicable, some assumptions need to be made. Since the solution is not exclusive to a specific sector, the main focus will be on general schedule. Breakdowns in the system will be neglected. Thus, lines will be operational all the time. The solution will not proceed through instant changes, but by creating the general schedule with pre-planning. Changes and errors in the line processing times will be eliminated by using historical data therefore, processing times will be deterministic, they will depend on product speed and quantity. Setup times and cleanup times will

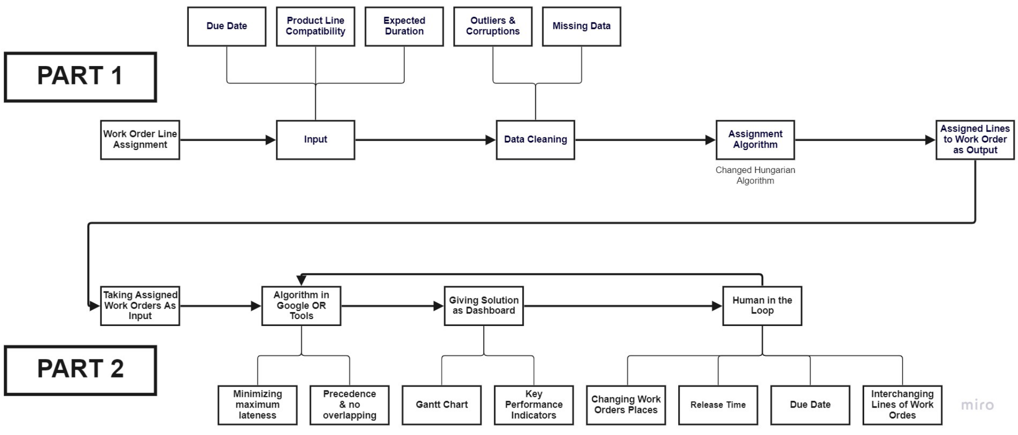


Figure 6.1: The Structure of the Solution on Flow Chart

be included in the processing times for the sake of simplicity of parameters.

6.3.2 Business Constraints

Supply Chain Wizard stated that the solution method proposed should not take a long processing time, and during literature review, it is considered to be the computation time. In addition, there are some restrictions to be regarded such as product-line compatibility, product-line speed variability, product release date and final product date. These constraints are considered when creating an appropriate solution for scheduling.

6.3.3 Objectives

In this project, the aim is to come up with a system that schedules work orders to the lines and provides an interface consisting of a Gantt chart with relevant KPI cards. These KPIs are the number of scheduled jobs, the number of late jobs, the tardiness value of each tardy work order, maximum lateness and makespan. The dashboard will help the user to keep track of some KPI values so that they can update the input according to the desired KPI value. In conclusion, a tool that solves the specified scheduling problem will be provided with "human in the loop"[2] logic, which enables flexibility to update inputs according to KPI values.

6.3.4 Solution Approach

The solution consists of three main parts which are assignment, schedule, and Human in the Loop. The main structure of the solution can be seen on the flow chart in Figure 6.1.

[2]This is the process of combining machine and human intelligence to obtain better results.

	A	B	C	D	E	F	G
1	Line	Work Ord	Duration Val	Label	Due Date	Release Date	Product
2	LineA	WoABCD	57.0	1	2/2/21 13:00:00	2/2/21 00:00:00	ProductABCDF
3	LineB	WoABCDE	19.3	2	2/3/21 13:00:00	2/2/21 00:00:00	ProductABCDE
4	LineC	WoABCDF	71.1	3	2/4/21 13:00:00	2/2/21 00:00:00	ProductFCDA
5	LineD	WoABCF	96.8	4	2/5/21 13:00:00	2/2/21 00:00:00	ProductDBAF
6	LineE	WoABFE	67.1	5	2/6/21 13:00:00	2/2/21 00:00:00	ProductEFDA
7	LineF	WoABCD	2.3	6	2/7/21 13:00:00	2/3/21 00:00:00	ProductABCDF
8	LineA	WoABCDE	84.8	1	2/8/21 13:00:00	2/2/21 00:00:00	ProductABCDE
9	LineB	WoABCDF	63.4	2	2/9/21 13:00:00	2/2/21 00:00:00	ProductFCDA
10	LineC	WoABCF	8.1	3	2/10/21 13:00:00	2/3/21 00:00:00	ProductDBAF
11	LineD	WoABFE	20.5	4	2/11/21 13:00:00	2/2/21 00:00:00	ProductEFDA
12	LineE	WoABCD	58.4	5	2/12/21 13:00:00	2/2/21 00:00:00	ProductABCDF
13	LineF	WoABCDE	78.2	6	2/13/21 13:00:00	2/2/21 00:00:00	ProductABCDE
14	LineA	WoABCDF	68.3	1	2/14/21 13:00:00	2/2/21 00:00:00	ProductFCDA
15	LineB	WoABCF	47.5	2	2/15/21 13:00:00	2/2/21 00:00:00	ProductDBAF
16	LineC	WoABFE	50.7	3	2/16/21 13:00:00	2/4/21 00:00:00	ProductEFDA
17	LineD	WoABCD	98.3	4	2/17/21 13:00:00	2/2/21 00:00:00	ProductABCDF
18	LineE	WoABCDE	49.4	5	2/18/21 13:00:00	2/2/21 00:00:00	ProductABCDE
19	LineF	WoABCDF	56.5	6	2/19/21 13:00:00	2/3/21 00:00:00	ProductFCDA
20	LineA	WoABCF	5.3	1	2/20/21 13:00:00	2/2/21 00:00:00	ProductDBAF

Figure 6.2: Sample Dummy Input Data for Google OR Tools Algorithm

Inputs

The solution methodology starts with a line assignment algorithm. The first input used for the assignment algorithm is a matrix, which has been derived from the historical data of the work orders, containing lines as columns and work orders as rows. One crucial insight that can be reached through this matrix would be that if a line is not compatible with a certain work order an arbitrarily large number is entered in order to allow the algorithm to not consider incompatible line-work order combinations as a possibility. The values inside the matrix are the duration of the process. After the assignment algorithm processes, work orders are assigned to the lines, and they are represented in the output data. Work order is a unique value, hence using this unique key value, the other necessary data for the input of the scheduling algorithm is gathered. Other aspects that added next to work order and line are duration value, label of line, due date, release date and product. Label of line is an input created. Labels are given to the lines to simplify the algorithm's computation. Release date is a value to indicate the earliest time a certain line becomes idle. Due date indicates the due date of the work order. Duration value is the total duration (including the duration of the expected setup, cleanup and run time) of a certain work order in minutes. Product is the id of the manufactured product via work order. Check Figure 6.2 for the screenshots of the inputs. Note that the values are random values and not the exact ones due to confidentiality. After this point, the outputs of the assignment algorithm are used to determine the main outputs in the OR Tools model, such as Gantt Chart and KPIs.

Assignment Algorithm

The observation from the company's historical data revealed that there are some cases in which products associated with the respective work orders might have alternative lines to work on, which brought about the opportunity for increasing utilization across the lines through an assignment algorithm. For this sake, an adjusted version of the Hungarian Algorithm has been utilized as an assignment method. The adjustment includes a reference to Lawler's method in the algorithm SPASS to solve issues with sparse cost matrices (Carpaneto and Toth, 1983). In addition, a simple logic that allows work orders to be evenly distributed to the lines in terms of line utilization has been added. For instance, if a work order has equal duration among the lines the algorithm tends to choose the line with fewer jobs assigned. The algorithm is coded via Python. The computational complexity of the original Hungarian Algorithm was $O(n^4)$. Moreover, the algorithm takes the aforementioned input matrix.

Finally, the algorithm gives us an output matrix that shows every assigned line to every work order. Then, we use this output as input for the constraint programming based on Google OR Tools.

Constraint Programming Based on Google OR Tools

Google OR Tools package is implemented on Python by using the Constraint Programming (CP) in the background. Hence, a solution with faster running time is assessed. In the end, Gantt Chart of the schedule is obtained. We tried to guarantee that the final schedule is optimal or at least feasible in the verification section. The CP model solution can be analyzed in two parts. The first is what the solution offers and how it adapts to changes in business problems, and the second is how it produces solutions.

The first part of the solution analysis is more about generic model structure. Initially, before adding the objective and the constraints to the model, we obtain the horizon value of the schedule which shows us the latest end date of the problem, also, all parameters and constraints taken into the model must be integers. In this way, the algorithm searches for a solution in a much more restricted solution space by limiting the possible placements of the jobs on the timeline. The objective is set and constraints are added to the model after it indicates the horizon.

The objective is to minimize maximum lateness. For this matter, maximum lateness is defined as a decision variable in a constraint that signifies maximum lateness is greater than or equal to all other lateness values. By minimizing this decision variable, goal is reached and the objective is set.

There are two significant constraints. Firstly, precedence constraint defines precedence relations among couples of work orders. Secondly,the no overlapping constraint, a time interval is assigned to each work order in the schedule. No overlap constraint ensures that time intervals of the work orders assigned in each line do not overlap. After adding two main constraints, specifications of human in the loop are considered within the model. These constraints will be discussed in detail in the human in the loop section.

After we add the constraints and set the objective function, the Python code provides us with the Gantt Chart, assigned time intervals of the jobs and several human interactions.

$$I_{ik} : \text{the time interval that the job i assigned in line k}$$
$$I_{ik} \cap I_{jk} = \varnothing \text{ for all line k and jobs i and j } (i \neq j) \text{ (No overlap constraint in set form)}$$
$$S_{i,k} : \text{the starting time of job i assigned in line k}$$
$$E_{i,k} : \text{the ending time of job i assigned in line k}$$
$$S_{i,k} \geq E_{i,l} \text{ for i (Precedence constraint if the jobs have different tasks in different lines).}$$

The second part of the solution analysis is more about the CP model's background work which is inside the black box. To reach the outputs, OR Tools' CP model uses CP-SAT (Constraint Programming – Boolean Satisfiability) solver in the background. CP-SAT solver is constructed on top of an SAT solver with the Lazy Clause Generation(LCG) enhancement implemented Garey and Johnson (2003).

Mixing these two solver methods helps us create faster solutions with minimum loss of information. This new hybrid solver is based on SAT, LCG, and finite propagation that is ensured by assessing the solution horizon in the coding part Ohrimenko et al. (2007). With the horizon limitation and LCG, the solution approach alters the problem to NP-Complete from NP-Hard by limiting the solution space and searching over informative scans which is the main benefit of LCG Cook (1971). Hence, the solution's complexity is decreased from exponential to polynomial. This makes the solution approach eligible to assess bigger problems.

Human in the Loop

The dashboard including Gantt Chart and KPI values appear after the user runs the program based on CP model. The Gantt Chart reflects the schedule and relevant information generated through the CP model.

The chart also has user-friendly properties. One of them is that when the user puts the cursor on the work order, attributes of the selected job can be seen from the list which appears by standing on the work order action. For the user, this makes the chart easier to read and follow considerable features of the work order. Also, the user can zoom in to see smaller details in the lines. In addition, KPI values appear under the dashboard so the user can obtain and use KPI values for his/her further analysis.

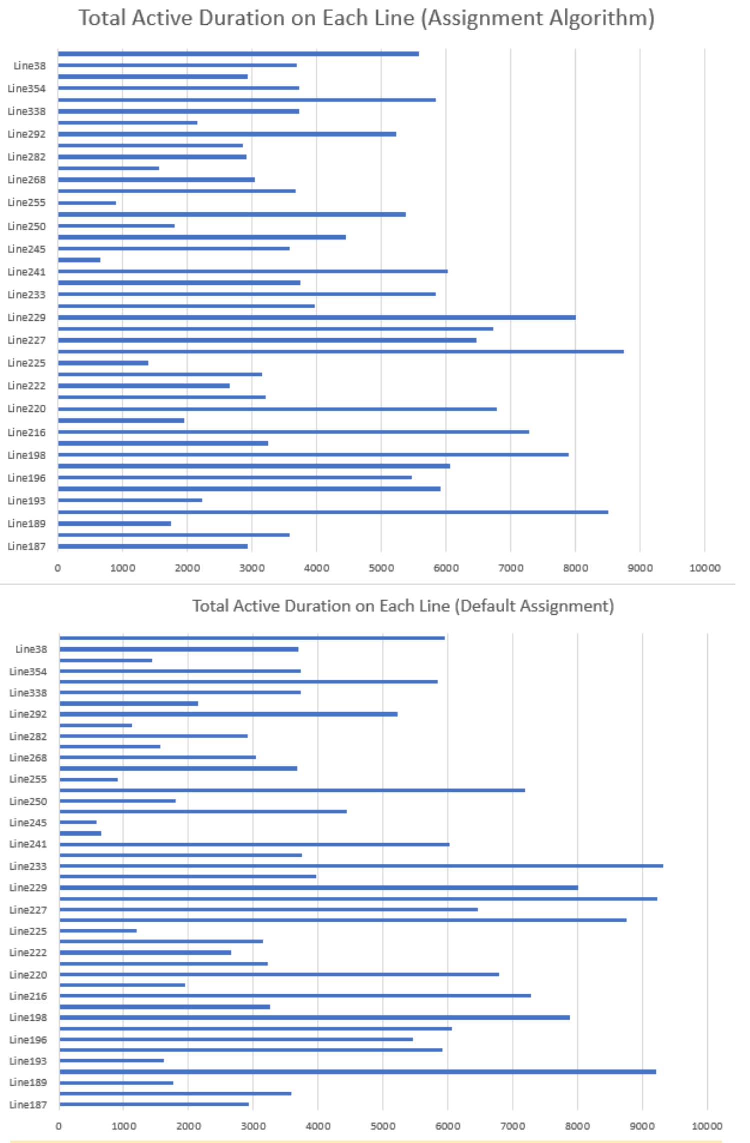
After the examination of the dashboard, the user may desire to adjust the location of work orders or may want to obtain some KPI values. For this purpose, the user interface has tools that put constraints into the model and make allocations. The user can specify the due date or the release time of a particular work order. Also, the user can alter the place of work orders across different lines or in the same line. Changing or adding release time, due date and work order swaps in the same line are done by adding new constraints. Even though the changes are done with different background operations, these changes can be reflected in our results rapidly as the solution is editable and operates fast.

When user adjusts, the User Interface (UI) updates itself and indicates new version of the Gantt Chart and KPI values. In this way the user can obtain the specific schedule with the help of Human in the Loop logic.

6.4 Validation

6.4.1 Assignment

The assignment algorithm was tested with the same data used for Google OR. Here the assignment of the work orders to the lines is tested with the alternative data. The duration of alternatives is calculated by using companies' product speed data (in units of product per minute). The duration of production of a certain is calculated via formula: quantity/speed. Cleanup and setup times of the specific work order are also included to the obtain total duration. As the validation criteria, the decision was to use maximum and minimum durations and the standard deviations of total durations in the line. It is believed that if the standard deviation of the durations decreases, the assignment of work orders are more homogeneous. Moreover if maximum value decreases and minimum value increases, the difference between lines is less than before. As a result of our comparison, it has been observed that the standard deviation of the lines improved by 17%. Additionally, the maximum duration is decreased and minimum duration is increased. These changes in statistics are the result of more balanced lines in terms of their work orders. Moreover, there are bar graphs in which lines and their total duration are represented for both cases. Check Figure 6.3 for comparison table and for the graphs. All in all, the assignment algorithm's goal was to create more balanced lines considering the possible alternatives. As the stats are represented after using the assignment algorithm, a more homogeneous distribution is achieved. It is also believed that this homogeneous distribution will result in improvements for the algorithm. We are expecting a small improvement versus scheduling without this algorithm and a bigger improvement versus current system that company is using.



STATISTICS	STANDARD DEV.	MAXIMUM	MINIMUM
COMPANY'S SCHEDULER	2534	9335	583
DYNAMIC SCHEDULER	2102	8755	655

Figure 6.3: Comparison of Default Assignment vs Algorithm Per Line

6.4.2 Google OR

The company data is tested with Google OR Tools-based constraint programming solution. Three different weeks were selected for the test in 2021. Work orders that started in these weeks, assigned lines, duration of work orders and due dates were imported into the Python code. Release date

Key Performance Indicators	Company's Current Statistics	Dynamic Scheduling Program's Statistics	Improvement
Average Tardiness (Minutes)	12605	11714	7.1%
Average Earliness (Minutes)	31308	33942	8.4%
Maximum Lateness (Minutes)	57586	55666	3.3%
Makespan (Minutes)	27154	9233	66.0%
Number of Late Jobs	108	106	1.9%
Number of Jobs	229	229	-

Figure 6.4: Comparison of Algorithm Results and Company's Solution

constraint is added to compare this data entering the algorithm with default assignment made by the company. In other words, when system starts to assign jobs, it does not proceed by thinking that timeline is completely empty. The completion times of the works that have already started and are currently in progress are taken as the release date. The results that are obtained in an example study conducted are as follows in Figure 6.4.

Considering this sample, the number of late jobs is decreased by 1.9%. At the same time, the average tardiness value decreases by 7.1%. Moreover, maximum lateness is decreased by 3.3%, average earliness increased by 8.4% and makespan is decreased by 66%. The algorithm is tested with three different inputs and there exists an average reduction of 4.1% for the number of late jobs. These improvements we have obtained from the examples, the fast operation of the algorithm and the openness to development are among the reasons why we prefer this solution.

6.5 Integration and Implementation

The new system will use Python for coding and use Streamlit run to create the instant dashboard. The structure of data in the Excel sheet is changed to make the data compatible with the algorithm. Hence, the solution uses different computer programs than Supply Chain Wizard. Also, the company do not have a scheduling algorithm that orders work in a sequence. Rather, their logic is similar to a scheduler in a calendar. Users can adjust the locations of work orders without overlapping. However, the new system comes up with a solution that considers precedence relation and lateness value. In addition, the company uses a "drag and drop" technique to change the locations of two different work orders. However, in the new system, the user can enter the two work orders which are wanted to be changed.

In dashboard design, output of the minimum-maximum lateness algorithm is represented. It includes four constraints, an example of them can be seen on Figure 6.6. First constraint shows the changing order of two work orders. Second constraint demonstrates the release time of a work order. Third constraint is used in determining due time of a work order. Fourth one is to change the assigned line of a work order. The solution is shown in a data frame. Statistics demonstrate key performance indices

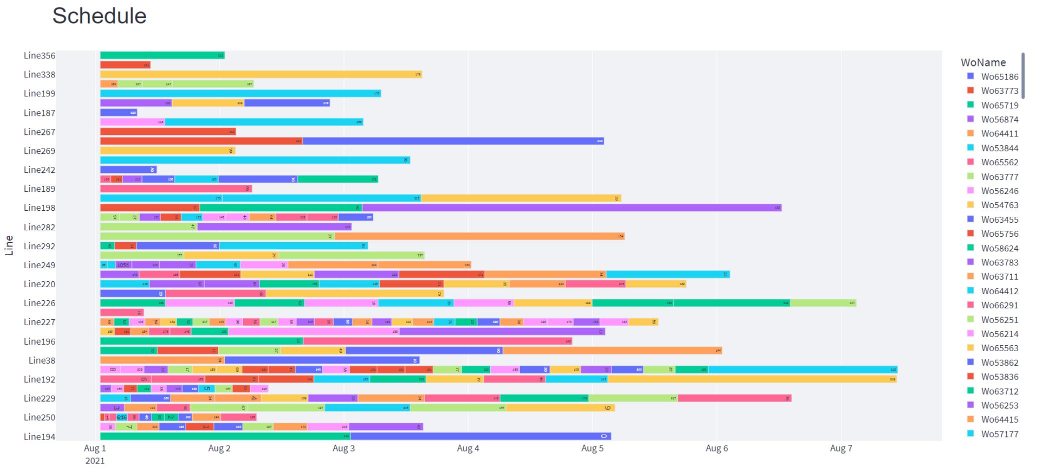


Figure 6.5: Gantt Chart Output of Google OR Tools Scheduling Algorithm

(KPIs) which are maximum lateness, computational time, number of jobs, average lateness, makespan and line efficiency. See Figure 6.5 for Gantt chart.

6.6 Benefits to the Company

The main benefit is the "human in the loop" logic. There are weaknesses in using only coding or manual implementations in the scheduler. For instance, manual usage is disadvantageous due to slow reaction to changes and toughness of following KPIs and constraints. On the other hand, machine use is disadvantageous due to its capability of only working with structured data and the toughness of adding domain knowledge. By hybrid application, in theory, these disadvantages will be removed.

The users will be supported by both an automated schedule generating model and the manually editing ability for creating their schedules. There are constraint insertion sections in the dashboard and the dashboard provides the user with KPIs and Gantt charts. In this way, if there is a situation that the user is unsatisfied with, if there are some restricted situations in real life, the user can add the constraint.

6.7 Conclusions

The system has several KPIs such as makespan, maximum lateness, average tardiness, and average earliness. Overall, the main improvements are at maximum lateness as the objective function and makespan. Since the objective is to minimize maximum lateness, and the main reason we use the assignment algorithm is to balance the lines to get a smaller makespan, higher improvement rates on those KPIs are observed. The project was developed

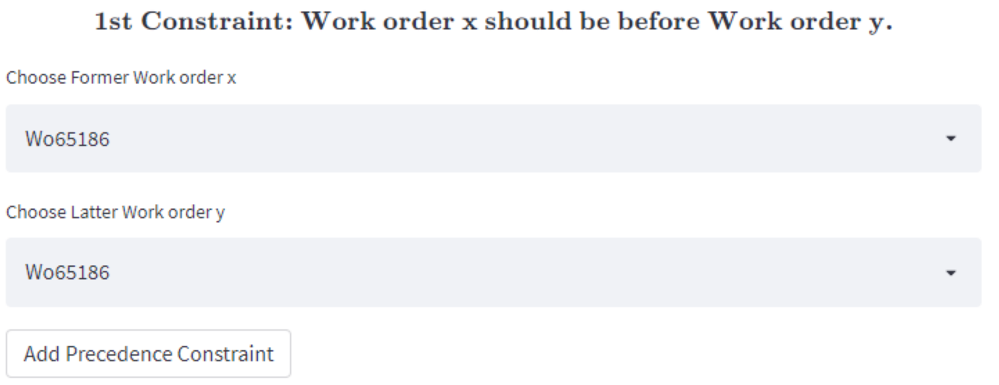


Figure 6.6: An Example Constraint from the Dashboard for Precedence

with modifications for the benefit of the company, with the decisions taken during the negotiations with the company throughout the project process. The flexibility of the system allowed adding new constraints for Human in the Loop logic to be easy and operate quickly. The last version of the system satisfies all conditions that are desired by Supply Chain Wizard. The algorithm created is suitable for the company to develop further in future.

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Erken Satış Verilerini Kullanarak Tekrar Siparişlerin Enazlanması | 7

Seçil Giyim

Proje Ekibi
Mert Can Arıcı, Egemen Bank, Cuma Ali Kesici,
Mert Kılıç, Ezgi Kıran, Alptekin Öksüz, Yaren Özgenç

Şirket Danışmanı
Gülcan Tıkız, Üretim Planlama ve Tedarik Yöneticisi

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Özet

Seçil Giyim ürünlerine olan talep, modayı belirleyen trendler nedeniyle oldukça belirsizdir. Seçil Giyim, sezon içerisinde popüler olan ürünleri için sıklıkla yeniden sipariş oluşturma ihtiyacı duyar. Genellikle, sezonun geri kalanındaki talep miktarı doğru bir şekilde tahmin edilemediği için tekrarlanan siparişlerin sayısı birden fazladır. Bu durum, aşırı üretim maliyetlerine (yüksek kurulum maliyetleri nedeniyle) ve talep açığına (yüksek üretim süreleri nedeniyle) yol açar. Proje, sezon başı satış verilerini kullanarak sezonda kalan talebi doğru bir şekilde tahmin edecek bir talep öğrenme yaklaşımı sağlamayı amaçlamaktadır.

Anahtar Sözcükler: Tahmin, Moda Endüstrisi, Talep öğrenimi, Bayes İstatistiği

Minimizing Repeat Orders through Learning from Early Sales

Abstract

The demand for Seçil Giyim's products is highly uncertain due to high fashion content. Seçil Giyim often needs to create repeat replenishment orders for its popular products within the season. In many cases, the number of repeat orders is more than one, as the amount of demand in the remainder of the season cannot be accurately predicted. This leads to excessive production costs (due to high set up costs) and demand shortages (due to high production lead times). This project aims to provide a demand learning approach that will accurately predict the remaining demand in the season using early in season sales data.

Keywords: Demand Learning, Forecasting, Fashion Industry

7.1 Company and System Descriptions

Seçil Giyim was founded by Faik Güngör in 1981. There were only nine employees at the start and only pants and skirts were produced. There are three additional brands except Seçil which are SCL, Galaxi, and Ilmio. Seçil products are basic apparel, SCL products are veiling apparel, Galaxi products are oversize apparel and Ilmio products are dresses. All of the brands make production for women. There are 300 sales points and 49 Seçil stores among different cities in Turkey. Seçil Giyim's main facility is located in Balgat/Ankara and there are over 500 employees working for them. During the Covid-19 era, Seçil Giyim's priority became e-commerce. Seçil Giyim aims to be a global brand in the apparel industry and they are making their decisions towards this goal.

In the current system, company forecasts the demand at the beginning of the season and places production orders based on these initial forecasts. Seçil Giyim has a department that has experience and foresight in this industry and this department does initial forecast. Initial forecast is the first production or order amount for a specific product and also a product's expected number of total sales. When demand for a product is believed to be more than production amount then company places a repeat order.

In some cases, the company has to make more than one repeat order leading to increased costs, and demand shortages due to long due times. In addition, there is seasonality in the company's products since they are in textile industry online at www.secilstore.com. The seasonality of products is currently divided by the winter and summer seasons. The company makes production of the winter season's products starting from the beginning of the summer while the summer season's products production begins at the beginning of the winter. As time passes in any season, the company must catch up with the demand by repetitive production if their stock keeping unit (SKU) is running low in inventory relative to its demand. Since there are lots of kinds of products, it is agreed with the company that we work on subgroups after Seçil Giyim provides us the subgroups in order to have tidier data and analyze it easier. In this way, we can combine products without any fashion knowledge as well. The amount of the repeated production orders is currently decided without performing any scientific analysis.

7.2 Problem Definition

The company stresses the accuracy of the frequency and the amount of the repeat production orders since they do not have any methods to overcome this high level of uncertainty. The reason for many repeat orders for a given SKU is that Seçil cannot accurately predict the demand in the remainder of the fashion season. When the demand is expected to exceed the supply (initial production+ first repeat order), Seçil has to launch a new repeat order. What Seçil expects from this project is to come up with a methodology and solution to identify hot selling products and accurately predict their total demand (based on early sales information) in the season, so that they can plan the production or procurement effectively without having to create many repeat orders of the same SKU.

In order to find the causes of the problem that the company faced, we started to determine the product groups that have a larger sales portion in whole sales by creating pivot tables that give us the top selling brands, categories, colors, and products for each year. We found that the first production amounts of the products are much greater than the total sales of these products. This difference between the first production amounts and the total sales reflects the change of repeat orders during the sales period.

If the amounts of repeat orders can be forecasted accurately then Seçil can place only one repeat order and fixed cost of manufacturing so that procurement can be minimized. Moreover, if predictions used in repeat orders are accurate, company can allocate its resources and workforce much better which helps achieve objective of meeting customer demand without having loss of sales and late deliveries. The solution should also determine the particular time in the early season at which hot sellers are identified and their future demand is predicted, in other words, how much early sales information should be used. Obviously, accuracy of the prediction will be better if the solution uses more sales data, for instance, prediction is made after observing sales for more weeks. However, delaying the decision can also lead to problems in production as the lead times can be very long.

The company is mainly struggling with the uncertainty of their after sales forecasting quantities. Since Master Production Schedule (MPS) and Materials Requirements Planning (MRP) are determined before for a specific product, forecasting plays an important role. The current system can not make any forecasting about the after market behavior of the newly released product. If the market behavior of the product can be forecasted accurately, then the number of repeated production for that particular product can be decreased. Moreover, if the repeated production decision is more accurate then loss of sales, inventory-on-hand will be minimized and capacity allocation will be more efficient.

7.3 Proposed Solution

7.3.1 Critical Assumptions and Major Constraints

In order to develop and implement the possible forecast methods for future sales, initial forecast for the products has a significant impact on the accuracy of the outputs of the method that we are going to use. We will assume that initial forecast is given. The possible effects on the market such as economic circumstances, advertisement budget that is allocated for products, etc. are assumed to be the same for the forecasted future period. The other critical assumption is about no salvage. In other words, we assume that if the production and repetition amount of a product exceeds the total sales, then we do not take them into consideration as next year's inventory.

During the sales period, inventory is an important constraint for the sales of products. We assume that all subsidiaries and the main brand use the same inventory. Therefore, final products of the main production and sub production stock up in the same inventory in addition to the products that are bought from the subcontractor.

Our objective is to help Seçil Giyim with their decisions about the repeat orders within the fashion season. We are planning to decrease the number of repeat orders according to the latest sales data observed by the company. The number of repeat orders will be decreased and the total produced quantity will more closely match the total demand in the season. Applying these improvements into our final model, the company will be able to predict the demand in future periods better.

7.3.2 Solution Approach

In order to minimize number of repeat orders, we used statistical methods to forecast demand based on early season sales information. To calibrate our statistical models, we used historical sales, forecast, and prediction data from earlier seasons. The necessary outputs and inferences were planned to

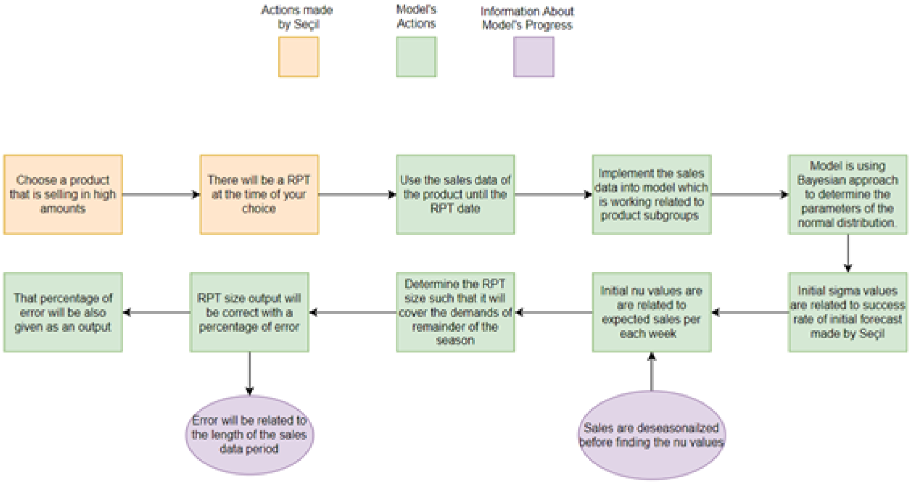

Figure 7.1: Conceptual Model for the Solution Approach

be made by using proper data analysis techniques and methods in programming environment such as RStudio. These outputs of sales data were used in the stage of determining suitable forecast method or a method that scales the initial sales data with the demand for the future sales. Possible methods were analyzed according to the requirements of problem and then methods that satisfy requirements most were tested with respect to their accuracy by using test sales data of the company. Finally, model with satisfactory accuracy was implemented into an interface that allows users to select different options about the decision of the repetition time and amount.

Conceptual Model

We divide our conceptual model into three major parts in order to illustrate the action taken by who and when basically. The major parts are set as Actions made by Seçil, Model's Actions and Information about Model's Progress. Selecting a product which is selling in high amounts and deciding on the time of the repetition are made by Seçil. Seçil identifies hot sellers. Then, our model suggests that we decide on the repetition time and size by the use of sales data until the repetition date. Finally our model gives some output related to the repetition size with a percentage error which also be given as an output. Figure 7.1 shows the conceptual model.

Mathematical Model (Bayesian Method Theoretical)

Since our problem's solution relies on the observation of the past data, our model's fundamentals are based on Bayesian statistics Eppen and Iyer (1997) where we will use conjugate distributions that consist of posterior distributions and prior distributions with estimated parameters. The posterior distribution's parameters are dependent on the prior distribution that has initially estimated parameters. Combining this approach with the Bayes theorem; whenever a new observation would be involved in the data set, the posterior distribution needs to update its parameters both according to the parameters of the prior distribution and according to the newly added observation. Suppose a prior distribution is distributed with the parameter theta would be p(theta) θ and our initial data set is [x], when a new observation x will be involved in this data set our prediction of the posterior distribution will be given as

$$p(\overline{x}|[x]) = \int_{\theta} p(\overline{x}|\theta)p(\theta|[x]d\theta) = \int_{\theta} p(\overline{x}|\theta)p([x]|\theta)p(\theta)/p([x])$$

by Bayes theorem. For our problem, if the observed sales data of a hot selling product can be fitted into a distribution, then we would obtain a prior distribution with known parameters. As the sales period of this product continues, the parameters of the distribution of this product would be updated each week by considering the past week's distribution and new observed weekly sales. Assume that a product's weekly sales is distributed normally with parameters μ and σ, while μ is distributed normally with parameters μ_0 and σ_0. Whenever a new weekly sale data are observed after n weeks, the weekly sales distribution constructs a posterior distribution and its parameters will be updated as

$$\mu = \left(\frac{1}{\sigma_0^2} + \frac{n}{\sigma^2}\right)^{-1} \left(\frac{\mu_0}{\sigma_0^2} + \frac{n\overline{x}}{\sigma^2}\right) \quad \text{and} \quad \sigma = \left(\frac{1}{\sigma_0^2} + \frac{n}{\sigma_0^2}\right)^{-1/2},$$

where $\overline{x}$ is the average of realized sales in n weeks. To build forecasts for repeated orders, we can use the updated μ since it would be an unbiased estimator while updated σ is an indicator for the error. If the updated μ is multiplied with appropriate factor, then an estimation for the total demand for the remaining sales period will be obtained.

Solution Method

To identify how sales of the product behaves in the sales period according to these segments, weekly factors were found. Dividing the actual total sales in a specific week to the total sales would give the weekly factor. There might be weeks with no sales during the sales period. Therefore, we have to adjust the weekly factors accordingly. Adjustment can be made by taking summation of the weekly factors of the corresponding weeks where sales were made and dividing the original weekly factors to this summation. Then we have to adjust the weekly sales for a given week. Dividing the actual sales with the multiplication of the adjusted seasonal factor of the given week and total sales period of the product would adjust the weekly sales: adjusted sales of week i = Actual Sales / ((adjusted seasonal factor of week i) $\times$ (total sales period of the product)).

After adjusting the weekly sales, we estimated the coefficient of variation (CV) of the segmented categories by using adjusted weekly sales for all segmented categories. To estimate CV of one specific product, standard deviation of adjusted weekly sales of the product is estimated and mean of the adjusted weekly sales of the product is estimated. Dividing the standard deviation to the mean would give us the CV of the specific product. Taking the average of products' CVs estimates the CV of the segmented categories. Since we estimated the CV of segmented categories now we have more ideas about how weekly sales of the segmented categories vary. However, CV is not enough to overcome the variation. Therefore, we need standard deviation (σ) of the product's weekly sales. σ is estimated by multiplying μ_0 with CV of the given segmented categories: $\sigma = \mu_0 \times CV_{\text{segmentedproduct}}$.

Since μ_0 is the mean of the distributed weekly sales, it can be assumed that μ_0 is the initial forecast for the product. Since μ is distributed with μ_0 and σ_0 we have to estimate the σ_0. The interpretation of σ_0 is "How much do we rely on the initial forecast?" Therefore, σ_0 is estimated by multiplying μ_0 with the appropriate factor. This appropriate factor can be found by "fine tuning" method:

$$\sigma_0 = \mu_0 \times \text{Factor}$$

For simplicity, assume that product's weekly sales is distributed normally with parameters μ and σ while μ is distributed with μ_0 and σ_0. μ_0 corresponds to the initial forecast. Since we know the initial forecast for the total sales for that product, multiplying this forecast with the adjusted factors would give us the expected sales amount in that corresponding week. By using conjugate prior (Bayesian Method), we are able to estimate posterior distribution's parameters after each week. If the σ is higher for that week, then our forecast would not be accurate enough for the remaining period. In other words, σ_0 measures how confident the company is about their initial estimate while σ measures the volatility of demand.

The μ_0 for that specific product was estimated by dividing initial forecast to number of periods that sales of product happened. To implement conjugate prior, we need to estimate the cumulative adjusted sales for the sales period since posterior parameter of μ has the expression $\sum_{i=1}^{n} x_i$ which corresponds to adjusted sales in our case while n is the corresponding sales period. After each week, we build forecasts by multiplying posterior μ with the remaining adjusted seasonal factor and the total sales period. The solution method implementation on Excel can be seen in Figure 7.2.

B72 f_x =B69*D65

	A	B	C	D
63				
64				Average of Coefficient of Variations
65				1,1
66				
67				
68				
69	M_0	10,0625	factor	
70	sigma_0	2,515625	0,25	
71	Mu			
72	sigma	11,06875		
73				

Figure 7.2: Calculation of σ

7.4 Verification and Validation

7.4.1 Verification

To verify the model, some different cases will be investigated to show that even in an extreme case, the model will perform in an expected way or not. We carried out verification in three different tests.

- Continuity: We tried our model with different products that are part of different subgroups and different colors. Since we take products' SKU, sub group and their sales data until that point as an input; it is thought that if the model is tested with different products, all of the inputs will differ. Results obtained for skirt and blouse examples are illustrated in Figures 7.3 and 7.4, respectively.

- Degeneracy: Different σ_0 values are used to observe the forecast result. Our σ_0 value shows how much we trust on the initial forecast. This value determines how fast the mean of our distribution updates itself with upcoming sales data. We tried different σ_0 values and observed expected results. We also analyzed the outcome with large standard deviation.

- Consistency: We tried to switch the season lengths. We tried to cut the season before the sales season was complete and we also tried to increase season length by adding adjusted sales amounts as the new sales data.

SKU	1010071810200600	Weeks	Forecast	Remaining Sales	Inventory	
Brand	SCL	1	36,29501129	38	154	
Subgroup	Etek	2	20,77420603	28	144	
Color	Yeşil	3	14,1608149	24	140	
Year	2018	4	20,7955698	18	214	<=Repeat Order
		5	24,98592124	16	212	
		6	9,96922457	14	210	
		7	10,50534205	12	208	
		8	10,45046168	10	206	
		9	9,989607702	8	204	
		10	3,505507136	6	202	
		11	1,240291553	2	198	
		12	0	0	196	

Figure 7.3: Example for SCL Green Skirt

		Week	Forecast	Remaining Sales	Inventory	
SKU	10100118104083	32	84,95013157	172	148	
Brand	Seçil	33	83,18432192	146	122	
Subgroup	Bluz	34	149,6484067	138	114	
Color	Safran	35	125,636307	126	266	<= Repeat Order
Year	2018	37	108,5161804	122	262	
		38	119,0166938	116	256	
		39	114,4422693	114	254	
		40	77,34868681	112	252	
		41	64,07175286	110	250	
		43	51,5131145	94	234	
		44	47,16485938	86	226	
		45	51,46693661	78	218	
		46	41,2467292	68	208	
		47	34,6138527	62	202	
		48	31,07592104	60	200	
		49	19,95981634	56	196	
		50	15,41734773	38	178	
		51	6,731082035	16	156	
		52	0	0	140	

Figure 7.4: Example for Seçil Saffrony Blouse

7.4.2 Validation

We decided to complete the validation of our model on a single product. An individual SKU that has one repeat order is chosen to validate the model, since the model can represent a better alternative for the current system. After choosing a product which has only one repeat order, the purpose is to compare the result of our model's forecast at the time Seçil puts the repeat order with what actually happened.Then we observed that the outcome of the repeat order from our model is more accurate than the repeat order made by Seçil. Therefore, we have achieved that the model could work in order to have a better alternative for the company.

7.5 Implementation and Interface

We decided to use R Shiny to implement the project. Data from the previous years in an Excel sheet will be read by R. This data will be used for the determination of the product subgroup, brand and color factors which will be further used for the forecast calculations. After users put the required inputs, they will run the model and the results will be obtained. They can implement model to their current operations by using the model whenever a product is selling more than expected and Seçil needs to have a repeat order for the product. Figure 7.5 displays a glimpse of the user interface.

7.6 Deliverables and Conclusion

7.6.1 Deliverables

As we underlined before that Seçil Giyim has many products, it will have sales amounts that vary according to the time, so the frequency of using this

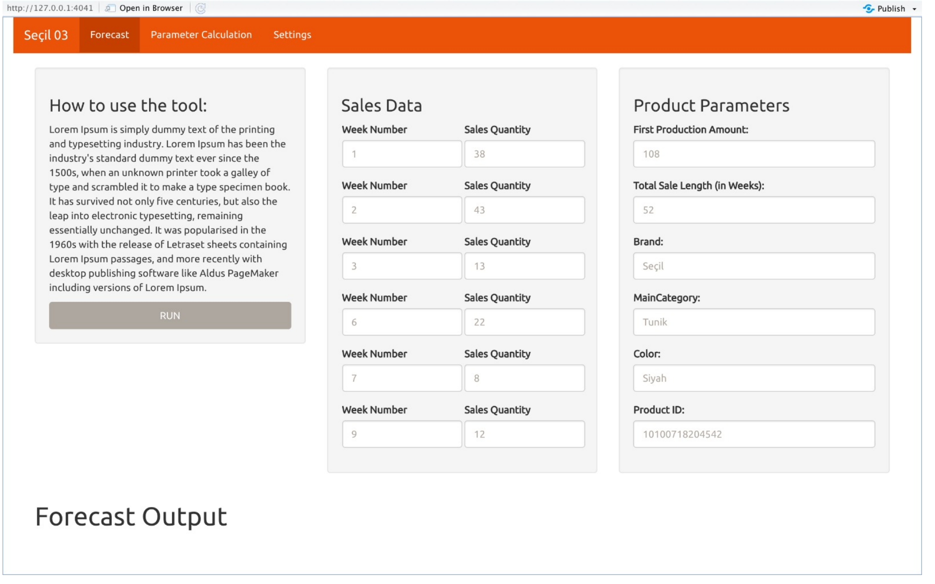

Figure 7.5: Possible Interface Image

project will also vary according to the product types. Since the production methods of the products are also different, the lead times are also a variable. If a product takes a long time to supply, the company may want to measure the demand with a forecast using shorter-term data. In addition, more accurate forecasted demand is obtained by using longer-term sales data as data in a product group; these are short and easier to supply. This indicates the usability of the project by the company.

Users will choose the cumulative sales amount according to their needs and according to the specific product to check the optimal repetition amount. This amount is found with the help of the Bayesian Model. Mainly the company will enter 4-6 weeks of sales data of the products as input in this system, and the model will propose the amount that should be produced as a repeat order according to the sales observed so far, initial forecast and the initial production order. The solution will also provide different alternatives on the subject of when to create such repeat orders depending on how many weeks of sales that were observed before. The company will benefit from our model that decides on when the repetition will be made and the repetition size. In addition, the company can use the Bayesian model in order to decide on the production amount. This is decided accordingly by the relation between the expected sales and actual sales. If actual sales are higher or lower in any case, the expectancies will change accordingly.

7.6.2 Conclusion

In the current system of Seçil Giyim, the forecasted demands of the products are initially made, but this forecasting is not accurate enough. The company needs repeat orders for products whose demands are underestimated. Because the remaining demand cannot be accurately predicted, the company often needs to create multiple repeat orders for the very same SKU. Inaccuracy of the forecasts also lead to not being able to satisfy the demand due to long lead times and excessive inventory. The project will use a scientific methodology to estimate the remaining demand in the season based on early sales information. Our model decreases the need to create multiple repeat orders, leading to decreased production costs. It also helps reduce excessive inventory remaining at the end of the season and reduce demand shortages.

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8 Geçmiş Satış Verileriyle Güncellenmiş Distribütör Talep Tahmini

Eti Gıda

Proje Ekibi

Doğa Çelikkan, Nadin Gegin, Ali İlhan Haliloğlu,
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Şirket Danışmanı
Özgür Seven
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Özet

ETİ Gıda Sanayi ve Ticaret A.Ş.'nin geleneksel satış kanalına hizmet veren distribütörlerinin satışlarının daha iyi tahmin edilmesi üzerine çalışıldı. Daha iyi satış tahmini ile, distribütörler için daha doğru satış hedeflerinin belirlenmesi, bu sayede distribütörlerin iade ve revizyon taleplerinin azaltılması amaçlandı. Yeni satış tahmin modelinin talepteki dalgalanmalara daha etkin bir şekilde yanıt vermesi hedeflendi. Çeşitli metotları içerisinde barındıran tahminleme sistemi, tahminlemesi yapılan markalar için en uygun metodu seçtikten sonra tahminlerin ürün seviyesine ayrıştırdı. Yeni sistem ile ürünlerin yaklaşık %55'inde talep tahminleri iyileştirildi.

Anahtar Sözcükler: Satış tahminleme, distribütör, geleneksel kanal, satış hedefi belirleme

Distributor Demand Forecast Updated with Historical Sales

Abstract

A new demand forecasting model was developed for ETİ Gıda Sanayi ve Ticaret A.Ş.'s distributors, who operate in the traditional sales channel. With better sales forecasts, the aim is for ETİ to assign more accurate sales forecasts to distributors, and thus reduce the revision and return requests from distributors. The new forecasting system is aimed to be more sensitive and reactive to fluctuations in demand. The new system contains several forecasting methods, and after selecting a suitable forecasting method for each brand, disaggregates brand level forecasts to SKU level forecasts. The new system improved sales forecasts in approximately 55% of SKUs.

Keywords: Sales forecasting, distributor, traditional sales channel, sales target determination.

8.1 Company Description

ETİ Gıda is among the leading companies in the Fast Moving Consumer Goods (FMCG) industry in Turkey. The company started its activities with a biscuit factory in Eskişehir in 1961, founded by Mr. Firuz Kanatlı as a sole proprietorship. ETİ Gıda Sanayi ve Ticaret A.Ş. was later established in 1972, with an even more diverse product mix. ETİ Gıda currently has seven production facilities in Turkey: five in Eskişehir, one in Bilecik and one in Konya (ETI, 2022).

8.2 System and Problem Description

8.2.1 Analysis of Current System

ETİ begins its sales planning process by establishing the year-end closing sales forecast for each customer group, which are then divided for each product group. These are used to determine the product space, with active and passive products. Later, in ETİ, an intuitive forecast is made incorporating certain factors such as seasonality, in order to determine the sell-out data. The final sales forecast includes the distributor input on a weekly basis. These data are entered manually to the demand planning system. After the forecasts are completed, they are sent to the supply chain department for revision and approval in case some estimates cause trouble in production or packaging. After the final approval, a detailed sales plan is made to determine the quantity to be shipped for each product category to each sales channel.

Overall, ETİ uses a push system while working with its distributors. Based on forecasts, distributors are pushed the amount of products determined by ETİ. Distributors have a limited chance for requesting revisions - each distributor is assigned a different percentage interval, which are predetermined by ETİ, depending on historical data and return rates. If distributors are assigned too much product then, this increases their chance of returning the additional products to ETİ, which creates additional costs for ETİ .

8.2.2 Problem Definition and Scope

The current sales and shipment system are unable to respond to the changes in demand actively. The current sales forecasting model is not performing well in terms of forecast accuracy; therefore, the sales planning and shipment are affected negatively. Possible effects that influence sales, such as promotions done by distributors, customer activities, seasonality, are not taken into consideration in a consistent manner, leading to low accuracy in forecasts.

Although the company faces similar problems for many product groups and distributors, the project scope is limited to improving the sales forecasts for a pilot distributor located in Ankara (Distributor T) and a pilot category (Category B). This distributor and category combination was chosen, as Distributor T was the distributor with highest sales volume in Ankara, and Category B was its sales category with the most sales. With this combination, we had a long and continuous data set, as this distributor had regular sales across the whole time period. Working with the distributor with the largest sales volume also allowed us to create a larger financial impact with this study.

The outcomes of the pilot study and the decision support system provided by the project team can later act as reference for ETİ to implement similar practices for improvements in other product categories.

8.3 Proposed System and Model

8.3.1 Proposed System

Historical sales data received from ETİ is at the stock-keeping unit (SKU) level and on monthly time basis. It spans the time period between January 2019 and October 2021. The data provides, for each distributor, how much (in TL) the distributor bought of that SKU from ETİ in a given month.

As a modification on raw data, some SKUs are consolidated, specifically those which are the replacements of old SKUs that had a different product code due to newly released packaging and weight changes. These new SKUs

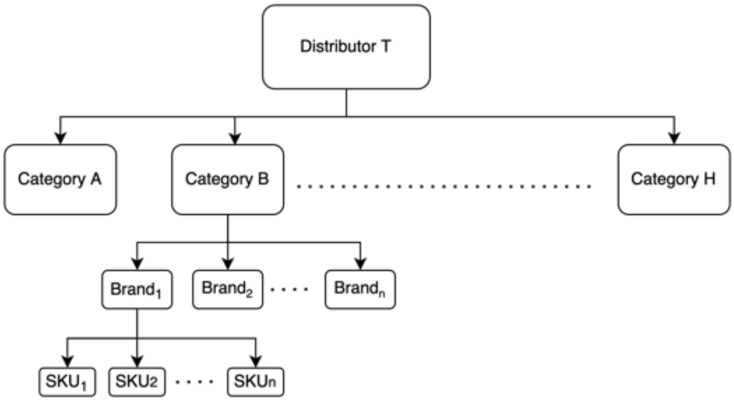

Figure 8.1: Hierarchy of Sales Data

does not have historical sales data, but after consolidating them with their old corresponding SKUs, it is possible to generate forecasts for them as well.

Although historical sales data is in SKU level, due to ETİ's dynamic assortment, making forecasts in the SKU level is not seen as a viable approach. We also know that aggregate forecasts are usually more accurate. Therefore, as an alternative, we benefit from hierarchical nature of our data, and do forecasts at different levels of aggregation. By summing up the SKU level data with respect to brands and categories, the data is aggregated into "Brand Level" and "Category Level". Figure 8.1 shows our data hierarchy.

Forecasting system is created using "R" programming language. The system uses the "Middle-Out" approach, which is used for forecasting hierarchical data. For the "Middle Out" approach, a middle level is chosen and forecasts are generated for all series at this level. Then, the middle-level forecasts are disaggregated to series below this level, and aggregated to series above this level (Hyndman and Athanasopoulos, 2018). In our case, we use the brand-level as the middle level. We forecast sales for each brand individually, then disaggregate these to the SKU level. We sum the brand level forecasts to achieve the category level forecasts. Figure 8.2 shows a representation of these approaches.

To be able to perform the Middle-Out approach, we require forecasts at brand-level. As the forecasting horizon, we forecast the $T + 1$ and $T + 2$ month's sales by training the model at the beginning of month T, where T represents the current month. This is in-line with ETİ's current forecasting practices. Figure 8.3 shows our conceptual model. To generate these forecasts, we form a set of forecasting models listed below:

- Moving Average of order 1..12
- Exponential Smoothing

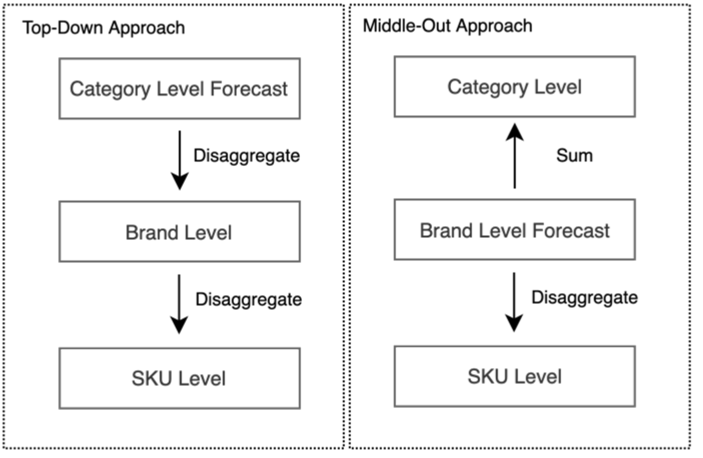

Figure 8.2: Top Down and Middle Out Approaches: Representation

- Holt, Holt-Winters (Additive and Multiplicative)
- Linear Regression with year and month as predictors
- ARIMA, SARIMA

Our forecasting system designates the past 6 months as a "test period". If we denote the current months as month T, during the test period, we start at the beginning of month $T-6$, take all previous data (months 1 ... $T-7$) as the training set, and forecast the brand-level sales of months $T-5$ and $T-4$ using all of the models in the model set given above. Then, we move on to the next month, $T-5$ and repeat the same procedure as before, so that we end up doing several iterative forecasts in a rolling time-horizon

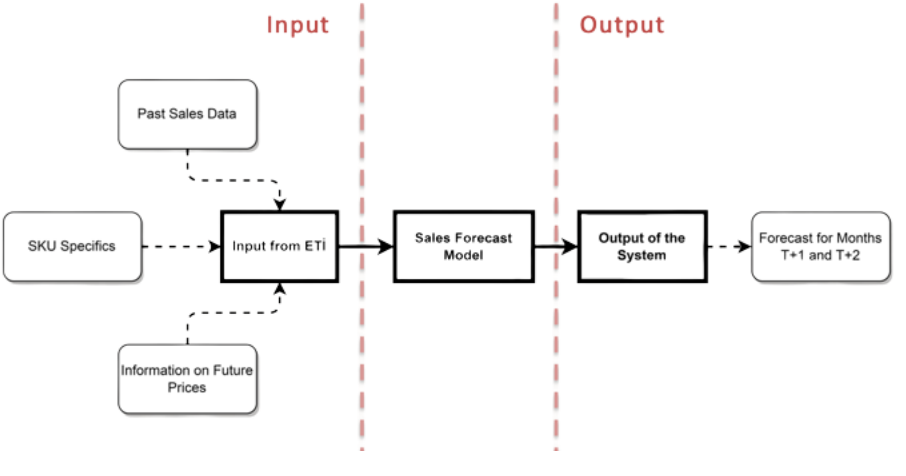

Figure 8.3: Conceptual model

fashion for 6 months. In summary, we use a six month testing period, and train all models during that testing period with all available months' data. As an example case, if we were in July 2022, we would use January - June 2022 as the test period. During testing, we would start in January 2022, and use data from January 2019 to December 2021 to train the model. After training, we would generate forecasts for February and March 2022. During the next iteration of testing, we would start in February 2022 and use January 2019 - January 2022 as the training data set. Then, we would generate forecasts for March and April 2022.

After the test period is over, we compare the results of the forecasts made during the forecast period with actual sales, using a hybrid measure of Mean Absolute Scaled Error (MASE) and Bias, with MASE having 40% weight and Bias having 60% weight. MASE gives an insight into how well the model the chosen model is forecasting compared to a naive model. Meanwhile, bias shows whether the chosen model is chronically under-forecasting or over-forecasting by calculating sum of forecast errors divided by sum of actual values (Hyndman and Athanasopoulos, 2018). Bias is given special importance here, as we believe that a low bias model is important for ETİ's purpose. A low bias model will not output chronically low or high forecasts, which could result in chronic under and over-stocking for distributors.

In summary, hybrid of MASE and Bias allows us to select forecasting models performing better than naive models, and making low chronic error. After selecting the forecasting models that have performed best over the past 6 months for each brand, we use the selected models to forecast months $T + 1$ and $T + 2$'s sales, where month T is the current month.

8.3.2 Notes on Model Development

Before settling on the above described forecasting system, we also tried using the "Top-Down" hierarchical forecasting approach, which performed worse compared to the "Middle-Out" approach. A representation of both approaches can be seen in Figure 8.1.

To expand on our model set, we also tried adding regression, ARIMAX and SARIMAX models to our model-set, which could utilize regressors/predictors. We tried adding the following predictors to these models:

- Number of SKUs offered in the current month
- Number of SKUs launched in the current month
- Number of SKUs launched in the last month
- Brand Price Index: Average unit price of SKUs in a brand

- Relative Price: Relative price of a brand compared to other brands in the category
- Price Drop: Whether the brand price index has dropped compared to the past month
- Monthly Consumer Price Index of Turkey
- Monthly Credit Card Spendings of Turkish Card Users (Published by Interbank Card Center - (BKM, 2022))
- COVID-19 Pandemic: A multinomial variable with levels 1-5 that represent increasing strictness of COVID restrictions.

For selecting predictors, we implemented a brute-force selection approach, which considered all 1, 2 and 3 combinations of our 9 possible predictors and inserted them to eligible models. We limited maximum number of predictors to 3 in order to prevent over-fitting due to having too many predictors. These models with regressors were added to the model set and their performance was compared to others. Even though, in most cases, they were performing relatively well, we decided to rule these models out after verification stage, as we observed that these models were not showing consistent results during simulation and the predictors had counter-intuitive coefficients. Some predictors, majorly the economic parameters like CPI, also carried the risk of showing major changes in the future due to Turkey's current economic volatility, which could affect forecast results unpredictably.

8.4 Verification and Validation

For verification stage, we check whether the forecasting model selection algorithm produces consistent model choices. Once the system selects forecasting models for each brand, these models are given as input to the $simulate()$ function in R, which simulates data from the distribution of the inputted model. Simply, this gives us a simulated set of historical sales data. We collect the simulated data, and enter this data into the system instead of the actual historical sales. After running the system again with the simulated data as input, we check whether the system selects a reasonable model for the brands, knowing which models their data was generated from.

For the validation stage, we use the last six months as the "test" period and generate rolling horizon forecasts for all models at the beginning of each month. After, we select the model that performed best across the six-month forecasting horizon for each brand by comparing forecasts to actual sales. Then, by using the chosen model, we generate forecasts for the months T,

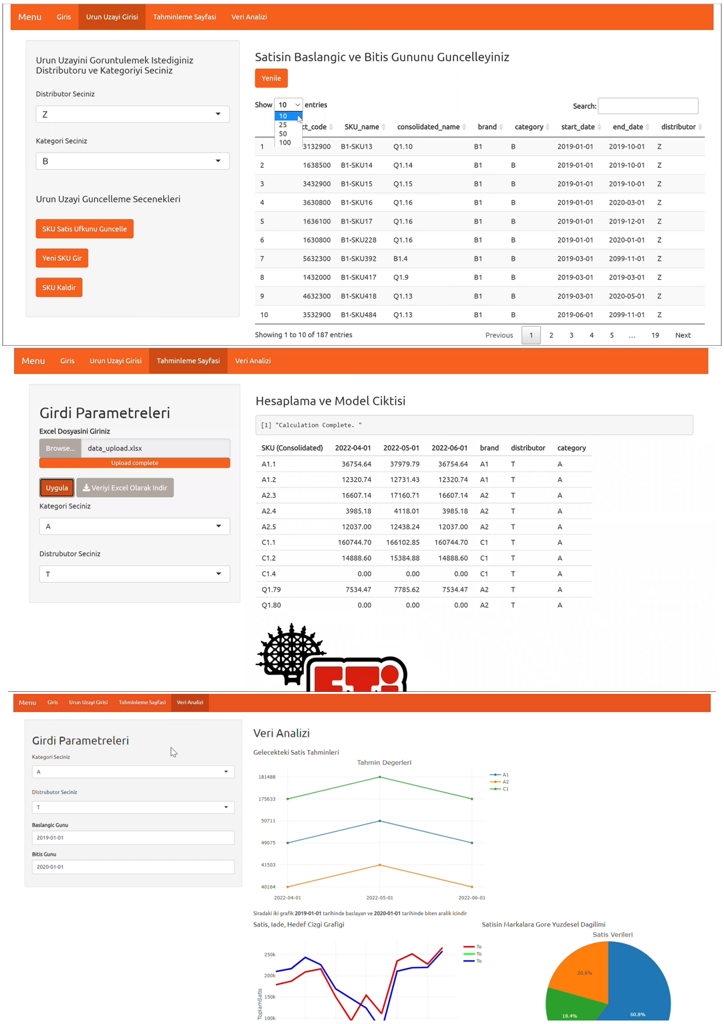

Figure 8.4: Hierarchy update (above), forecasting (middle), and data analysis pages

$T+1$, and $T+2$, which are in the unseen future. We assume that we were three months behind our last data and used data before in the same year as the test period to perform validation. We then forecast the brand level sales for these three months that we had the data, without using them. Our aim is to observe that the model we choose after the test period would provide high accuracy forecasts between these periods.

8.5 Implementation and Integration

The user interface is designed using R's RShiny package. The user interface has 4 sections: instructions, hierarchy update, forecasting and visual analysis of forecast results. Screenshots of the user interface can be seen in Figure 8.4. The user interface requires an Excel file input containing historical sales data from ETİ. It also requires an up-to-date hierarchy file, which contains the product codes and names of SKUs, and information on whether they are in the product-space. We were unable to integrate with ETİ's database due to confidentiality purposes, therefore, we designed the system to ask for input from the users.

For the pilot study, the user interface and user manual are delivered to ETİ in April. The pilot study consists of ETİ testing the system, comparing the forecast results with the actual sales, and providing feedback on possible areas of improvement.

8.6 Benefits to the Company

For the pilot product category and distributor, the proposed system presents better forecasting accuracy. With better forecasting, ETİ will also be able to react to changes in demand better and indirectly improve its shipment planning activities. The provided benefits can be found below.

- Increased Forecasting Accuracy:

  The increase in forecast accuracy reduces the revision and return rates, coming from the distributor and indirectly altering the shipment plans. The expected reduction in return rates will reduce the costs, as ETİ is responsible for re-purchasing all the unsold goods from the distributors. Reducing the number of revision requests will prevent losses as in lost sales. Currently, as the distributors have a percentage interval within which they can make a revision, it is not possible to increase the order that ETİ sets despite the higher market demand, hence better forecasting can also increase profits by increasing the quantity sold. For cost savings in a wider scale, we recommend ETİ to implement this system for other product categories as well.

- Less Management Time Spent on Evaluating Revisions: Currently, the data are manually entered to the algorithm in order to compute the sales forecasts. The proposed system reduces the management time spent on sales forecasting and distributor stock allocations. Also, less time is allocated to revision evaluation, since now the management needs to approve a smaller number of revision requests and adjustments to shipment plans that cover those requests. Thus, management hours spent on similar tasks is reduced, and the saved time can be spent on more critical tasks that require managerial attention.

- Higher Responsiveness to Demand: The proposed solution strategy leads to a quicker response to changes in demand, which may be caused by external market factors, distributor activities, seasonality, changes in customer preference and promotions.

8.7 Conclusion and Future Work

The project covers one category and one distributor and uses a Middle-Out approach. For each brand, a selection of models giving the best predictions in the last 6 months period are found. At the brand level, the most appropriate percentage of sales in the previous 6 months is selected, and disaggregation is performed. Compared to ETİ's distributors' sales targets, our model forecasts were better in 51 of the overall 93 SKUs, which is approximately 55% of SKUs. To conclude, this project improves ETİ's sales forecasting system, thereby reduces revision requests, product returns, and generates better allocations to distributors, which enables ETİ to react to changes in demand dynamically and indirectly improves the shipment planning activities. We believe that this forecasting system will provide better forecasts gradually, as the training data set will expand as time passes.

As future work, we recommend trying to add predictors or regressors to the system when more data is available, which will prevent over-fitting. This system can also be used as a benchmark for future forecasting systems to be implemented. Moreover, we recommend ETİ to implement this system for other product categories and distributors. Considering our pilot study, we provide results for one distributor and one category. However, the system is designed to be flexible and applicable to other categories and distributors, therefore, we recommend ETİ to consider implementing the system for other distributors and categories.

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9 Hammadde Satın Alma Karar Destek Sistemi Tasarımı

İşbir Yatak

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Özet

Şirkette gerekli malzemeyi doğru zamanda ve doğru miktarda almak için planlama ve satın alma departmanları birlikte çalışmaktadır. Planlama departmanının gerekli malzemeleri planlamak için bir yöntemi vardır. Ancak Planlama Departmanının yıllık planlarıyla aylık satın almalar arasında uyuşmazlıklar yaşanmaktadır. Bu durum satın alma departmanının problem yaşamasına neden olmaktadır.Mevcut sistem değerlendirilmiş ve satın alma departmanı için daha verimli bir satın alma yöntemi hazırlanmıştır.

Anahtar Sözcükler: Satın Alma, Envanter, Planlama.

A Decision Support System for the Raw Material Procurement

Abstract

In the firm, Factory the Planning and Procurement Departments work together to purchase the required material in the correct amount on time. To achieve this, the planning department has a method to plan the required materials. However, there is a discrepancy between the monthly and yearly plans and procurements. Therefore, this situation causes the procurement department to purchase inefficiently and unclearly. The current system is evaluated, and an efficient purchase method for the procurement department is proposed.

Keywords: Procurement, Inventory, Planning.

9.1 Company and Problem Description

Isbir Holding was established in 1968, and I¸sbir Yatak was established in 1999 as the youngest investment of Isbir Holding. There are two assembly lines in the manufacturing area and two main types of products that are produced in these lines, one of them is quivered mattress, and the second is sealed mattress. Due to prices of sponge and spring steel being relatively high and those products being frequently used, İşbir has decided to procure essential raw materials from their own facilities. These raw materials are used according to receipts of products. The Planning Department decides on the needed amount and needed arrival times of the raw materials by using the Material Requirements Planning (MRP) and the Bill of Material (BOM) for a three-month period. After this decision the Procurement Department decides on which suppliers to purchase from and the order quantities to be purchased by evaluating the lead times, prices and minimum order quantities for suppliers. Using this decision the Procurement Department finalizes the purchases.

As we have been informed by the representatives of the company, the planning schedule is generated in the Planning Department initially. They analyze the sales data from the previous periods, mainly the previous year, and then generate an estimation of the forecast for the upcoming year. With the forecast being in consideration, they generate a master production schedule (MPS) for the upcoming 12 months with monthly time buckets taking into account the production capacity of the company. The initial MPS is then divided into 3-month long horizons with time buckets as weeks in order to see a more detailed picture of the production schedule. Furthermore, the plan is differentiated for each raw material which is extracted from the bill of materials of the products. After the MPS is set, the Procurement Department approves of the plan and starts the purchasing process. After different suppliers have been called and various price offers have been taken, they are evaluated in an Excel sheet for comparison purposes. The comparison is done within the scope of the cost and the trust to the supplier and the quality of their products. When the work order is concealed, the logistic period starts for the products. The goal of the Procurement Department is to acquire the best deals for the raw materials and trade goods in order to lower the cost of the company's procurement process. While the Procurement Department is trying to minimize the purchasing costs by ordering in bigger batches in order to take advantage of volume discounts, this can lead to an excessive inventory cost thus increasing the total cost in the procurement process.

We have analyzed the complaints of the company with the symptoms which arise from their problems and decided that the most beneficial addition to the company ordering and planning process would be to introduce a decision support system that have inputs such as budget, inventory capacity, unit volumes of items, demands, lead times, safety stock levels, minimum order quantities for suppliers and the MRP report. This decision support system model gives the amount of raw materials and trade goods to be ordered from specific suppliers in the beginning of periods as output. To make better deals and satisfy the minimum order requirements stated by suppliers, the Procurement Department tends to purchase the required materials regardless of the Planning Department's plans. Therefore, the company needs a more obvious purchase process to satisfy both suppliers and the Planning Department. Throughout the project, the following deliverables have been carried out to achieve the goals for improving the company's purchase process.

9.2 Proposed Model and System

When we consider the current problems that Isbir Yatak is facing, we concluded that we can prepare a decision support system to be able to overcome the problem. It is a combined system of a mathematical model and an SQL database. It also has a user-interface to change the parameters of the model. Since demand, unit prices of raw materials or lead times of the factory may change every month, our model should be able to update its parameters. To be able to adapt these changes to our model, we prepared a user-interface which a user can change or add the required information to the system.

9.2.1 Mathematical Model

To be able to solve the problem that İşbir Yatak is facing, we developed a mathematical model (Nahmias and Olsen, 2015). You can see the mathematical model and explanations below.

Sets, Parameters and Decision Variables

Sets	
I: Set of raw materials, $i \varepsilon \{1, ..., N\}$	T: Length of the horizon in months, $t \varepsilon \{1, \ldots, L\}$
J: Set of suppliers where each alternative payment and delivery, $j \varepsilon \{1, ..., M\}$	

Parameters	
M_{ij}: Minimum order quantities for each supplier j for each item i	PC_{it}: Penalty cost for backorder
P_{ijt}: Price of raw materials i at the beginning of period t from supplier j	IB: Initial budget at the start of the horizon
C: Total inventory capacity	R_t: Cost of renting a new depot in period t
II_i: Initial inventory levels for each product i at the start of the horizon	u_i: Unit volume of raw material i
D_{it}: Demand for raw material i for period t	τ_j: Lead time for supplier j
I_{it}^+: Inventory level on hand at the beginning of period t for product i	SS_{it}: Safety stock level of product i for period t
I_{it}: Inventory level for raw materials i at period t	I_{it}^-: Backlogged inventory at the beginning of period t for product i
SS_{it}^-: Penalty cost for having inventory less than safety stock level	SSC_{it}: Penalty cost for having inventory less than safety stock level
SS_{it}^+: Amount of inventory level above safety stock level	

Decision Variables	
Y_{ijt}: Amount of raw materials i ordered from supplier j at the beginning of period t	A_{it}: Orders that will arrive at period t for item i

$z_t = \begin{cases} 1, & \text{if a new depot is rented in month } t \\ 0, & \text{otherwise} \end{cases}$	$w_{ijt} = \begin{cases} 1, & \text{if supplier } j \text{ is used for item } i \text{ in month } t \\ 0, & \text{otherwise} \end{cases}$

Mathematical Model

$$\min \sum_{j=1}^{M}\sum_{t=1}^{L}\sum_{i=1}^{N}[(P_{ijt} * Y_{ijt}) + (R_t * z_t) + (PC_{it} * I_{it}^{-}) + (SSC_{it} * SS_{it}^{-})]$$

s.t

$$A_{it} = \textstyle\sum_{j=1}^{M} Y_{ij(t-\tau_j)} \qquad \forall i \ \varepsilon \ N \ , \forall t \ \varepsilon \ L \quad (1)$$

$$I_{it} = I_{it}^{+} - I_{it}^{-} \qquad \forall i \ \varepsilon \ N \ , \forall t \ \varepsilon \ L \quad (2)$$

$$II_{i1} = I_{i1} \qquad \forall i \ \varepsilon \ N \quad (3)$$

$$I_{it} + A_{it} - D_{it} = I_{i(t+1)} \qquad \forall i \ \varepsilon \ N \ , \forall t \ \varepsilon \ L \quad (4)$$

$$\textstyle\sum_{i=1}^{N} I_{i(t+1)}^{+} * u_i \leq C + M * z_t \qquad \forall t \ \varepsilon \ L \quad (5)$$

$$I_{it}^{+} - SS_{it}^{+} + SS_{it}^{-} = SS_{it} \qquad \forall i \ \varepsilon \ N \ , \forall t \ \varepsilon \ L \quad (6)$$

$$\textstyle\sum_{j=1}^{M}\sum_{t=1}^{L}\sum_{i=1}^{N} P_{ijt} * Y_{ijt} + \sum_{t=1}^{L} R_t * z_t \leq IB \quad (7)$$

$$Y_{ijt} \leq M * w_{ijt} \qquad \forall i \ \varepsilon \ N \ , \forall j \ \varepsilon \ M \ , \forall t \ \varepsilon \ L \quad (8.1)$$

$$M_{ij} - Y_{ijt} \leq M * (1 - w_{ijt}) \qquad \forall i \ \varepsilon \ N \ , \forall j \ \varepsilon \ M \ , \forall t \ \varepsilon \ L \quad (8.2)$$

$$z_t, w_{ijt} \ \varepsilon \ \{1, 0\}, \quad Y_{ijt} \geq 0, \quad A_{it} \geq 0 \qquad \forall i \ \varepsilon \ N \ , \forall j \ \varepsilon \ M \ , \forall t \ \varepsilon \ L \quad (9)$$

While developing our model, our objective was to minimize the total cost of procurement decisions. In the objective function, there are penalty costs for backorder and safety stock level to be able to minimize the backorder amount and remaining under the safety stock level for each raw material. Explanation of each constraint can be seen below.

1. Collected Raw Material Constraint: This is a constraint to be able to collect all orders from different suppliers for a specific raw material while considering the lead time of that supplier.

2. Backorder Constraint: This is the inventory constraint that allows the model to have either backorders or positive inventory.

3. Initial Inventory Constraint: This is an initialization constraint. Since İşbir Yatak currently has inventory on hand, we are introducing that inventory to our model.

4. Inventory Balance Constraint: It updates the inventory for each period t, by considering the inventory at time t-1 demand scheduled receipts.

5. Capacity Constraint: This constraint has two tasks. First one is that it makes sure that the total volume of arriving orders does not exceed the total capacity. Second one is to decide whether to rent an additional depot or not. If the total capacity of the warehouse is not available it considers renting a new one.

6. Safety Stock Level Constraint: This constraint is for the safety stock level of each item.

7. Budget Constraint: It considers prices of ordered items and if there is a renting decision adds that amount to this constraint.

8. 8.1 and 8.2 are Minimum Order Quantity Constraints: These are if-then constraints that make sure that we are above the minimum order quantity of the supplier that we order from.

9. Domain Constraints: Renting and using supplier decision variables, z_t and w_{ijt}, are binary and amount of collected and purchased materials, A_{it}, Y_{ijt}, are continuous variables.

9.3 Validation

Validation We formed our mathematical model and then we coded it into Python with the "mip" module. In this way, we transformed our mathematical model into an open-source optimizer that allowed us to convert Python to an optimizer by "mip" module. Then, we could solve our mathematical model with this program. After we saw a solution in Python, we checked our model whether it worked properly or not by the verification processes with data that are created by us. We saw that our model gave an appropriate solution that was expected by us according to our intuition. After this process, we ensured that our model worked properly. To see the credibility of our model, we conducted the validation process for our model.

Item No	Supplier No	Time Period	Amount Purchased
2	6	1	1379.95
3	1	1	1634
3	3	2	468
4	1	1	1024
4	3	2	242
5	1	1	102
5	3	2	17
13	6	1	6927
14	6	1	2726
16	3	2	1252
16	6	1	5
18	1	1	4019

Figure 9.1: Model validation.

To achieve this, we firstly extended our model to real situations using real data. We noticed that we had large input sets so we decided to use SQL to create a database. After we created the SQL database, we filled it with real data given by the company. Then, we needed to draw data from our database in Python. To achieve this, we composed our parameters with SQL queries in Python thus it read the database and formed parameters automatically. In this way, our model is automatically updated whenever our database is updated. Then we added error codes that include negative inventory message, lower inventory than safety stock level message, critical level of the remaining budget message, and new inventory needed message. To validate our model, firstly we took an expert opinion about our constraints and intuition of our model. After we got expert approval, we ran our model with real data given by the company for a particular period.

We were aware that our objective function was not an exact cost function since it included artificial costs that were backorder costs and inventory level that was under the safety stock level cost. Therefore, we tried to determine these costs to make a procurement decision logically. To achieve this, we first set our backorder cost as \$10,000,000 and penalty safety stock level cost as \$100,000. We noticed that these numbers were small for our model since the model tried to increase the level of backordered materials and set inventory level less than the safety stock level due to small penalty costs. Therefore we increased them gradually and finally we determined these costs as final values \$200,000,000 and \$1,000,000 respectively. Then, we observed that our model tried to purchase materials that did not cause backorder and had a higher inventory level than the safety stock level. In this way, our model could meet the demand, have a higher inventory level than the safety stock level, and could not face backorder, the solution can be seen in Figure 9.1. This situation was desired by the company with our intuition. Then, we printed only procurement costs that included only the purchased materials cost of our model and we found $1,094,524.82. To compare, we analyzed the company's procurement processes and calculated their procurement costs which were found as $1,379,101.27. It showed that if the company used our model, they would get 26% fewer procurement costs while they were meeting their demand. Therefore we observed that our model could provide a 26% cost reduction. After this point, we analyzed our initial budget since the initial budget was provided by the Finance department, however the initial budget might have a great impact on the solution. We set different numbers for the initial budget and ran our model repeatedly. We observed that the lower boundary of our model was $700,000 for the initial budget since our model could not satisfy the requirements when the initial budget was less than $700,000. Therefore, we proposed that a budget, higher than $700,000, should be used when our model ran. Then, we compared a higher budget that was equal to $1,100,000 to a lower budget that was equal to $700,000. We observed that all budgets in these two cases were spent by our model to meet demand and provide higher inventory levels than the safety stock levels for each material. The model was successful to meet demand but the model had to pay penalty costs since there were inventory levels less than safety stock levels in both two cases. However, we noticed an important difference between these two cases. All budgets were spent but the lower budget case paid penalty costs much more than the higher budget case since inventory levels were under the safety stock levels that can be seen in Figure 9.2. We determined these costs as artificial costs but this situation showed that if the initial budget were low, the company had a high risk to face run-out inventory.

9.4 Integration and Implementation

The group used Excel and SQL as database and user interface, Python as an open-source optimization program for analyzing the given data by the company, interpreted the data to find a solution, and made a purchasing algorithm that can be easily used and implemented for the procurement department. The company uses SAP, so they can integrate our code into their systems. We created an SQL database and integrated it into our code in Python. Our decision support system worked based on up-to-date data. After the project, the company representatives will need these algorithms and tools if they decide to use the solution of the group.

		Amount Below Safety Stock	Amount Below Safety Stock	
Item No (I)	Time Period (T)	When Budget = 700,000	When Budget = 1,100,000	Difference
2	2	1281,94	0	-1281,94
13	2	7671	744	-6927
14	2	5094	2368	-2726
23	3	2291,52	0	-2291,52
24	3	4500,33	427,61	-4072,72
26	2	11728,65	5627,37	-6101,28
26	3	4748	0	-4747,55

Figure 9.2: Safety stock level difference in terms of budget.

9.5 Benefits to the Company

The benefit that our model providing to the company is related to their purchasing strategy. Due to the constraints in some critical materials, the company was leaning more towards an intuitive purchasing strategy. Our model allowed the Procurement Department and the Planning Department to fuse their expectations for the future and settle on economic order quantities which minimized the cost of purchasing while utilizing the inventory space efficiently by also minimizing the cost of inventory. Also, the company is now able to choose their suppliers more efficiently and consider their priorities for each item which changes from item to item and according to the purchasing period.

9.6 Conclusion

To conclude, after the initial meetings with the company officials we decided that a well developed model will help Isbir to solve their procurement-inventory related problems. So as a group we developed model that considers inventory levels, checks safety stock levels, decides the order quantities while taking into account the prices from different suppliers and inventory costs. All of this satisfies everything the company asked from us. Furthermore, the flexibility of our program to be used for different materials is another aspect of their expectations.

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Bakioğlu Holding

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Beste Yıldız
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Endüstri Mühendisliği Bölümü

Özet

Bak Ambalaj müşterilerinin talep miktarını ve bu talepler için gerekli olan hammadde miktarını geçmiş ayların sipariş verilerini analiz ederek yapmaktadır, fakat bunlar doğru sonuç vermemektedir. MTO yapısına göre çalışan şirket bitmiş ürün stoğu yapamamaktadır çünkü müşteriler siparişlerinde değişiklik yapabilmektedirler. Müşterilerin sipariş teslim süre beklentisi, hammadde tedarik sürelerinden kısa olduğundan zamanında teslimler yapılamamaktadır. Bu sorunu çözmek için geliştirilen tahminleme sistemi aylık hammadde ihtiyaç ve sipariş miktarlarını öngörerek arada kalan problemli süreyi azaltmaya çalışır. Geçmiş sipariş verileri kullanılarak geliştirilen algoritma gelecek 12 ayın sipariş ve hammadde miktarlarını en az hatayla tahmin edecek şekilde tasarlandı ve şirketin sistemiyle uyumlu arayüzüyle kullanıma hazır hale getirildi.

Anahtar Sözcükler: Sipariş Teslim Süresi Problemi, Tahmin Algoritması, Talep Tahmini

Raw Material Demand and Order Quantity Forecasting System

Abstract

Bak Ambalaj makes forecasts using previous order data of the customers but they cannor get accurate results. They cannot keep finished product inventory, as customers may make changes in their orders. The problem is that the customer's expected lead time is 15 days but orders are delivered in about a month due to lead time of the raw materials. Considering similar problems and solutions, a literature review was conducted. With the demand forecasting system, monthly raw material needs and order quantities are predicted, thus eliminating the problematic time which is between the average raw material supply time and the average delivery time. In this direction, a forecasting algorithm was developed using the historical order data provided by the company. This algorithm is designed to predict the order and required raw material quantities for the next 12 months with the least error rates. It has been made suitable for use with an interface design suitable for the use and system of the company.

Keywords: Order Delivery Time Problem, Forecasting Algorithm, Demand Forecast

10.1 Company Information

Bak Ambalaj, a flexible packaging manufacturer, has been serving leading companies in various sectors since 1973. Bak Ambalaj, which is located in İzmir Atatürk Organized Industrial Zone and carries out its activities in 5 different facilities, provides a continuous and sustainable service to its customers. The company exports 74% of its production, especially to Western European countries. The company produces printed, imprinted, and laminated flexible packaging films for various sectors. Products of the company are packaging films or pouches for snack foods, biscuits, bread and fresh food, dried foods and pasta, coffee and tea, sugar and chocolate confectionery, chemicals and hygiene.

10.2 System Analysis

Customer orders are delivered in different sales units such as kilogram, meter, square meter, or piece. There are three types of customers. The first type consists of customers who send their demand information regularly to the company. The second type consists of customers who do not send their demand information regularly. The last type consists of customers who do not send any demand information and expect the company to make rolling forecasts by analyzing historical data. The main raw material used in the manufacturing processes of the company is film. There are a total of 235 types of film that are being used in production stages. However, when the thickness variety of these films is considered, there are a total of 621 types of film that need to be analyzed. Data analysis is made by using the time series method in R program in order to observe seasonality and autocorrelation between the film types. Data analysis is also conducted for 11 mostly used products. These analyses helped us to choose the most appropriate forecasting technique amongArima,ETS,Prophet with Xgboost,Ranger, andXgboost (Udom, 2014).

10.3 Problem Definition

Orders placed are generally delivered in about a month. However, the customer's expected lead-time is 15 days. The 15 day period in between is expressed as the dark period for the company. The difference between the expected lead-time of the customers and the lead-time of the suppliers causes this dark period. The purpose of this project is first to find prediction algorithms to forecast customer demands and film types, second to design a user interface for the company to enter customer related data and operate the algorithm to predict the customer demands, third to compare the predicted data with the realized customer orders and/or with the previous period forecast and lastly by using this data, calculate the critical raw material needs.

10.4 Solution Approach

While estimating the demand for the next 12 months with the 3 year order and raw material data provided to us by Bak Ambalaj, three different estimation methods were used primarily. These are Autoregressive Integration Moving Average (ARIMA), Seasonal Autoregressive Integration Moving Average (SARIMA), and exponential smoothing methods. When comparing ARIMA to other models utilizing MAPE (Mean Average Percentage Error), the ARIMA model exhibits superior outcomes than other models after applying five data sets of raw material from a plastic distributor using four forecasting methodologies.Exponential smoothing forecasts are weighted averages of previous observations, with the weights decaying exponentially as the observations get older. The larger the related weight, the more recent the observation. It can be used with seasonal and trend patterned data. ARIMA(Autoregressive Integrated Moving Average) models are more general than exponential smoothing. All ETS models are non-stationary while ARIMA assumes the data is stationary. For the cases of nonstationary data, differencing is used to convert the data into stationary by computing differences between consecutive observations. Moreover, if the data has seasonalitySARIMA (Seasonal ARIMA) can be used.

In addition to these models, since different models can be selected for each product and each film type, three more new models that are also important for machine learning, which we found as a result of our literature research, were used. These are the Prophet with Xgboost, Ranger, and Xgboost models. Other reasons for adding these forecasting models can be shown that running time is reduced by 25% and it can be transferred to the user interface more easily.

After conducting a comprehensive data analysis, it is observed that there are some products and film types which are ordered or used rarely. This may cause inappropriate forecasting for these products and film types. Therefore, for rarely used products and films we implemented a demand categorization method for more accurate forecasts. There are 4 different demand pattern categories which are smooth, erratic, lumpy, and intermittent (Kostenko and Hyndman, 2006; Tharmathasan, 2021; Hyndman and Athanasopoulos, 2018; Montgomery et al., 2015).

Train and test sets were applied to compare the performances of these models. According to these selected train-test sets, the performance metric results calculated automatically by the software were compared. Four performance metrics were used for comparison between the models. These are Mean Absolute Error (MAE), Root Mean Squared Error(RMSE), Mean Absolute Percentage Error(MAPE), and Mean Absolute Scaled Error (MASE). After demand categorization, there is an accuracy testing part included in the code. This part shows which one of the methods fits best to our problem with less error. Different forecasting measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and MASE are used by R with the accuracy part (James G. and Tibshirani, 2021).

This code provides a way to try different forecasting methods and select the appropriate one. Appropriate method was chosen according to the smallest error results with comparison. Similar forecasting codes was applied for each film type and product type. Data set can be denoted by y_1,...,y_t , and it is split into two sections: the training data ($y_1, ..., y_N$) and the test data ($y_{N+1}, ..., y_T$). The h-step-ahead forecast can be written as $\hat{y}_{N+h|N}$. The forecast errors are the difference between actual values in the test set and the forecasts produced using only the data in the training set:

$$e_t = y_t - \hat{y}_{t|N} \text{ for t = N + 1,..., T}$$

.

If all forecasts are on the same scale such as y_t and e_t are both in meters, MAE or RMSE can be used:

Mean absolute error: MAE = mean($|e_i|$)

Root mean squared error: RMSE = mean($\sqrt{e_i^2}$)

MAPE can be used if forecast accuracy on several series with different scales need to be compared, unless the data contain zeros or small values, or are not measuring a quantity:

Mean absolute percentage error: MAPE = mean($|p_t|$) where $p_t = 100\frac{e_t}{y_t}$

If MAPE is inappropriate, MASE can be used for several series with different scales. Q is a scaling statistic computed on the training data.

For a non-seasonal time series: $Q = \frac{1}{N-1}\sum_{j=2}^{N}|y_j - y_{j-1}|$

For seasonal time series: $Q = \frac{1}{N-m}\sum_{j=m+1}^{N}|y_j - y_{j-m}|$

Mean absolute scaled error: MASE = mean($|q_j|$) = $\frac{MAE}{Q}$ (Hyndman and Athanasopoulos, 2018)

After the performance of each forecasting model was analyzed according to MASE and RMSE values which are better for ARIMA model, it was seen that the least margin of error for each product and film type was provided in different models. As a result of the negotiations with the company, it was decided to print each model used with the user interface for each film type and for each product and to select the most suitable model. In this way, all of the outputs are compared with each other.

10.5 Verification and Validation

In order to see that our model works correctly and as desired, the models and the software (packages) were verified. For the package verification part, we compare the results of an applied forecast using a different package with the results we found by forecasting the same data with our package. Obtaining the same results shows that it was seen that the packages we used were working correctly. For the model verification part, the values found during the data analysis were used. The models automatically select the parameters, we manually entered the values found in data analysis and we compared the results. The results matched the model's self selected results and it verifies that our models work as intended.

For validation the forecasts results error percentages are calculated. Due to the density of the number of film types and the number of orders, the most used film types were selected as samples and each model for the most used film types and only used the date of December 2021, January 2022, and February 2022 are used for validation. Figure 10.1 shows the error rates, according to which the MAPE values of our sample data are generally in the range of 10%-30%. This shows that we made appropriate forecasts despite using a specific sample and a specific date, and these results were discussed with the company and found appropriate. With more input (data), these results can be even better (Hilston (2017)).

RMSE				
	Prophet w/xgbo	ranger	xgboost	arima
Film Type 1	25,28	21,10	29,06	13,53
Film Type 2	18,92	19,82	20,91	7,49
Film Type 3	39,95	31,55	41,15	21,59
Film Type 4	16,90	18,04	17,70	15,86
Film Type 5	57,75	54,43	59,50	37,22
Film Type 6	12,42	23,23	12,37	12,24
Film Type 7	50,69	63,39	51,38	82,68
Film Type 8	35,99	29,19	59,75	3025,92
Film Type 9	48,64	27,70	53,93	22,06
Film Type 10	29,68	27,92	32,73	24,61

MAPE				
	Prophet w/xgbo	ranger	xgboost	arima
Film Type 1	21,37%	18,23%	26,68%	13,13%
Film Type 2	17,76%	18,77%	19,90%	6,55%
Film Type 3	31,33%	26,48%	35,97%	16,40%
Film Type 4	15,17%	16,68%	15,69%	14,16%
Film Type 5	57,66%	54,29%	59,42%	36,31%
Film Type 6	11,83%	21,16%	11,72%	10,23%
Film Type 7	50,00%	57,15%	47,99%	61,97%
Film Type 8	29,72%	21,87%	58,53%	2899,26%
Film Type 9	47,68%	24,39%	53,24%	16,42%
Film Type 10	27,90%	26,76%	31,28%	22,04%

Figure 10.1: Root Mean Squared and Mean Absolute Percentage Errors

10.6 Benefits and Implementation

The company does not have a special system for forecasting orders. It uses customers' forecasts, however, only 10% of the customers send their forecasts to the company. We created a system that analyzes old order data and gives forecasts with small errors. The most important benefit we provide for the company is providing accurate forecasts for both products and film types. Forecasts can be used separately by the company with selecting necessary data such as film type or order quantity for future order quantities with kg unit. In this way, the company can reduce the delay problems to be experienced with customers by controlling the forecasts and placing the necessary orders at the right time.

In addition, a user interface was provided to the company so that they could reach these forecasts more easily; see Figure 10.2. The design of the application is decided with the company and it consists of two parts. The first part is the selection screen and the second part is transformed into the Excel program as the result screen. In the user interface, data entry was provided by the company and they can get forecasts. At the same time, the charts of the forecasts can be accessible in the other window. When the interface design is finished with R Shiny, a user manual was provided to the company; RStudio Team (2020), Granjon (2020). The company can download the R program and control the interface on their systems.

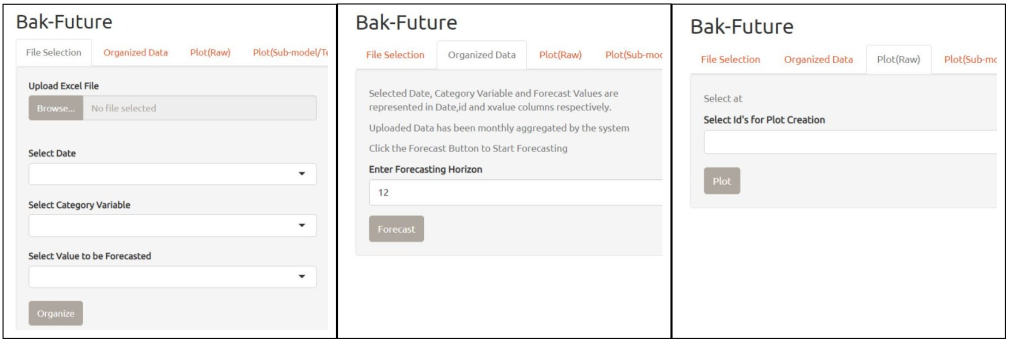

Figure 10.2: User Interface

10.7 Conclusion

Bak Ambalaj needs a demand forecasting algorithm which is giving outputs byExcel. Furthermore, the company wants to integrate the outputs into their system with a user interface. Therefore, it is decided to use theR Programming Language to implement these forecasts. By doing verification and validation analysis it is approved that algorithm outputs from the R software are accurate. Moreover, to implement algorithm to user interfaceR Shiny is used and useful tool is developed.

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Arçelik Kurutma Makinesi İşletmesi

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Özet

Şirkette ithal malzemelerin ay bazında stok seviyeleri, sipariş miktarları ve tahminleri bir Excel dosyası üzerinden takip edilmektedir. Malzeme bazında hesaplanan katsayıya göre, verilmesi gereken sipariş adetleri belirlenmektedir. Servis seviyelerini arttırmak, envanter maliyetlerini düşürmek ve şirket için sistematik ve uygun bir sipariş yöntemi oluşturmak amacıyla bu proje geliştirilmiştir. Materyallerin takibi için de ayrı bir uyarı sistemi oluşturulmuştur. Kullanılan yazılımlar bir arayüzle birleştirilmiştir. Proje sonucunda şirketin sipariş uygulamalarında gelişmeler görülmüştür.

Anahtar Sözcükler: Emniyet stoğu, envanter yönetimi, talep dalgalanması, matematiksel model, açık sipariş uyarı sistemi

System Design for Ordering Import Materials

Abstract

In the firm, monthly stock levels, order quantities and forecasts are received and tracked via an Excel file. According to the safety stock coefficient calculated on the basis, the preferred order quantities are determined in the current system. The project is designed with the aim of planning a systematic and appropriate algorithm for orders and determining safety stocks for Arçelik, along with installation of a warning system for materials in the same plan. By making use of the results and application of the software used, the proposed system caused improvements to the orders and inventories at the Arçelik Tekirdağ Drying Machine Factory.

Keywords: Safety stock, inventory management, demand fluctuation, mathematical model, open ordering system

11.1 Company Information

Arçelik was established in 1955 at Sütlüce, Istanbul. Currently, the company has 40.000 employees worldwide, with over 28 production facilities in 9 countries, alongside Sales and Marketing organizations in 48 countries and 12 global brands. Its brand portfolio includes Beko, Grundig, Blomberg, ElektraBregenz, Arctic, Leisure, Flavel, Defy, Altus, Dawlance, and Voltas Beko. The company is Europe's 2nd largest white goods company in terms of market share based on units. Furthermore, Arçelik is the market leader with the brands "Arctic" in Romania, "Defy" in South Africa, and "Dawlance" in Pakistan. Furthermore, the company also leads in the white goods market of Turkey, with products such as air conditioner units, TV sets, and small home appliances.(Arçelik, 2020)

Production in the Drying Machine plant, located in Tekirdağ, started in 2004 within Arçelik, while the company established a new facility in 2007. The Arçelik Drying Machine Plant follows a Make-to-Stock (MTS) production strategy. The products are manufactured according to sales forecasts and expected customer demands. In order to meet customer demands, Arçelik's Drying Machine Plant uses a custom-built system from SAP as its ERP (Enterprise Resource Planning) software for processes such as production, production planning, materials management, and procurement. In addition to SAP, they also rely on spreadsheet software such as Microsoft Excel for retrieving data from reports generated by the SAP system, primarily because sometimes manual interference might be necessary. Therefore, Arçelik representatives should periodically update Excel files containing information from these said reports as well.

11.2 System and Problem Descriptions

Arçelik uses SAP and Excel to manage its imported material planning. Planners retrieve data from SAP Reports, explained in Figure 11.1, such as from Material Requirement Report, Instant Material Report, Imported Material Stock Report, Product Tree Component Report, Annual Production Plan to Excel files, which they have to update manually, as stated earlier.

ZIHT Material Requirement Report

It is the report where they can view their monthly requirements for the materials given as direct use or entrusted to the sub-industry.

ZM33-ALV Instant Material Report

It is the report where they can view the unrestricted stock, quality control stock and blocked stock of the material instantly.

SNP - Annual Production Plan

It is the report shared by the master planning team, where production numbers of product codes can be viewed on a monthly basis for one year.

Figure 11.1: SAP reports

Material planners of the Drying Machine Plant determine a multiplier while planning the orders of imported materials. They consider parameters such as lead time, whether it has an alternative material or not, demand fluctuation, and local supplier option availability. While doing material planning, they find the ending inventory of (n)th period by multiplying the requirement of (n+1)th period with the multiplier. While planning the

$$\frac{I_n}{D_{n+1}} = k$$

I_n: Inventory level at the end of n^{th} period

D_n : Demand for n^{th} period

k : Multiplier

Figure 11.2: Multiplier calculation

orders, they obtain a different multiplier, called a "calculated multiplier", which, for (n)th period, is found by dividing the demand of the (n+1)th period to the ending inventory level of the (n)th period.

11.3 Current Inventory Management Issues

Arçelik specifically mentioned that all processes regarding imported materials were manually operated and maintained, which led the system being highly subject to various errors caused by manual entries. These errors originated from the varying techniques used by the engineers for determining order amounts. Since this method is not systematic, the order amount requirements may not meet the demand in some periods.

Furthermore, aside from inventory management issues, the company declared they could not properly track the scheduled arrival dates of imports and how inbound materials would arrive earlier or later than the estimated arrival dates. The management also faced issues regarding stocking the unplanned arrival of material shipments, which would again disrupt entire planning system. This creates issues regarding inventory and production planning, as the entire supply chain can be abruptly impacted, given unexpected material arrival, without any warnings for the early or late arrivals.

11.4 Data Analysis

The MPS file from Arçelik, which is an annual production report released every two weeks, contains master production planning data of how much of the ending products will be produced on a monthly basis.

The ending products consist of many materials, where fluctuating demand for the final product also influences the demand fluctuation of the materials. In order to make a more accurate observation, we determined which ending products and materials are interconnected, before filtering them from the data. We calculated the weekly average demand and deviation for each month after determining the weekly and monthly total demand amounts. These values are used in safety stock calculation and will be explained in the next section in more detail.

While investigating if there is seasonality, we determined seasonal factors for each material at each period. In this manner, December, January, February represents the 1st season, March, April, May represents the 2nd season, June, July, August represents the 3rd season and September, October, November represents the 4th season. In terms of finding seasonal factors, the monthly average demand values are used. Firstly, the overall average score is computed by using the MPS values for each material concerning 12 months, then the monthly mean value for material is divided with that score. The seasonality factors are shown in Table 11.1.

SEASONAL FACTORS				
	1st Season	2nd Season	3rd Season	4th Season
Material A	1,68	0,77	0,65	0,91
Material B	1,41	0,38	0,97	1,23
Material C	1,15	0,65	1,11	1,10
Material D	0,91	0,35	1,18	1,56
Material E	1,12	0,60	0,73	1,54
Material F	1,10	0,63	0,74	1,56

Table 11.1: Seasonal Factors for Each Material

11.5 Safety Stock Calculation

We computed the safety stock levels for each material Arçelik orders to minimize the received order volatility in our decision model. For that reason, we've previously looked into different approaches that we may implement. Because the orders are stochastic in this scenario, we employed a strategy that is designed for stochastic demands.

$$SS = Safety\ Stock$$

$$Z = Z\ Value\ of\ Service\ Level\ Percentage$$

$$L = Lead\ Time$$

$$d = Mean\ Demand\quad (monthly)$$

$$s_L = Standard\ Deviation\ of\ Lead\ Time\quad (monthly)$$

$$s_d = Standard\ Deviation\ of\ Demand\quad (monthly)$$

$$SS = Z \times K$$

$$\text{where}\quad K = \sqrt{(L+1)s_d^{\ 2} + s_L^{\ 2} d^2}$$

Figure 11.3: Safety stock calculation

By using equations in Figure 11.3, we are able to calculate the safety stock for each material. What we obtained is the service level Arçelik wants to achieve for materials, which is 99%, along with the average ending inventories. The current service level is below the aimed service level, and is unsteady. If occured service level is less than the determined service level, we understand that the safety stock requirements are not met; see Table 11.2. We believe for every material, service levels should be the same because of the calculation method we used: If this variation is high, then this means the safety stock of that item would be also high (Gorman, 2021).

11.6 Mathematical Model

Our primary goal in the model is to minimize the overall cost incurred by the company through this inventory management system. This includes all

Material	K	Average End of Inventory Levels	**Determined Safety Stock**	Occured Z	Percentage	**Determined Z**
Material A	713.80	1,714.69	**1,192.04**	2.402	98%	**1.67**
Material B	3,537.64	8,351.00	**5,907.87**	2.361	98%	**1.67**
Material C	3,835.10	24,825.15	**6,404.61**	6.473	99%	**1.67**
Material D	1,684.72	3,697.31	**2,813.49**	2.195	95%	**1.67**
Material E	15,721.79	99121	**26,255.40**	6.305	99%	**1.67**
Material F	17,785.68	25,369.38	**29,702.09**	1.426	95%	**1.67**

Table 11.2: Calculated (Determined) Safety Stocks

costs incurred from the units that were purchased from suppliers, the cost of carrying inventory across multiple periods, the costs incurred through potential backorders, and a penalty that the company takes into account if its inventory goes below the designated safety stock levels.

Furthermore, since each supplier has their own unique lead time, in this model we define up to 3 suppliers to determine how many orders received from each 3 suppliers. The orders from each supplier are listed individually when equating it to the total quantity received.

Additionally, since we have both the minimum quantity of ordering and an upper bound on how much we can order from a single supplier, we add them in our constraints as well, which are taken into consideration if we order from the said suppliers.

While on one hand we have constraints defined to represent materials being ordered from suppliers, on the other hand, we also define constraints that influence inventory levels we carry. Since there is inventory carrying cost associated with inventory levels of materials, we added constraints that help us determine potential inventory that is in the system. The inventory holding cost was computed using an opportunity cost from individual suppliers. In order to compute this inventory level, we use information about the material required for production, material received from suppliers, and the inventory of the previous period. In the situation that the system is not able to satisfy the demand, the model panalizes backorders with associated costs. These costs make up the constraints relevant to the inventory in our mathematical model. Model can be viewed in Tables 11.3 and 11.4.

11.7 Implementation

In order to implement and test the mathematical model that we have developed, we used the Xpress MP software from FICO. Using this software, we loaded our model alongside verification data set values which are given arbitrarily for our parameters, to test the extent to which this model would accurately replicate the way that Arçelik would implement its inventory management system. Since we start the demand periods in the computation from the closest upcoming demand period, we also manually add the current inventory before the system starts (I_0),which we received from ZM33-ALV Instant Material Report, to ensure that our mathematical model does not crash when run with the given data set values. By running the model code in the Xpress MP program, we were able to observe that the model was able to operate successfully based on added parameters such as the earliest order lead time and unit costs of purchases.

After verifying that the model works with fixed safety stocks which will be mentioned in the next part, we aim to implement the safety stock cal-

Sets:

S = Set of suppliers→ $i \in \{1,\dots, S\}$	T = Time period→ $t \in \{1,\dots, T\}$

Parameters:

C_t = Penalty cost for safety stock violation in period t	R_t = Required amount of material needed for production at time t
H_i = Inventory holding cost for each supplier i	S_i = Minimum amount that can be ordered from supplier i in one period
l_i = Lead time of supplier i	J_i = Maximum amount that can be ordered from supplier i in one period
I^+_t = Physical inventory level at period t	Z_t = Minimum amount of inventory that can be in stock (safety stock level)
I^-_t = Backorder level at period t	U_i = Unit cost for purchases from supplier i
I_0 = Initial inventory level ($t = 0$)	B = Backorder cost
M = Large number	

Decision Variables:

P^-_t = Additional amount of inventory that is required to meet the safety stock level	P^+_t = Amount of inventory that exceeds the stated safety stock level
A_t = Amount received at time period t (in units)	K_{it} = Amount ordered from supplier i at time t
$X_{it} = \begin{cases} 1, & \text{if ordered from supplier i at time period t} \\ 0, & \text{otherwise} \end{cases}$	

Table 11.3: Sets, parameters, and variables of the mathematical model

culation methodology mentioned above into the model. This would ensure that with changing materials and periods, safety stocks would also change.

The success of the current model implemented for a single material inventory management system shows that it can be used to solve for different materials, as we add the required parameters. Doing this on Xpress MP is tedious and requires thorough knowledge of the software. As such, in order to allow the representatives at Arçelik easier access to our solution, we decided to implement the model in a workable program that is coded using Python. We have successfully replicated our mathematical model in Python and have validated the results that we obtain, by cross checking it with the outputs of the model in XPress MP. This helped us ensure that we faced no issues in migrating our mathematical model to the Python platform.

Objective Function

$$\min \sum_{t=1}^{T}\sum_{i=1}^{S}(K_{it} \times U_i) + \sum_{t=1}^{T}\sum_{i=1}^{S}(I^{+}_{t} \times H_i) + \sum_{t=1}^{T}(I^{-}_{t} \times B + P^{-}_{t} \times C_t)$$

s.t

$$I_t = I_{(t-1)} + A_t - R_t \qquad \forall t \in T$$

$$K_{it} \le J_i \qquad \forall i \in S, t \in T$$

$$K_{it} \le M \times X_{it} \qquad \forall i \in S, t \in T$$

$$K_{it} \ge S_i - M \times (1 - X_{it}) \qquad \forall i \in S, t \in T$$

$$I_t = I^{+}_{t} - I^{-}_{t} \qquad \forall t \in T$$

$$I_t - Z_t = P^{+}_{t} - P^{-}_{t} \qquad \forall t \in T$$

$$A_t = K_{1,(t-l_1)} + K_{2,(t-l_2)} + K_{3,(t-l_3)} \qquad \forall t \in T \text{ (assuming that there are three suppliers)}$$

$$A_t \ge 0\,,\ X_{it} \in \{0,1\}\,,\ P^{+}_{t}, P^{-}_{t} \ge 0 \qquad \forall i \in S, t \in T,\ \forall t \in T$$

Table 11.4: Mathematical model

With the mathematical model now properly set up, we developed a User Interface (UI), Amadeus, that would help the representatives from Arçelik to properly interact with the model, as such be able to utilize it without requiring complex understanding of how the model operates. Our understanding of the UI is that it will be a simple interface that will help Arçelik representatives enter information about suppliers and the number of periods for which they wish to optimize their inventory, alongside any mmodel parameters. Once these inputs are received from the users, the system would perform the optimization and output the results in a legible report format that would be easy to interpret and understand.

11.8 Validation

Our validation is run with 5 sample materials that Arçelik gave us. In order to validate our model we chose the "Material D" item as our example for the case below. We compared the results of our runs and given orders' quantities, where we ran our model for 9 months by using the unit cost, holding cost, lead time, minimum order quantity, maximum order quantity, beginning inventory information and safety stock values that we calculated. Before starting our runs, we multiplied safety stock values with the square root of seasonality levels. This way we added the seasonality factor to our calculations.The safety stocks of the company that we used in validation is calculated by using the same method Arçelik uses in order to compare our results. Then, we finished our runs and obtained order quantities and ending inventory levels for both our and Arçelik's safety stocks. In order to have a better view, we took a six month slice of our results as Arçelik requested, as seen in Figure 11.4. The runs gave similar results in both cases, our

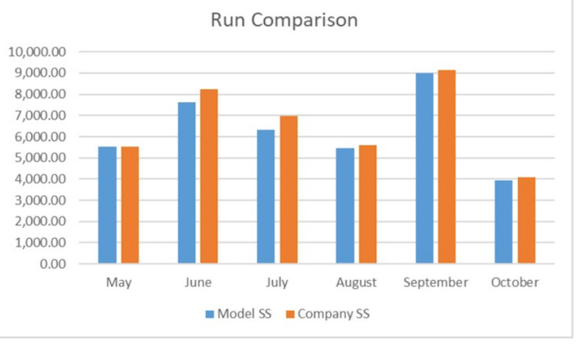

Figure 11.4: Six month run comparisons

safety stock calculations resulted in a 4.25% decrease in inventory carried, therefore validating our safety stock calculation. After we finished safety stock validation, we compared our results using our safety stock values with actual end of inventory levels, as seen in Figure 11.5.

End of inventory levels are on similar levels. Our model decreased inventory levels by 8.3%. As a result we can conclude that the model is valid.

11.9 User Interface (UI)

The UI was developed using the Python programming language, where we used the tkinter python package to construct the UI, with the mathematical model integrated into it. Our decision for choosing Python to develop the UI was primarily because it is an open-source programing language, which means that the representatives at Arçelik will have no issues in running the

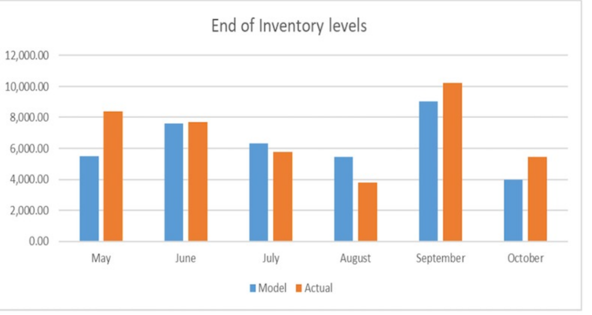

Figure 11.5: End of inventory comparisons

program.(Mitchell et al., 2011) The UI contains multiple windows, with the first being a home screen where users can choose between multiple options to choose their goal. The main window where the algorithm runs requires an Excel file containing all the parameters to be used in the model to be uploaded. Following this upload, the user progresses to the next window where they are prompted to give the requested input. With the input and the parameters set, the user can simply execute the model function and get the desired output regarding when to order. The screenshots of the UI in its different stages are seen in Figures 11.6 and 11.7.

11.10 Project Outcomes

The purpose of our project is to devise a material ordering system that works to minimize or eliminate personnel error, when being operated manually by Arçelik. For the development of this system, the safety stock level and periodic order quantity is determined using the mathematical model, along with supplier choice and order amounts. The main performance measures are selected as the cost that includes purchase cost as well as inventory holding costs. We created a user-friendly tool for Arçelik as described above. By

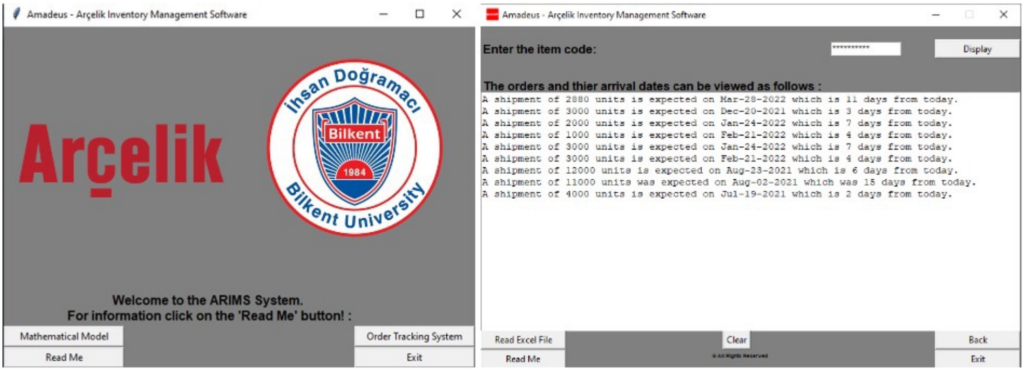

Figure 11.6: Main Page & Order Tracking System

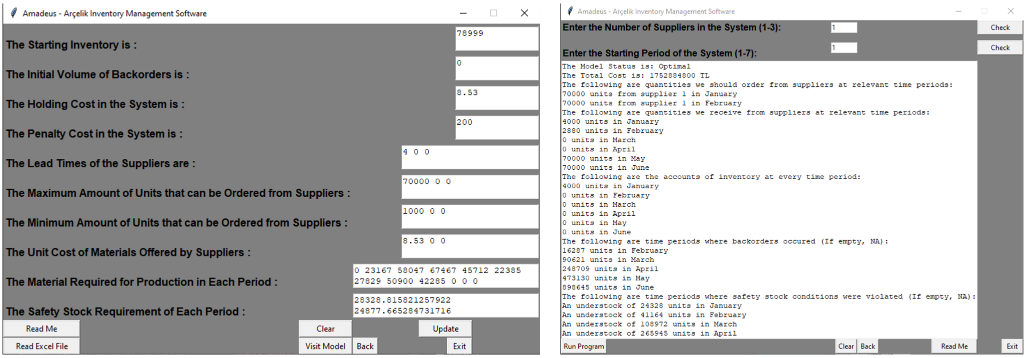

Figure 11.7: Mathematical Modelling Program

using this program, Arçelik could systematize their ordering methodology, improving their service levels to the level that they wish while keeping their costs in a reasonable range. We saw that with the suggested model, total cost for materials decreased between 2.7% - 13.2%. Therefore, this proves that our model is also cost-effective.

Another crucial outcome is an open order and alert tracking system which will warn users in the situation of insufficient inventory. This is done by notifying the users when the system detects stock outs or inventory levels lower than safety stocks while using the algorithm. This way, Arçelik can decide on whether they can pull the orders closer depending on the remaining time left to the actual date of receiving the order. Additionally, the system is able to notify when the departure is approaching in one month in order to conduct booking operations according to exact departure time.

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12 | Karma Modelli Montaj Hatlarında Operasyon Planını Eniyileyen Karar Destek Sistemi

Arçelik Buzdolabı İşletmesi

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Özet

Hat dengeleme operasyonları Arçelik Buzdolabı İşletmesi'nin karlılığını büyük oranda etkilemektedir. Mevcut durumda hat dengeleme işlemleri elle yapılmakta ve bu durum zaman ve verimlilik kayıplarına yol açmaktadır. Bu proje ile mevcut hat dengeleme operasyonlarının yerine kullanılacak bir Karar Destek Sistemi geliştirilmiştir. Bu sistem içinde montaj hatlarında en iyi operasyon planını bulan bir algoritma tasarlanmış ve bu algoritma bir kullanıcı arayüzü ile şirketin kullanımına sunulmuştur. Bu proje ile şirkete önemli operasyonel faydalar sağlanmış ve çevrim süresi pilot model için %23 oranında azaltılmıştır.

Anahtar Sözcükler: Karar Destek Sistemi, Hat Dengeleme, Karma Üretim, Çevrim Süresi

A Decision Support System for a Mixed-Model Assembly Line Balancing

Abstract

Assembly line balancing is very crucial for the profitability of Arçelik Refrigerator Plant. Currently, line balancing operations are done manually which results in wasted time doing non-value-added activities and loss of productivity. With this project, a decision support system is developed in order to replace current manual operations conducted for line balancing. Within this system, an algorithm is designed to find the optimal operational plans in the assembly lines and it is presented for the company's use through a user interface. As the outcome of this project, substantial operational benefits are provided to the company. Moreover, a 23% decrease in cycle time for the pilot data set is observed and as a result of this decrease financial benefits are expected to be provided.

Keywords: Decision Support System, Line Balancing, Mixed Production, Cycle Time

12.1 Company Information

Arçelik was founded in 1955 as a domestic white goods producer of Turkey. Today, Arçelik has 12 brands and 30 research and development centers with more than 40,000 workers. In addition, it continues to provide products and services in 146 countries with 28 manufacturing facilities. In 1975, Arçelik refrigerator production plant was established in Odunpazarı, Eskişehir. Since then, this plant has produced more than 100 million refrigerators (Arçelik Global, 2022).

12.2 System and Problem Descriptions

12.2.1 System Analysis

Currently, engineers in Industrial Engineering Department are responsible for the operations schedule in the assembly lines. Operation schedule plans are determined based on the net working time per shift. There is an Overall Equipment Efficiency (OEE) coefficient that Arçelik considers. Therefore, shift duration is calculated as net working time per shift $\times$ OEE $\times$ 60 seconds. Target cycle time is calculated as shift duration/PV where PV is the target production volume.This cycle time is determined for each model then a production schedule is arranged to satisfy target production volume with the target cycle time. An important feature of Arçelik Refrigerator Plant is that, mixed production is implemented in the assembly lines meaning that two or more products are produced in one assembly line at the same time. The data, which includes operation times, operation contents, precedence and co-requisite relations, fixed stations and ergonomic requirements, is stored in spreadsheets. In order to satisfy the target cycle time, operations are grouped manually according to the observations and experiences of the engineers. However, manual line balancing operations are time-consuming and dependent on the experiences of engineers. Also, it is hard to handle the different requirements of each model.

12.2.2 Problem Definition

Current manual line balancing operations cause a decrease in productivity, restriction in product mix, hardship in implementability and consumption of workforce for non-value-added activities. Moreover, excessive idle times are observed in some stations meaning that there is a room for improvement in cycle time. Hence, this project focuses on decreasing the cycle time and providing a system that can replace manual operations considering different assembly lines and different types of products that are produced in these assembly lines.

12.3 Solution Approach

12.3.1 Critical Assumptions and Major Constraints

Critical Assumptions

The following assumptions are taken into consideration throughout the project:

- The durations of the operations are considered deterministic.
- Disadvantages of mixed production such as the increase in the number of materials around the operator which may affect operation times are disregarded.
- It is assumed that there are no material restrictions, i.e., the materials are assumed to be present at a required level all the time.

Major Constraints

As observed in all production systems, there are many factors that limit the critical objective value in this project. The constraints for this project can be summarized as follows:

- The shift duration at the factory is 21,675 seconds.
- There are precedence and co-requisite relationships between the operations. The precedence relationship states that one job must be

conducted before another job. Other business units may intervene, but the order of priority should not change. Jobs with a co-requisite relationship imply that one job must be conducted right after the other job in the same station hence they should be compact and no other operations should interfere.

- Operations that can be conducted in a station depend on the ergonomic situation of that station. This means that the locations of the station where operators can work and the operation location that will be conducted on the model must match.

- The locations of some operations are fixed to certain stations and they cannot be changed.

12.3.2 Mathematical Model and GAMS Integration

Sets

$M = \{1, 2, \ldots, M'\}$ is the set of models where M' is the number of models
$I_m = \{1, 2, \ldots, I'_m\}$ is the set of operations for model m where I'_m is the number of operations of model m, $\forall m \in M$
$W = \{1, 2, \ldots, W'\}$ is the set of workstations in order where W' is the number of workstations

Parameters

$$y_{miw} = \begin{cases} 1, & \text{if operation } i \text{ of model } m \text{ is fixed in workstation } w \\ 0, & \text{otherwise} \qquad \forall m \in M, \forall i \in I_m, \forall w \in W \end{cases}$$

$$P_{mij} = \begin{cases} 1, & \text{if operation } i \text{ precedes operation } j \text{ for model } m \\ 0, & \text{otherwise} \qquad \forall m \in M, \forall i \in I_m, \forall j \in I_m \end{cases}$$

$$S_{mij} = \begin{cases} 1, & \text{if operation } j \text{ is a successor of operation } i \text{ for model } m \\ 0, & \text{otherwise} \qquad \forall m \in M, \forall i \in I_m, \forall j \in I_m \end{cases}$$

$$E_{miw} = \begin{cases} 1, & \text{if operation } i \text{ of model } m \text{ can be processed in workstation } w \\ & \text{according to ergonomic requirements} \\ 0, & \text{otherwise} \qquad \forall m \in M, \forall i \in I_m, \forall w \in W \end{cases}$$

Decision Variables

$c =$ cycle time

$$x_{miw} = \begin{cases} 1, & \text{if operation } i \text{ of model } m \text{ is assigned to workstation } w \\ 0, & \text{otherwise} \qquad \forall m \in M, \forall i \in I, \forall w \in W \end{cases}$$

Objective Function

minimize c

Constraints

$$\sum_{w \in W | E_{miw}=1} x_{miw} = 1 \qquad \forall m \in M, \forall i \in I_m \quad (12.1)$$

$$x_{miw} = 1 \qquad \forall m \in M, \forall i \in I_m, \forall w \in W \mid y_{miw} = 1 \quad (12.2)$$

$$\sum_{k \in W} k x_{mik} \leq \sum_{l \in W} l x_{mjl} \qquad \forall m \in M, \forall i \in I_m, \forall j \in I_m \mid P_{mij} = 1 \quad (12.3)$$

$$\sum_{l \in W} l x_{mjl} - \sum_{k \in W} k x_{mik} = 0 \qquad \forall m \in M, \forall i \in I_m, \forall j \in I_m \mid S_{mij} = 1 \quad (12.4)$$

$$x_{miw} = x_{njw} \quad \forall m \in M, \forall n \in M, \forall i \in I_m, \forall j \in I_n \, \forall w \in W \mid i = j \quad (12.5)$$

$$\sum_{i \in I_m} t_{im} x_{miw} \leq c \qquad \forall m \in M, \forall w \in W \quad (12.6)$$

$$c \geq 0 \qquad (12.7)$$

$$x_{miw} \in \{0, 1\} \qquad \forall m \in M, \forall i \in I_m \quad (12.8)$$

Explanations for Constraints

(1) Assignment constraint: Ensures that each operation is assigned to exactly one station.

(2) Fixed station constraint: Certain operations must be assigned to certain stations and this constraint ensures the fixed station requirement.

(3) Precedence constraint: Ensures that if operation i must be conducted before operation j, then operation j can be assigned to the same station as operation i or the stations coming after it. This constraint is adapted from the precedence constraint provided by Yadav et al. (2020).

(4) Co-requisite constraint: Ensures that if there is a co-requisite relation between operations i and j, then they must be assigned to the same station. Co-requisite constraint is adapted from the precedence constraint provided by Yadav et al. (2020) and the co-requisite constraint provided by Akpınar and Bayhan (2011).

(5) Ensures that the same operations of different models are assigned to the same workstation.

(6) Cycle time constraint: Ensures that total processing time for all models in each station is not exceeding cycle time.

(7) Ensures that cycle time is non-negative.

(8) Binary constraint

This mathematical model is implemented into GAMS as requested by the company.

12.3.3 Decision Support System (DSS)

Data Analysis

The data used throughout the project consists of operation times, operation description, precedence and co-requisite relations between operations, ergonomic requirements of the operations and information about fixed stations. For Data Analysis, first data collection step was performed by gathering the data from Arçelik. Then, the data were examined and the exploratory data analysis necessary for this process was performed. In this step, missing data was determined and filled with the consultancy of our Industrial Advisor from Arçelik. One of the most important points in our project was to determine how the available data will be used in the DSS. In order to process the data in a way that it can be used by GAMS, we used the features of Excel VBA. We considered the operational data for an available model as a reference and we divided the available data into subsections as operations, operation times, workstations, co-requisite and precedence relations, fixed station information and ergonomic requirements. Then, data for each of these subsections is transferred into matrix forms.

User Interface

We designed a user interface to enable users to use the program easily. Inputs will be entered into this interface, the program will be executed, and results will be obtained. In this way, we ensure that the created solution can be used by the people without the need for technical knowledge. The user interface is designed using Excel VBA.

The user interface basically works in three stages: forming the data, executing the GAMS model, and viewing the results. In data formation, ergonomic requirements matrix, fixed station matrix, priority and co-requisite matrices, and operation times matrix are created. Then, for executing the GAMS model, necessary data is exported to GAMS via the user interface

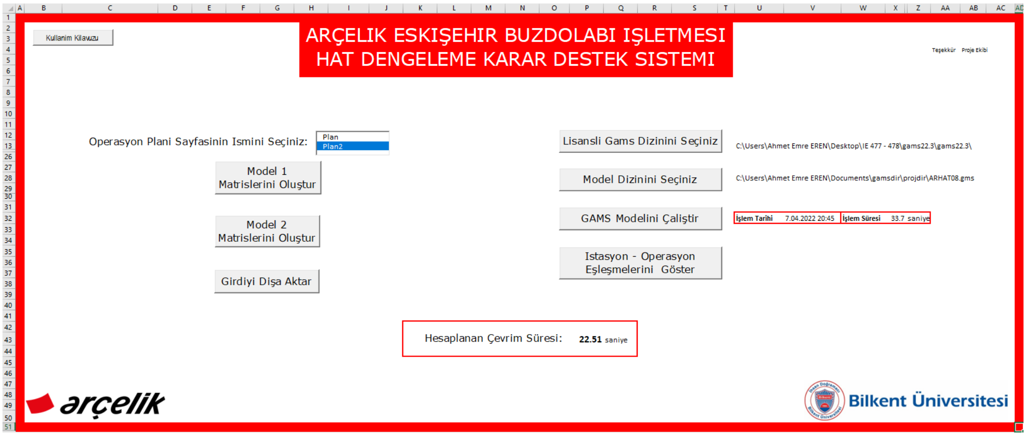

Figure 12.1: User interface

in appropriate forms and the model is run through Excel VBA. After the execution is completed, the user interface imports the results and presents them to the user. Our user interface is designed in accordance with the current plan used by the company for ease of use. Figure 12.1 shows the opening page of our user interface. A user manual describing the working mechanism of the system is prepared in order to guide the user. It explains the input and output screens in detail as well as the necessary steps for setting up the system.

12.3.4 Animation

In order to visually present our solution and compare the current and new systems, we designed an animation model with Arena. After creating the systems, for each process box, an animation tool which represents the corresponding resource's status (idle or busy) is utilized. Moreover, the resource usage of the stations with minimum and maximum cycle time to demonstrate the difference between them is plotted. Lastly, the time passed as the animation keeps running and the corresponding number of refrigerators manufactured are calculated with animation tools. The animated models of current and improved system are shown in Figure 12.2.

12.4 Verification

For verification of our GAMS model, firstly a small data with which optimal solution can easily be observed was added into GAMS manually in order to check whether the constraints are working properly and the optimal solution is as expected. Then, we run the model with different number of workstations and different number of operations. By checking our constraints and parameters we verified that our model considers the constraints correctly.

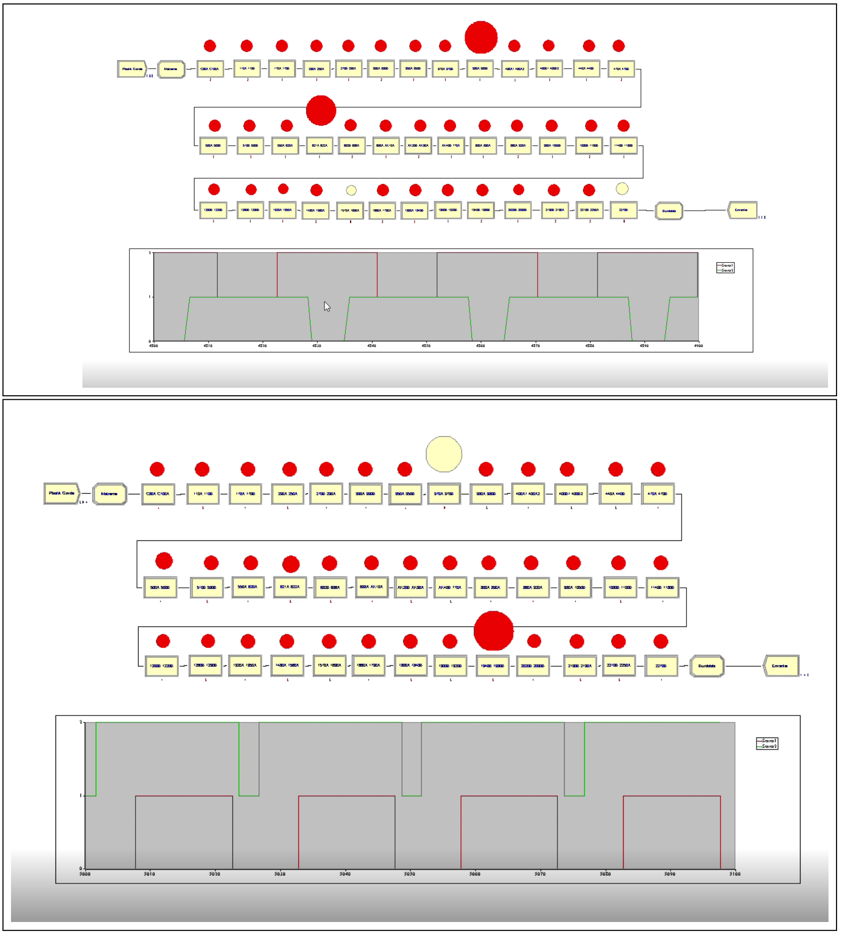

Figure 12.2: Animations of the current (above) and improved systems

As the second step of the verification, we considered extreme situations. We analyzed the behavior of the model in cases such as when each operation needs to be assigned to the same station, all the operations follow each other as co-requisite. In each of these analyses, we have observed that our model works as expected.

12.5 Validation

In order to validate our proposed model, first we worked with the current operation plan that is used by the company. With additional constraints, we forced the model to assign operations to the stations in which they are currently being processed. The resulting cycle time of the model was the same as the current cycle time hence we validated that our model correctly calculates the cycle time in the same way that the company does. In the next step of the validation, we solved our model with the whole data that we have. We have validated that the solution of this model does not conflict with any of the major considerations or constraints of the system.

12.6 Benefits to the Company

With the DSS that is provided, the main benefit that is expected to be achieved is the percentage annual increase in the number of refrigerators produced as a result of decreased cycle times. In addition, with our solution approach, the inefficiencies in the current system that are resulted from manual operations will be eliminated with the use of optimization tools. In order to quantify our benefits, we conducted benchmark analysis between the new system and the current system. In our analysis, we considered the following Key Performance Indicators (KPI): cycle time, the average utilization of workstations, process time deviation between workstations and production volume. Considering the optimal operation plan of our DSS for the pilot data set, a 23% decrease in cycle time is observed and as a result of this decrease, 30% increase in production volume is obtained. The average utilization of workstations is increased by 31% and the standard deviation between workstation times is decreased by 4%.

Our proposed solution iimproved all of the KPIs. Our main goal was to decrease the cycle time and consequently, increase the production volume, and we successfully achieved this. As a result of this increase in production volume, financial benefits will be provided to the company.

Scenario Analysis

Other than cycle time, it is important for the company to obtain workstation times that are close to each other in order to eliminate excessive idle times. Even though the optimal solution from our algorithm also performs better compared to the current system in terms of standard deviation between workstation times and average utilization of workstations, we performed a scenario analysis to minimize the maximum difference between workstation times. We performed this analysis by changing our objective function to maximum difference between workstation times and adding another constraint that ensures cycle time does not exceed a certain threshold. As a result, we obtained an operation plan which decreases the standard deviation by 60% and decreases the maximum difference by 75% when compared to the current system. These numbers are 58% for standard deviation and 73% for maximum difference when compared to our solution obtained from the model that minimizes only the cycle time. Moreover, the operation plan obtained with the scenario analysis still has the same cycle time as our main solution, which is the minimum cycle time that is achievable. With this analysis, another result we obtained is that we have multiple optima

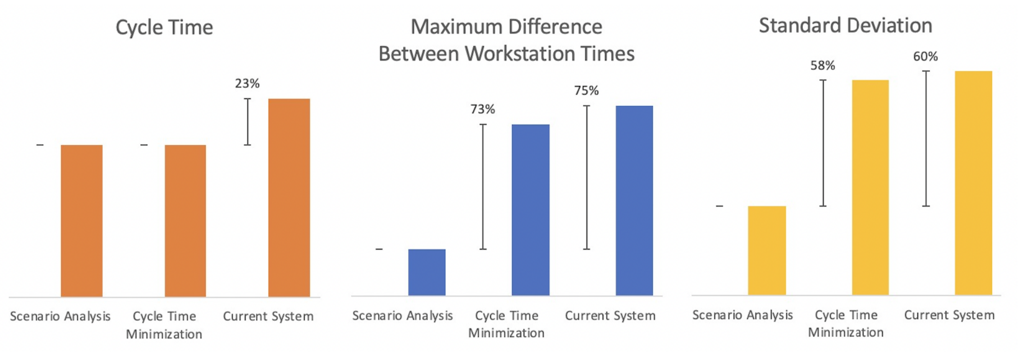

Figure 12.3: Comparison for scenario analysis, cycle time minimization model and current system

for this problem with the pilot data set. A visual representation of our comparison for cycle time, maximum difference between workstation times and standard deviation between workstation times for current system, cycle time minimization model and scenario analysis can be found in Figure 12.3.

12.7 Conclusion

Throughout the project, our main aim was to minimize the cycle time and reduce the manual line balancing system's disadvantages. As the outcome of our project, we obtained a 23% reduction in cycle time and we provided the company with a DSS that radically eliminates the workforce for line balancing. Moreover, with our scenario analysis, we even improved our solution by considering Arçelik's requisition and substantially reduced the deviation between station times. Finally, with our user interface, we presented our DSS for the company's use.

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13 Kılıflı Yatak Üretim Planlama ve Çizelgeleme Karar Destek Sistemi

İşbir Yatak

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Özet

Bu projede İşbir Yatak Ankara Fabrikasındaki üretim, çizelgeleme ve talep tahmin sistemleri ile ilgili sorunlar incelendi. Kılıflı yatak hattında toplam kârlılığı iyileştiren iki haftalık üretim planlama modeli ve toplam üretim süresini düşüren günlük çizelgeleme modeli geliştirilmiştir. Ayrıca indirim ve talep arasındaki ilişkiyi göstermek için regresyon çözümlemesi geliştirilmiştir.

Anahtar Sözcükler: Üretim Sistemi, Üretim Planlama, Çizelgeleme, Talep Tahmin

Decision Support System for Production Planning and Scheduling of Sheathed Mattresses

Abstract

In this project, the problems related to production, scheduling, and demand forecasting systems at İşbir Yatak Ankara Factory were examined. A two-week production planning model, which improves overall profitability, and a daily scheduling model, which reduces the total production time, were developed in the sheathed mattress line. In addition, a regression analysis was developed to show the relationship between discounts and demand.

Keywords: Production System, Production Planning, Production Scheduling, Forecasting

13.1 Company Information

İşbir Yatak is a mattress manufacturer operating under İşbir Sünger Inc. and serving in 25 countries under the name of "İşbir Bedding". The company aims to accomplish quality and customer satisfaction by producing healthy and comfortable products. To achieve this, they benefit from Open-cell Visco Technology, Polymer Spring Technology, Quallofil Allerban Technology, and Nano-technology in their manufacturing system İşbir Yatak (2021). The company also manufactures pillows, plinths, and headboards other than mattresses.

13.2 System Analysis

In the current system, İşbir Yatak manufactures two types of mattresses: sheathed and closed. They supply sponges, glues, plastic springs, and fiber. Mattresses differ in terms of sizes, sponge types, bedsprings, type of glue, cotton, fiber, and fabric that is used in mattresses. For example, sheathed mattresses are removable, so they can be removed, washed, and put back, meaning that sheathed mattresses are washable, whereas closed ones are not. Moreover, in the production of the sheathed mattresses, water-based adhesive glue, a special type of glue, is used.

Sheathed mattresses are produced according to the following steps: Firstly, the sponges are sent to the preparation station where springs are put, and sponges are trimmed. After that, sponges enter the sheathed mattress line. In the sheathed mattress line, there are five serial machines: the gumming (which uses water-based adhesive), the pressing, the oven, the stretching, and the sheath covering machines. In the sheathed mattress line, firstly the sponges are assembled to each other by the gumming machine. Then, in the pressing and oven machines, these sponges are stuck to each other, and the glue is dried. Finally, in the stretching and the sheath covering machines, sponges are stretched and they are covered by sheaths. The firm's current production planning system is based on the change in demand for mattresses according to seasonality. The firm sells more mattresses in summer due to high demand rates, so they keep stocks in winter to satisfy high demands in summer. Therefore, their manufacturing system is make-to-stock (MTS). To apply MTS, they utilize the machines as much as possible. The capacity of the production line is used to satisfy the current demand and to keep stocks. In summer, instead of keeping stocks, they satisfy the current demand, so their manufacturing system is classified as make-to-order (MTO). Therefore, they switch between MTO and MTS policies.

The operations of mattresses are scheduled so that the makespan is minimized. For this, they apply the Shortest-Processing-Time (SPT) rule for the gumming machine to get a schedule. After getting a schedule, then they apply this schedule for the rest of the sheathed mattress line, considering the First-Come-First-Served (FCFS) rule. This scheduling decision is made according to the batch sizes and the processing times of products at each machine because they aim to reach their daily production targets as soon as possible.

The firm currently uses the AAA (additive error, additive trend, and additive seasonality) version of the Exponential Triple Smoothing Method (ETS) for the forecasting operations. The FORECAST.ETS function in Excel is used for point estimation for each product by considering seasonality and trend. They only consider previous months' sales data for forecasting, so they set their production targets according to these forecasted values. After that, these production targets are shared with the manufacturing department. If the sales are less than expected, extra stocks occur. To sell these extra stocks, the company applies discounts.

13.3 Problem Definition

There are two types of problems: one type is related to production, and the other is related to forecasting. Therefore, forecasting-related and production-related problems are handled separately. The problems are classified as production planning, scheduling, and forecasting. For the production planning, the company cannot adjust its production system to volatile market demand to reach the minimum manufacturing cost. Moreover, the parameters such as holding cost, inventory cost, backlog cost, and the cost of the idle capacity of machines are not considered efficiently in the decision of the production process. So, there is no decision support system that considers these cost parameters.

Another problem is related to production schedules. While minimizing the makespan of the products in the sheathed mattress line, only gumming operation times are considered to get a schedule. However, there are four serial operations other than gumming, but they are not considered in scheduling decisions. Therefore, there is no algorithm or a system that considers other operations than gumming in minimizing the makespan.

Finally, the company's current forecasting method, which does not consider the relation between the change in price and the variation in the demand, is only based on previous months' sales data. Thus, there is no method to observe this relation between discount and demand in their current forecasting system.

13.4 Proposed Solution Strategy

13.4.1 Production Planning Model

The objective of this optimization model is to develop the company's current production planning system by minimizing the manufacturing cost. We achieved this by developing a linear programming (LP) model that determines the optimal number of specified products to be produced and their inventory levels. In addition, this model decides on the idle times of each machine in each period. At the end of each period (15 days), the model should be run with a rolling horizon approach, where the planning horizon proceeds by 15 days. When the next period of the planning horizon arrives, the model's parameters are updated if necessary, and it should be run again. This approach enables the company to adapt the production to the volatile environment rooted from insufficient raw materials, high demand variation, and machine breakdowns via a flexible and responsive planning system. The inputs are demands, production, holding, backlog costs and the operation times of mattresses considered in the model in each machine, idle costs and capacities of machines in the sheathed mattress line. The outputs are the optimal production amounts, inventory levels and idle times for each period which minimizes the manufacturing cost. The model includes production capacity, inventory balance and inventory capacity constraints. Transportation times between workstations are neglected. The model can be seen in Appendix 13.A.

13.4.2 Scheduling Model for Minimum Makespan

The production amounts given by the production planning model are considered as two-week production targets. To find the daily production targets, outputs of the production planning model are divided by 10. There are 10 working days in a two-week period, so the outputs are divided by 10 to create these daily production targets as homogeneous as possible. The change in the makespan depends on the batch size and the number of batches. If both increase, the makespan increases, and if both decrease at the same time, the makespan does so. If one increases while the other decreases, the change in the makespan depends on these increase-decrease ratios. If the increase rate is more than the decrease rate, the makespan increases; if it is less, it decreases. If these ratios are equal, the makespan will not change.

Once the daily production targets are set, the decision-maker creates batches consisting of the same type of mattress. They are considered as jobs. The time that each job spends in each machine is considered as the processing time of that job for that machine.

The objective of this model is to minimize the makespan at the sheathed mattress line so that the company reaches the daily production targets fast. The inputs are the number of batches created for each mattress, each job's processing times in each machine and a sufficiently large number. The outputs are the exit times from machines, makespan and a binary variable taking the value of 1 if job i enters the line just before job j, 0 otherwise. Therefore, considering the processing times of jobs, this model finds a schedule of jobs so that the makespan is minimized.

In the model, constraints 1-2 ensure that each job has exactly one successor and the last job has no successor. The next five constraints ensure that a machine cannot process two or more jobs simultaneously. Moreover, these constraints indicate that if job i is scheduled just before job j, then exit times job i are less than those of job j for all jobs and machines, so the constraints 3-7 do not allow cycles. Constraints 8-11 indicate that for all jobs, the exit times from machines should obey the precedence relations. Constraint 12 defines makespan, which is the maximum of all flow times of all jobs. Constraints 13-18 indicate that batches containing the same type of mattresses are scheduled consecutively, and the last constraints are domain constraints. The mixed-integer programming (MIP) scheduling model can be seen in Appendix 13.B.

13.4.3 Forecasting Model

For the forecasting, a regression analysis is done. The independent variables are discount decisions represented by a binary variable (1 if a discount is applied, 0 otherwise) and the dependent variables are the differences between forecasted values and real demand values. 2019-2021 demands are observed to see the effect of discounts. Excel is used to show the relation between the demand and the discount decision by the regression analysis. The company's current method remains in forecasting operations. This

Yatak Adı	A
Yatak Kodu	A1
Ay	Ocak

Yıl	Tahmin Edilen Talep	Gerçekleşen Talep	Promosyon	Değişim Miktarı
2017	100	150	1	50
2018	150	180	1	30
2019	200	165	0	35
2020	250	225	0	25
2021	275	350	1	75
2022	250	293	1	43

Figure 13.1: Forecasting Model in Excel (with dummy parameters)

forecasted value is updated by the regression analysis. Figure 13.1 shows the result of a regression analysis done with the help of an Excel template.

13.5 Validation

13.5.1 Production Planning Model

The validation of this model starts with defining constraints. In the production environment, there are some limitations and situations and these are mathematically expressed in the model to reflect the real conditions. Each machine has its own capacities in every period. Thus, there is a capacity limitation of machines in the sheathed mattress line, which is reflected by constraint 1. Moreover, this constraint indicates that the difference between capacities and working times of each machine in each period is equal to the idle time of each machine in each period. In a feasible production area, the capacities should be bigger than the required working time for all machines and in each period. Hence, all idle times must be nonnegative; this is defined in domain constraints.

The second constraint indicates that the inventory level of the previous period plus production amount minus demand is equal to the inventory level of the current period. This constraint defines the balance in the inventory in each period, and for all mattresses, productions enter to and demand exit from the inventory.

The inventory level is unrestricted in sign and equals the difference between on-hand inventory and backlogged demand for each period and mattress, defined by constraint 3. Since holding and backlogging are costly, this model tries to equate inventory levels to zero. However, the machines may become idle if the required production to satisfy demand is low. In this case, the model decides to continue some products' production to prevent these machines from being idle. Based on idle time, holding and production costs, the model decides on whether to continue production or let machines be idle for each period. Thus, it is the tradeoff for the model to find the minimum cost. At the beginning of each rolling horizon, there is a positive or negative inventory level that is transferred from the previous rolling horizon to the new rolling horizon. Moreover, there is a capacity for the inventory in each period that the company can hold. Furthermore, constraint 4 indicates that in all periods, there is a capacity for inventory levels.

By the direction of our Industrial Advisor (IA), to determine the production, holding, and backlog costs, we reached the labor and material costs of each item. Thus, these costs are reflected as the production cost in the model. For holding costs, these production costs are multiplied by the opportunity cost calculated by dividing the profit before tax by İşbir Holding's total assets. Furthermore, the production costs are multiplied by 4 since backlogging demand is not preferred and profitable according to the IA. Finally, to calculate the idle time costs, the capacity allocated to mattresses considered in the model is divided by 4. These values can be updated according to the decision maker.

13.5.2 Scheduling Model

For the validation of the scheduling model, the conditions and structure of the sheathed mattress line are reflected into the model. Therefore, the validation starts with the formulating the model and defining constraints to reflect the feasible production area. Firstly, each machine cannot process more than one batch simultaneously. Therefore, batches enter the machines one by one since there is no capacity for all machines to process two or more jobs. As a result, jobs have to be scheduled consecutively. This condition is reflected in the model with the constraints 1 and 2.

Moreover, because all machines can handle at most one job simultaneously, jobs must wait for the ongoing processes on the next machines to be completed in order to enter them. In other words, unless machines are idle, batches cannot enter them. This condition is reflected by constraints 3-7.

Furthermore, there are five machines, each completing one operation, and the operations have the precedence relationship of gumming, pressing, drying, stretching, and sheath covering. Therefore, these operations need to be completed one by one for all batches, so one operation cannot start before the previous operations are finished for all batches. Batches enter all machines according to this relation. Thus the exit times of jobs from each machine comply with this relation. This condition is stated in the model with constraints 8-11.

Switching among different types of mattresses in production can be time-consuming due to setup requirements. Consequently, the jobs including the same mattresses are scheduled one after the other. This is indicated by the constraints 13-18. Therefore with these constraints, the solution time of the model decreased because the size of the problem reduces. However, as the number of batches created increases, the runtime of the model increases.

Finally, there is a job 0, which is a dummy job indicating the first job to be scheduled. If $Y_{0i} = 1$, i is the first job to enter the line. The constraint 20 shows that for this dummy job, the exit times equal to zero.

To sum up, the feasible region of this model is created based on the conditions of the sheathed mattress line.

13.5.3 Forecasting Model

The company's data, including the discount and increase in demand information were observed. The data include turnovers, the number of sales and the material costs of each product. By dividing turnover to the sold number of the mattress, the unit prices are found in the 2019-2021 period. If there is a decrease in the unit price in time or a substantial increase in the demand, then it is concluded that there is a discount that is represented with a binary parameter. Then, the changes between real and forecasted demand values are observed with the discount information. After all, a regression analysis is conducted over these changes and discount decisions. Thus, a discount-demand function is subtracted from this regression analysis which is used for finding the possible changes between the forecasted and real demand in the future based on the discount decision. By this way, the company is eligible to see expected changes over forecasted demand in the case of discount or not.

13.6 Benchmarking and Benefits

One benefit of the project is that the company is able to decide the production amounts and inventory levels to minimize the manufacturing cost for sheathed mattresses and the idle time costs for the machines, considering cost parameters with the help of an optimization tool. The rolling horizon approach enables them to adjust their production plan into volatile market demand.

To compare the past decisions of the company and the model's decisions about the production amounts and inventory levels, the company's data, including capacities, productions, demands, costs and inventory levels for 2021, are examined, and total costs for 2021 are calculated based on the data provided by the company. Then, with the same input data, our model was run for one year (24 periods, each consisting of 15 days). According to the results, our model provides a 53.15% decrease in total costs. In other words, the model's objective function was calculated with the company's data and our model's outputs. It is observed that our model decreases the costs by 53.15%. This improvement ratio would vary between 40-60% depending on the parameters.

Another benefit is that the company receives a decision support system for scheduling the jobs in the sheathed mattress line so that the makespan

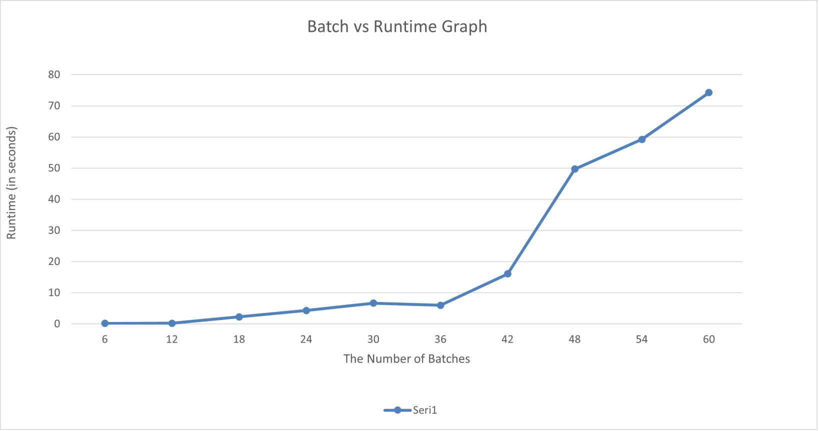

Figure 13.2: Runtime versus the number of batches

of products is minimized. To make a comparison between the model and the company's scheduling system, the processing times of mattresses in each machine are measured several times. It is observed that these processing times vary between 0.3 and 5 minutes. These fluctuations are based on machine breakdowns, low speed of workers, and setup requirements. Therefore, we created three scenarios about these processing times and compared our model and the current system under each scenario.

In Scenario 1, the processing times at each machine are kept between 0.30 and 5 minutes with 4 products and 20 jobs. It is observed that in scenario 1, total makespan decreases by 13%. In Scenario 2, the processing times at each machine are kept between 0.30 and 3 minutes. Then, we reached an improvement of 14.7% decrease in the makespan in scenario 2. In scenario 3, the processing times at each machine kept between 0.50 and 1 minutes. So, we reached an 8% decrease in the makespan in scenario 3.

As a result, we applied different scenarios with the masked-values of the firm in scenario 1,scenario 2, and scenario 3. By using our model instead of the current method, the company is able to decrease the makespan at the sheathed mattress line considering all machines. The improvement is between 5-20%, depending on the parameters. The runtime of the model is crucial for the company since the company runs it daily to get a daily schedule. The time measurement study was conducted on a laptop with 64-bit Operating System, Intel(R) Core(TM) i7-7700HQ processor, CPU @ 2.80GHz 2.81 GHz, and with a memory of 16 GB RAM. A graph showing the relation between the number of batches and the runtime can be seen in Figure 13.2.

The last benefit of the project is to enable the company to see the relation between discount and change in the demand via regression analysis written in Excel-VBA. We compared the difference between the real demands and the company's forecasting values before and after applying the discount effect by regression analysis. It is found that we made a 3-5% improvement in winter months by lessening the difference between the real demand and forecasting via applying the expected change with the independent variable discount decision. This improvement is expected to be between 4% and 8% for the summer months.

13.7 User Interface and Implementation

For the company, user interfaces for the production planning and scheduling are created in Excel, whereas the mathematical models are coded in Python. In these user interfaces, when the necessary parameters are entered to the buttons on the user interface, Excel attains these values to the cells on the Excel Sheet. Later, when the user runs the Python, it takes the necessary values from that Excel Sheet. Then, the results coming from Python are written to Excel.

For the production planning model, the user should decide on parameters like production costs for each product, and also the processing times for each machine of each product. Moreover, the demand of each product for each period and machines' capacities should be entered by the user. Then, by clicking the "Çalıştır" button, the model is executed. It is enough to click the "Temizle" button to clear the user interface and also related Excel cells. In addition, the user interface enables user to update the necessary inputs without changing all of the parameters.

For the scheduling model, the user can choose to write all the parameters from the beginning or update the necessary ones. If s/he chooses "Tüm Değerleri Baştan Gir", s/he should enter the processing time of each product for each machine and the number of batches created for each product. When the user enters the "Çalıştır" button, the model is executed. If s/he wants to delete the parameters entered before, s/he can enter the "Girdileri Temizle" button. In addition, the user interface is flexible for the user to update parameters without deleting all parameters with the "Değerleri Güncelle" button. Then, another form pops up and the user can update parameters.

For the forecasting model, the user should click on the "Değişimi Hesapla" button to open the interface. The mattress name, code, and the month that wanted to be examined should be entered by the user. Then, s/he enters the forecasted demand, real demand, and binary representation of whether there is a discount or not for each year. Lastly, the user should enter the year that s/he wants to learn the discount effect and binary representation for discount and forecasted demand for that year. Then, by clicking the "Hesapla" button, the regression analysis is executed, and the expected change is reflected on the related cell. Thus, by the cell formulations, it is added or subtracted from the forecasted value to decrease the gap between forecasted and real demand values. By "Temizle" button, the user can delete the boxes. The interfaces can be seen in Appendix 13.C.

13.8 Conclusion

The expected outcomes of the project are series of production and scheduling plans over a given time horizon. Another outcome is to enable the company to see how the customers respond to discounts. So, the company can adjust its production plan according to its sales strategies.

Bibliography

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Appendices

13.A The Planning Model

Datasets
N = The set of mattresses (the number of mattresses is accepted as 6)
T = The set of 15-day periods (the number of periods is accepted as 6)
M = The set of machines in the Sheathed Mattress Line (the number of machines is accepted as 5)
Parameters
h_i: unit holding cost of mattress i $\forall$ i $\in$ N
k_{jt}: the cost of unused capacity of the machine j in period t per minute $\forall$ j $\in$ M $\forall$ t $\in$ T
c_i: unit production cost of mattress i $\forall$ i $\in$ N
b_i: unit backlog cost of mattress i $\forall$ i $\in$ N
C_{jt}: the capacity of the machine j in period t in minutes $\forall$ j $\in$ M $\forall$ t $\in$ T
p_{ij} : unit processing time of mattress i in machine j $\forall$ i $\in$ N, $\forall$ j $\in$ M
IC_t : the inventory capacity in period t $\forall$ t $\in$ T
D_{it}: Demand of mattress i in period t $\forall$ i $\in$ N , $\forall$ t $\in$ T
Y_i: Initial inventory level of mattress i $\forall$ i $\in$ N
Decision Variables
X_{it}: Amount of produced mattress i in period t $\forall$ i $\in$ N, $\forall$ t $\in$ T
I_{it} : Inventory level of mattress i in period t $\forall$ i $\in$ N, $\forall$ t $\in$ T
I^+_{it}: On-hand inventory of mattress i in period t $\forall$ i $\in$ N, $\forall$ t $\in$ T
I^-_{it}: Backlogged amount of mattress i in period t $\forall$ i $\in$ N, $\forall$ t $\in$ T
a_{jt} :The unused capacity of the machine j in period t in minutes $\forall$ j $\in$ M $\forall$

t ∈ T
Model
min $\sum_{i=1}^{N} \sum_{t=1}^{T} (c_i X_{it} + h_i I_{it}^{+} + b_i I_{it}^{-}) + \sum_{j=1}^{M}\sum_{t=1}^{T} k_{jt} a_{jt}$
s.t
(1) C_{jt} - $\sum_{i=1}^{N} X_{it} p_{ij} = a_{jt}$ ∀ j ∈ M, ∀ t ∈ T
(2) $I_{i,t-1}$+X_{it}- D_{it}=I_{it} ∀ i ∈ N , ∀ t ∈ T
(3) I_{it}^{+}-I_{it}^{-}=I_{it} ∀ i ∈ N , ∀ t ∈ T
(4) $\sum_{i=1}^{N} I_{it} \leq IC_t$ ∀ t ∈ T
(5) I_{i0}=Y_i ∀i ∈ N
(6) X_{it}, I_{it}^{+}, $I_{it}^{-} \geq 0$ ∀ i ∈ N , ∀ t ∈ T
(7) I_{it} free ∀ i ∈ N, ∀ t ∈ T
(8) $a_{jt} \geq 0$ ∀ j ∈ M, ∀ t ∈ T

13.B The Scheduling Model

Datasets
N : The set of all batches (the size of $N = \sum_{i=1}^{6} Batch_i$)
M : The set of machines (the number of machines is accepted as 5)
Parameters
$Batch_i$: The number of batches created for mattress i ∀ i ∈ N
p_{ij}: The processing time of job i in machine j ∀ i ∈ N, ∀ j ∈ M
F: sufficiently large number
Decision Variables
A_i :The exit time of job i from the gumming machine ∀ i ∈ N
B_i :The exit time of job i from the pressing machine ∀ i ∈ N
C_i :The exit time of job i from the oven machine ∀ i ∈ N
D_i :The exit time of job i from the stretching machine ∀ i ∈ N
E_i :The exit time of job i from the sheath covering machine ∀ i ∈ N
W: The makespan of all products Y_{ij} :1 if job i precedes job j, 0 otherwise
∀ i ∈ N, ∀ j ∈ M
Model
min W
s.t:
(1) $\sum_{j=1}^{N} Y_{ij} \leq 1$ ∀ i ∈ N $i \neq j$
(2) $\sum_{i=0}^{N} Y_{ij} = 1$ ∀ j ∈ M $i \neq j$
(3) A_i - A_j - $FY_{ji} \geq p_{i1}$ - F ∀ i ∈ N, ∀ j ∈ N, $i \neq j$
(4) B_i - B_j - $FY_{ji} \geq p_{i2}$ - F ∀ i ∈ N, ∀ j ∈ N, $i \neq j$
(5) C_i - C_j - $FY_{ji} \geq p_{i3}$ - F ∀ i ∈ N, ∀ j ∈ N, $i \neq j$
(6) D_i - D_j - $FY_{ji} \geq p_{i4}$ - F ∀ i ∈ N, ∀ j ∈ N, $i \neq j$
(7) E_i - E_j - $FY_{ji} \geq p_{i5}$ - F ∀ i ∈ N, ∀ j ∈ N, $i \neq j$

(8) $A_i + p_{i2} \leq B_i$ $\quad \forall$ i $\in$ N

(9) $B_i + p_{i3} \leq C_i$ $\quad \forall$ i $\in$ N

(10) $C_i + p_{i4} \leq D_i$ $\quad \forall$ i $\in$ N

(11) $D_i + p_{i5} \leq E_i$ $\quad \forall$ i $\in$ N

(12) $W \geq E_i$ $\quad \forall$ i $\in$ {1,...,N}

(13) $Y_{i,i+1} = 1$ for i = 1,..,$Batch_1 - 1$

(14) $Y_{i,i+1} = 1$ for i = $Batch_1 + 1$,..,$\sum_{i=1}^{2} Batch_i$ - 1

(15) $Y_{i,i+1} = 1$ for i = $\sum_{i=1}^{2} Batch_i + 1$,..,$\sum_{i=1}^{3} Batch_i$ - 1

(16) $Y_{i,i+1} = 1$ for i = $\sum_{i=1}^{3} Batch_i + 1$,..,$\sum_{i=1}^{4} Batch_i$ - 1

(17) $Y_{i,i+1} = 1$ for i = $\sum_{i=1}^{4} Batch_i + 1$,..,$\sum_{i=1}^{5} Batch_i$ - 1

(18) $Y_{i,i+1} = 1$ for i = $\sum_{i=1}^{5} Batch_i + 1$,..,$\sum_{i=1}^{6} Batch_i$ - 1

(19) $A_i, B_i, C_i, D_i, E_i \geq 0$ $\quad \forall$ i $\in$ {1,...,N}

(20) $A_0, B_0, C_0, D_0, E_0 = 0$

(21) $Y_{ij} \in \{0,1\}$ $\quad \forall$ i $\in$ {0,...,N}, $\forall$ j $\in$ {1,...,N}

13.C User Interface

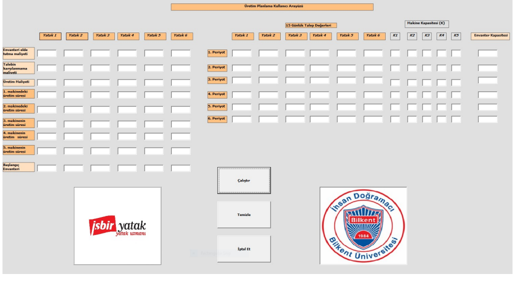

Figure 13.3: Planning user interface

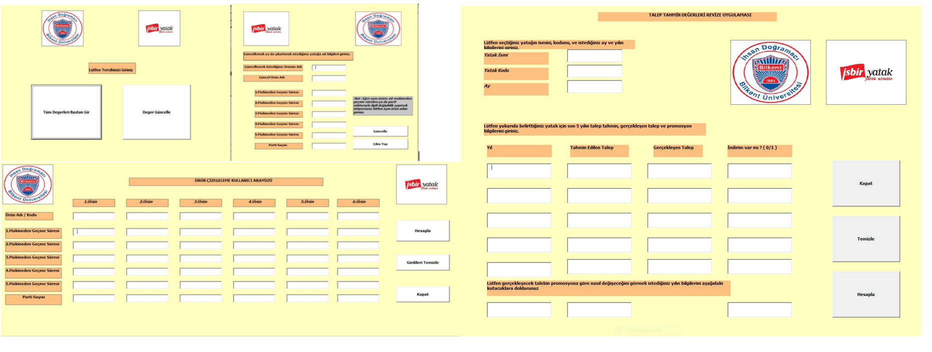

Figure 13.4: Scheduling and forecasting user interfaces

Konfigürasyon Değişiklik Yönetimi için Karar Destek Sistemi

14

FNSS Savunma Sistemleri

Proje Ekibi
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Özet

FNSS'nin mevcut üretim sisteminde, ürün veya ürün bilgilerinde değişiklik yapılma ihtiyacı duyulduğu zamanlarda, Konfigürasyon ve Veri Yönetimi Departmanı tarafından yönetilen toplantılarda tartışılan değişiklik kararlarının sonuçlandırılması uzun zaman almaktadır. Bu nedenle, çok kriterli karar analizi yöntemlerinden faydalanarak bir Karar Destek Sistemi (KDS) ile süreci hızlandırmaya ihtiyaç duyulmaktadır. Projenin amacı, değişiklik yönetimi sürecinde, kararların doğru parametre tanımıyla ve farklı departmanların hedeflerini değerlendirerek sistematik bir şekilde alınmasına yardımcı olacak, maliyet ve zamanı en aza indirgeyecek bir KDS geliştirmektir. Bu amaçla Python ve Excel VBA kullanılarak bir KDS geliştirilmiş, sürecin zamanında ve sistematik bir şekilde yürütülmesine büyük katkı sağlanmıştır.

Anahtar Sözcükler: Karar Destek Sistemi, karar verme, zaman yönetimi, maliyet iyileştirme, süreç analizi, konfigürasyon değişikliği yönetimi

Decision Support System for Configuration Change Management

Abstract

In the production system of FNSS, whenever changes in the current system, products or product information are necessary, Configuration Control Board meetings lead by Configuration Change & Data Management Department are conducted and it may take long periods of time to finalize a decision. As a result, the need for a Decision Support System (DSS) that would assign weights to distinct criteria which aims to catalyze the decision-making process is observed. The DSS will be developed by using one of the multi-criteria analysis methods.The aim of this project is to develop a DSS which, with the definition of correct parameters and assessing the objectives of distinct departments, helps to make decisions systematically while also minimizing cost and time. This aim is achieved through a DSS that is developed through Python and Excel VBA enabling the completion of the decision making process on time and systematically.

Keywords: Decision Support System (DSS), decision making, time management, cost improvement, process analysis, configuration change management

14.1 Company Information

FNSS is one of the largest Turkish defense companies, which was founded in 1998. Nurol Holding holds the majority share with a 51% stake in the company while the remaining 49% is owned by BAE Systems. FNSS, is a globally recognized defense company that specializes in modernizing, designing, engineering and producing land combat vehicles and turrets. Currently, FNSS mostly works on indigenous tracked and wheeled vehicles, turret design and modernizing older FNSS vehicles. These vehicles include the Kaplan series of tracked armored combat vehicles, PARS series of wheeled armored combat vehicles, engineering combat vehicles such as Kunduz or AACE, and many more including seven turrets.

14.2 Current System Analysis

Throughout the production process in FNSS, there are times changes in the current system are required. Different types of changes exist which might include minor changes that do not require any discussion or changes that require back and forth communication between several parties included in the decision making process. FNSS implements configuration management in their product development process to bridge the gap between vehicle design and the final product. This implementation is done through the inclusion of the proposals from different departments for engineering changes on sub-products. The department responsible for overseeing these change requests is the "Configuration Change Management" Department. FNSS manages these proposals of change in the following order: they first define the needs, start the change request process, then they follow up with the assessment of the request, and finally start the operational processes. Proposal changes originate from problems within the system and operations, enhancement trials, or customer requests and are all implemented on existing operations instead of deploying new processes.

To explain the matter more thoroughly, change management process starts with a new report of change and ends with the implantation of the improvement that is needed. The main components of the cycle can be listed as problem report demand made by filling a form, a change request made from the Enovia software called as an EC-R, examination of the request by Configuration Control Board (CCB), drawing release, another look on the change from the Change Implementation Board (CIB) and if CIB decides that is it applicable then, the change is implemented. Thus, due to the several steps included in the process the performance measures in the decision-making process include the time spent in the change cycle and the accuracy of the decisions made.

14.3 Problem Definition

The main issue for FNSS, regarding the Configuration Change Management Department, is the duration of the finalization of decision making process. This process tends to take extended periods of time to accomplish and gives rise to a need for a decision support system (DSS) to reduce time spent in the change cycle. The main actors whose inputs are used for Configuration Change Management meetings include five departments which are design, manufacturing, supply, planning, and program. Due to inclusion of several departments, differences in the objectives of the actors hinders the quick and effective detection of the optimal solution. Since, at the moment the decision making process is mainly based on human judgments, the inclusion of a system that will conduct numerical analysis enabling previous data which will include the weights of several departments will eradicate the problem of disruption to the system and will provide dynamic time optimization.

14.4 System Structure

The Decision Support System has two main components, the back-end where computations are conducted utilizing a Python script and the front-

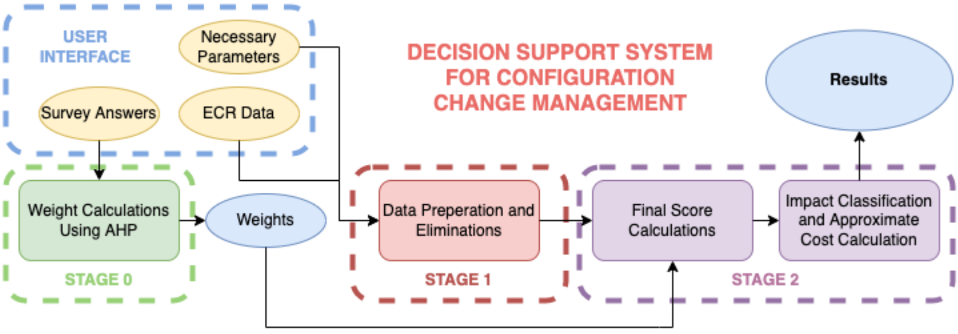

Figure 14.1: A Basic flowchart of system structure

end where the user inputs the necessary parameters and operates the system via an easy-to-use user interface made in Excel VBA. The system operates in three stages and as an output it classifies the given change requests into three groups: high-impact, grey area and low-impact. This is a completely new design that wasn't a part of the companies operating procedure when conducting configuration change management. A simple flowchart of the system structure is displayed in Figure 14.1.

14.4.1 Stage 0

Stage 0 of the system operation, is a setup stage where it is conducted once, only when the company decides to change the parameters of the DSS. We suggest re-adjusting these parameters every six months. To be able to classify change requests in accordance with the company's priorities, the system asks the user to answer survey questions. While answering the survey, users compare each criterion's importance relative to another one. The pairwise comparison of the criteria is collected according to SAATY'S 1-9 scale (Bruce L.Golden, Edward A. Wasil, Patrick T. Hasker (Eds.), 1989). After the survey questions are completed, the resulting pairwise comparison matrices are used to calculate weights for each criteria using Analytical Hierarchy Process (AHP) and the weights for each criteria is stored. With the help of the survey, the system learns the priorities of the company and hence it utilizes the experiences of the experts while making the classification. In terms of parameters the user specifies high-impact and low-impact thresholds between 0 and 1 and class code upper thresholds. These parameters will be further explained in the following sections.

14.4.2 Stage 1

Stage 1 of the system is an elimination and preparation stage where, the company specified conditions of:

- Change requests with change reason “Customer Request” are classified as high-impact since there are small margins where the change request can be modified.

- Change requests with change reason “Necessity” are classified as high-impact since this means that the change request stems from a major problem that must be changed.

- Change requests with disposition status “Administrative” are classified as low-impact since they are internal change requests that is either changing paperwork or at an early stage in production that have a low-impact.

After this elimination, data is converted into numerical form to be able to use them in score calculations.

14.4.3 Stage 2

Stage 2 of the system is the scoring stage where the remaining change requests after stage 1 are scored according to following criteria.

- Class Code: Class of the parts unit cost.

- Quantity: Total of on-hand inventory, open purchase orders and open shop orders of the part.

- Lead Time: The lead time of the part.

- Change Reason: The numerical score of change reason of the change request.

Change Reason Scores

Change reasons are given in text form and there are two main types of change reasons that are ”problem” and ”improvement”. There are 8 types of different problem reasons and 4 types of different improvement reasons. The system, using the weights obtained in Stage 0, calculates a change reason score for each change request. This change reason score is a score between 0 and 1 where higher the score, higher the impact of the change reason will be on the overall score of the change request.

Final Scores

After the change reason score for each change reason is calculated, the system calculates a score for each change request using the weights of the four main criteria stated above. The resulting score is the final score.

Classification

After assigning a score for each change request, the system, according to the representative thresholds, classifies the change requests as high impact or low impact. Any change request left in-between are considered to be in the gray area. The system outputs the original spreadsheet given as an input, adding the final scores next to each change request.

Approximate Cost Calculation

Following the classification of each change request, the system calculates an approximate cost of the change request and reports it to the user by using class code values and quantity information.

After all stages are complete, the system returns the results with the used parameters and weights in a single spreadsheet. Another copy of the results are saved into a different folder with the date of operation as per the request of the company. The Python script, also outputs the consistency ratio calculated to the user. The suggested consistency ratio is 0.1 or lower. The output of the system can be found in Figure 14.2.

14.5 Verification and Validation

In order to verify that the system runs as intended, tests were conducted using the example data provided by the company. These tests were to check whether the system was successful in conforming to the intended specifications by reading the correct data and utilizing them correctly in the application.

After the system was verified to be working as intended, the scores generated and the weights calculated were validated using some artificial change requests created for the purpose of testing whether a change in each criteria (when all other criteria remained constant) had the intended effect on the scores in accordance to the answers of the survey questions.

To validate that the weights calculated through the survey questions

	Ecr No	Change Reason Score	FINAL SCORE	Expected Cost
248	DCR-30683	0.1908	0.6809	13500
318	DCR-30728	0.1369	0.6802	15500
255	DCR-30683	0.1908	0.6748	13000
324	DCR-30728	0.1369	0.656	13500
71	DCR-30882	0.0194	0.6261	15500
337	DCR-30971	0.6704	0.6209	32000
361	TEST12	0.0638	0.1253	0
218	DCR-30968	0.2563	0.1239	0
328	DCR-30854	0.2563	0.1239	0
364	TEST15	0.0559	0.1216	0
72	DCR-30882	0.0194	0.1181	1000
188	DCR-30658	0.2563	0.1181	0
189	DCR-30658	0.2563	0.1181	0
136	DCR-30921	0.0194	0.116	1500

Figure 14.2: Simplified demonstration of the output spreadsheet

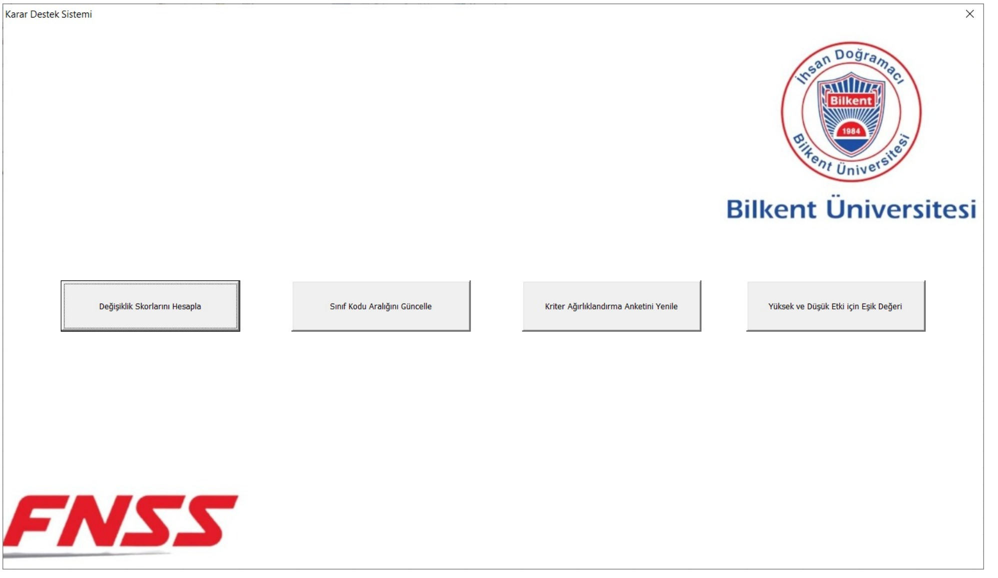

Figure 14.3: Main Page of the User Interface

were accurate, extreme cases that include all criteria having equal importance or each criteria dominating other criteria were tested. The weights generated were as expected and therefore we concluded that the system is valid.

14.6 User Interface and Implementation

The DSS is presented to the company through a meeting with industrial advisors at FNSS in 13th of April where the system is thoroughly explained via the user interface.

The DSS is designed in Python in order to access ideal packages such as; Pandas, xlsxwriter, openyxl, and Jinja2 where inputs obtained from the user interface designed in VBA and .xlsx files are transferred to the system and calculations made using NumPy library for python. This structure of the system will benefit the company since ECR files are already stored as spreadsheets. Hence, no further work will be needed and all information will be processed within one system.

The user interface provides the following functions in the main page as can be seen in Figure 14.3.

- Calculating the change request scores
- Updating the class code WAC per unit upper limit
- Updating/Filling the pairwise comparison matrix surveys

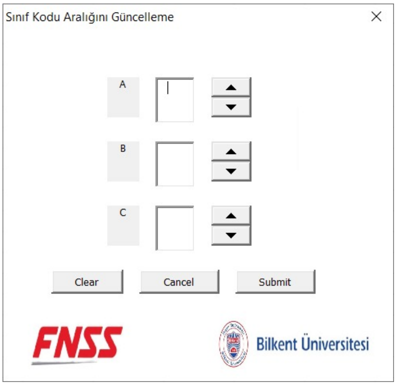

Figure 14.4: Updating Upper Limit of the Class Code Ranges in the Interface

- Updating the high and low impact threshold values

If updating the class code WAC per unit upper limit button is selected, the interface provides a sheet to input data since the company wanted to make WAC intervals adjustable over time. The page provided by the interface can be seen in Figure 14.4.

When update the thresholds for high and low impact button is chosen, the user can update the threshold values which are based on while categorizing the requests as high/low impact. By the button named "Updating/Filling the pairwise comparison matrix surveys", the user can access and fill out the survey in which they compare pairs of criteria. The answers of the survey are verbal but each answer is related to a number in Saaty's 1/9-9 scale. Thus, after the survey is submitted, the system automatically converts the answers to numbers and fills a spreadsheet with the corresponding pairwise comparison matrix. In the interface, there are three different surveys for the following: 4 main criteria, 8 sub-criteria under "problem" section, and 4 sub-criteria under "improvement" section. When the user finishes all three surveys and submits, if any inconsistent answer is given the system warns the user by emphasizing the pairs of criteria which are inconsistent with one another. This helps the user to easily acknowledge where they answered inconsistently so that they can fix without difficulty.It is recommended for the users to update their answers once a year to make sure the system is up to date. The page shown by the interface can be seen in Figure 14.5.

If calculating change request scores is selected, based on the input taken from the user via the other three buttons; the scores of each request is calculated by utilizing Python. After that a screen opens automatically in which information such as:

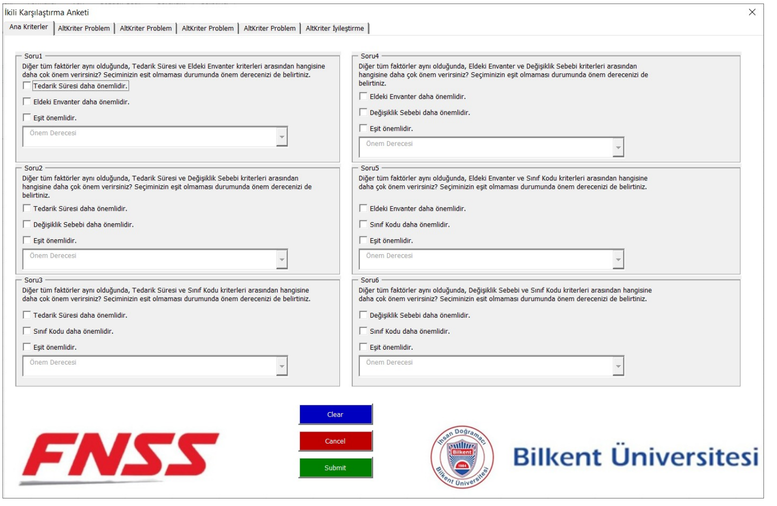

Figure 14.5: Pairwise Comparison Survey in the Interface

- weights of each criteria
- consistency ratios of the surveys
- the maximum, minimum, average and median scores

are provided to the user. Simultaneously, the output file which provides the final change request scores is prepared. In the output Excel file, all high impact change requests are filled with red color while the low impact ones are filled with green to make them more distinguishable for the user. Moreover, in order to facilitate the data collection process of the company, the system saves the old output files every time a new calculation is made.

14.7 Benefits to Company and Conclusion

The main purposes of the decision support system (DSS) include expediting the process of analyzing change requests in terms of minimizing time spent on meetings and associated costs and maximizing the accuracy of decisions handled. These objectives are aimed to be achieved while preserving the feasibility and efficiency of the common decisions to accommodate the involved departments' objectives. The system also provides means for quantifying importance of criteria and analysis of weights of decision aspects.

FNSS is currently undergoing digitalization involving all operations, following the developments occurring after the pandemic. They will be using this DSS to develop and find a balance between digitalization of their processes and preserving the active, dynamic communication face to face interaction brings to the work product. The DSS is to be installed to computers of all employees where the team members working a specific project are able to see data, weights, system outputs of any change request analysis to decide whether the subject will be discussed in the CCB. With this integration, low impact changes are handled online, CCB meetings proceed more effectively with the historical ECR data stored in the DSS and will take less time as digitalization will saves time since participation of employees to the meetings are only required when their project is being discussed.

As a result, a DSS that continuously improves and adapts to the changes occurring within the company is constructed. The system improves itself by learning certain parameters over the course of its use thus, its accuracy and productivity will increase as more data is stored in the system. The IT department will also be able to modify the system depending on their needs in the future as the system is not hard-coded, the functions are not fixed to certain input types and open to necessary adjustments. System structures and elements including survey results, weight allocations, stored analysis of change requests, department objectives, change reason scores, classifications and cost calculations are the primary outputs that the DSS provides. The contributions of the DSS will continue to gradually increase with its integration into the company structure and to further projects.

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Motor Kulağı Üretim Planlaması Karar Destek Sistemi | 15

Oyak Renault Otomobil Fabrikaları

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Özet

OYAK-Renault Otomobil Fabrikaları'nda montaj hattında kullanılmak üzere motor kulağı üretilmektedir. Operatör, tecrübe ve gözlemlere dayalı inisiyatif ile motor kulağı üretim miktarını belirlemektedir. Bu durum sistemde zaman kaybına, gereksiz stok tutulmasına ve operatörün yeterince verimli kullanılamamasına neden olmaktadır. Bu projenin temel amacı, işgücünden periyodik olarak tasarruf sağlarken üretim miktarını enbüyüklemektir. Bu nedenle, matematiksel bir model kullanılarak motor kulağı üretimi için bir üretim çizelgesi oluşturulmuştur. Bu sayede motor kulağı üretimi ana üretim çizelgesi ile paralel çalışmaktadır ve operatörün inisiyatifi yerine modele göre belirlenmektedir. Sonuç olarak, operatör her saatin %16.7'lik bölümünde motor kulağı üretimi dışında bir iş ile görevlendirilmeye uygun hale getirilmiştir.

Anahtar Sözcükler: Üretim çizelgeleme, matematiksel model, süreç içi iş envanteri, motor kulağı

A Decision Support System for Engine Brackets Production

Abstract

In OYAK-Renault, engine brackets are being produced to be used in the assembly line. Operator determines the production quantity of engine brackets based on experience. It causes a time loss in the system, unnecessary work in progress inventory and inefficient use of the operator. The primary purpose of this project is to maximize the amount of production while periodically saving workforce. A production scheduling for engine brackets was created by using a mathematical model. In this way, the production schedule of engine brackets is determined by the model instead of the operator's initiative. As a result, the operator is made available to be assigned a job other than the production of engine brackets for 16.7% of each hour.

Keywords: Production scheduling, mathematical model, work in process inventory, engine bracket

15.1 Company Information

OYAK-Renault is an automobile factory in Bursa producing under Groupe Renault. The factory has a manufacturing capacity of 378,000 automobiles and 920,000 engines per year. It is one of the factories with the highest manufacturing capacity, excluding Western Europe (OYAK Renault, 2021a). It has vehicle and mechanics factories. Car production is done in the vehicle factory whereas chassis, gearbox, battery and engine are produced in the mechanics factory. Currently, the company produces two Renault models: Clio and Megane Sedan (OYAK Renault, 2021b).

15.2 System and Problem Descriptions

15.2.1 System Analysis

Engine bracket keeps the engine in its place. In Renault, each model has different engine type. Each engine type has distinct engine bracket code number. There are two different machines for two groups of different engine bracket code numbers and two storage areas for raw materials. In engine bracket production, one operator works. Examining the flow chart in Figure 15.1, the manufacturing process of an engine bracket is as follows:

- If setup is needed, the operator chooses the code number in about 30 seconds. Then, the operator places the required mold in 45 seconds.

- After setting up the mold, the operator carries the required raw ma-

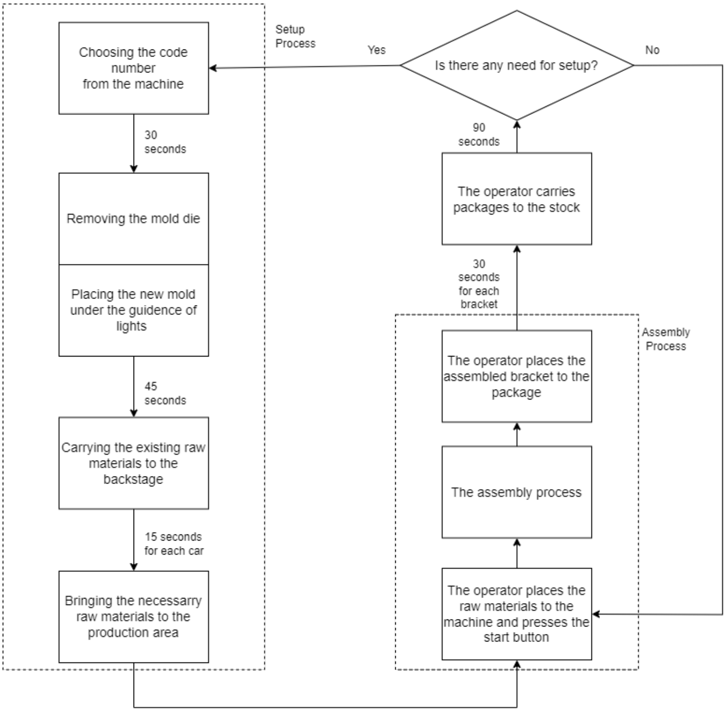

Figure 15.1: Flowchart of the Current Engine Bracket Production System

terials to the storage area behind the machine in two other carts and the raw materials of the previous setup to the other storage area in two carts. While one cart is for the metal materials, the other one is for the plastic materials. Replacing each cart takes about 15 seconds. The change of all materials takes 60 seconds. If one material is the same for some engine brackets, the process takes 30 seconds.

- After the setup process, assembly process of an engine bracket is done. Operator places the raw materials to the machine in 30 seconds.

- Then, the operator places the engine bracket in a box that stores 15 engine brackets. If two boxes of engine brackets are manufactured, the operator carries these two boxes into the storage area with a cart. The transportation takes 90 seconds including carrying into a storage area in 60 seconds and placing the boxes in 30 seconds.

In the storage area, there is a separate cabinet for each engine bracket code number. Each cabinet has a capacity of seven boxes and must at least have one box of engine brackets. Thus, there can be at least 15 units in the storage area and at most 105 units of an engine bracket for each code number. Every 57 seconds, a new car is produced. The engine brackets are collected from the storage area with the other necessary components of a car in engine installation via robotic carriers. The carriers are capable of carrying the supplements of four cars separately to the production line. Every 228 seconds, a carrier arrives at the storage area to pick up the required engine brackets. The information that the carrier will take the specified engine code number finalizes 2 hours and 40 minutes before producing the car which needs that engine bracket. Each carrier arrives at the production line in 30.5 minutes. Engine brackets join the production before they are needed and are put inside of the processed car until the step that it is used. The timeline of the process between the finalization of the production order of a car and assembly of an engine bracket to a car is shown in Figure 15.2.

Figure 15.2: Timeline of the Process

15.2.2 Problem Definition

In a day, there are 8-hour shifts for the engine bracket production. The operator tends to produce engine brackets that are the least in amount compared to other code numbers without a production schedule. Such a decision-making process causes unnecessary production of engine brackets accumulated in the storage area and thus, time loss. Moreover, it may block the operator to perform another job within his shift. Therefore, the operator may not be as efficient as they could be and it creates a time loss.

15.3 Model Development

In the process of literature review, it is found that a lot-sizing problem was solved by using the mixed-integer programming (MIP) method. The method was implemented in a scheduling environment with multiple-product, capacitated, single-machine and deterministic demand to minimize the summation of setup, production, inventory holding, and maintenance costs (Eppen and Martin, 1987). The constructed MIP works properly to find the optimal solution in an acceptable period of time (Eppen and Martin, 1987). Thus, considering that OYAK-Renault also demands a production schedule for engine brackets, the MIP method was proper to use to solve the problem.

Another mathematical model was developed by Fleischmann and Meyer to solve a lot-sizing and scheduling problem where different types of products are produced in a single machine (Fleischmann and Meyer, 1996). Similarly, results have shown that it is efficient to develop a mathematical model to solve the problem. As a result of the literature review, it is decided to use mixed-integer programming as the solution approach. The model takes the car production plan as demand input and creates an engine bracket production schedule as the output. The input is based on two different production plans: weekly and finalized production plans. The finalized plan is being used for the hour that we are going to schedule, and the weekly plan is being used for the following 23 hours. The main goal here is sustaining a foresee to the model. The output consists of 24 periods, each being 1-hour long. From each output, we use the first hour. The reason behind using 24 hours of data is being able to consider the potential demand of the following periods. In line with the company's expectations, this model assigns regular 10-minute breaks in each hour to the operator. In those 10 minutes, the operator can be assigned to other jobs. To solve the model, Excel is used with the OpenSolver package. Since the OpenSolver package is free to use, there will not be an additional cost.

The main purpose of the model is to make the operator available in the last 10 minutes of each hour. Therefore, we maximize the production quantity of engine brackets in our model while limiting the duration of the production by 50 minutes in each hour. However, we have also added an extra time variable which the model activates only when an extra time is needed in the production. This enables the model to exceed the 50 minutes of production time limit in periods where extreme cases occur.

To ensure that all the restrictions given by the company are taken into account, we included several limitations in our model in order to develop our constraints. These limitations include: the number of setups, inventory levels, total time, production capacity, amount of extra time, number of packages and carriers used. The model is presented in Appendix A.

15.4 Validation

The validity of the model was assessed utilizing the 3-day (October 25, 2021 - October 27, 2021) and the 2-week (the sixth day of the forty-eighth week until the third day of the forty-ninth week of 2021) datasets provided by the company. Based on these datasets, the model provided engine bracket production schedules. Both of the production schedules satisfied 100% of the engine bracket demands in all periods. In none of the engine bracket production periods, total production time exceeded 50 minutes. Consequently, if the provided engine bracket production schedules were used in the factory

	Satisfied Demand Rate	Free Time Created in 1 period	Does the Production Stops?
3-Day Data	100%	10 minute	No
2-Week Data	100%	10 minute	No
Scenario 1 (1 unit of demand from 8 types, 59 units of demand from 1 type)	100%	1 minute	No
Scenario 2 (67 units of demand from 1 type)	100%	10 minute	No
Scenario 3 (equal units of demand from each type)	100%	2.5 minute	No

Table 15.1: Scenarios

at the given times, the car production would have continued without any breaks. In order to test the model's reliability, 3 different demand scenarios were tried out and the results were examined. These scenarios were constructed in order to reflect the challenging cases that can come up during production. In each of these scenarios, 100% of the engine bracket demands are met and as a result, the car production does not stop. Table 15.1 shows which demand scenarios and actual datasets were tried out. The results were examined in terms of the satisfied demand rate, total free time created in a 1-hour period and continuity of the car production metrics. Based on these results, our model can provide reliable engine bracket production schedules that can satisfy the engine bracket demand and support the continuity of the car production.

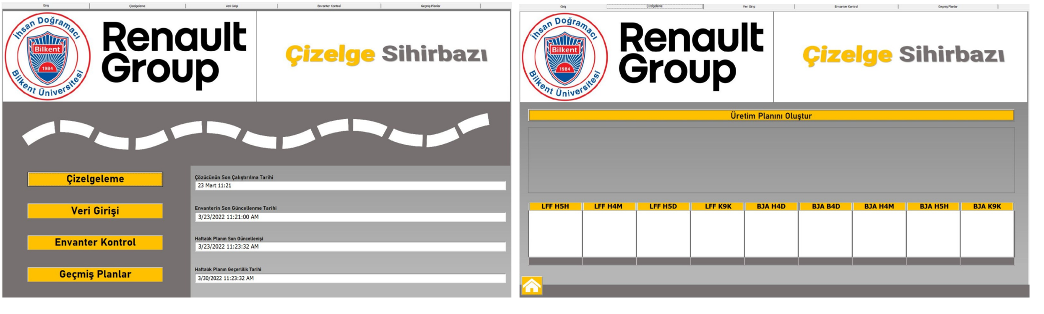

Figure 15.3: Entrance and optimization pages

Figure 15.4: Data input and inventory control pages

15.5 User Interface

To solve our model, an interface is created using Excel VBA. While running the mathematical model, the interface provides supporting operations such as inventory updating and data monitoring to control the system. "Üretim Planını Oluştur" button activates the optimization operation. The button also receives finalized production plan and the starting inventory levels as an input. To sustain the weekly production plan entrance, we use "Haftalık Plan Girişi" button. We use "Envanter Kontrol" and "Enventeri Güncelle" buttons to check and update the current inventory levels. Furthermore, we store the data of the previous solutions in where we can monitor the optimal production quantities for the previous 24 solutions to observe the process by using the "Geçmiş Planları Listele" button. Figures 15.3 and 15.4 show the user interface pages.

15.6 Integration and Implementation

The integration of our approach to the current system is based on three main steps. At first, installation of required attachments and programs is needed. These are Microsoft Excel and the OpenSolver attachment. The second stage is the integration of inputs into the model. As it is mentioned in the previous parts, our inputs are the weekly production plan, finalized production plan, and starting inventory levels. Our interface is accepting both of the production plans in Excel format. The final step is deciding on the implementation type. At this point, we deliver two different products. The first one is the manual implementation. In the frame of the manual implementation, at the beginning of each hour, inputs are uploaded and the button is used to generate the production schedule by the user. Furthermore, there may be a need to control the inventory levels and try to detect any possible mistakes. On the other hand, the other implementation type is autonomous implementation. In the frame of the autonomous implementation, there is not any need for a user. The interface runs itself at the beginning of each hour. Furthermore, because the model is run strictly, the possibility of encountering deviations in the inventory levels and the need to control inventory are negligible.

To compare both of these approaches, we can say that both the implementation types may have different advantages. The main advantage of the manual implementation is giving the opportunity to have more control over the model. If it is preferred to assign a person and screen each step, manual implementation will be beneficial. The main disadvantage of manual implementation is timeliness. Because the schedule may not be generated exactly one hour later than the previous run, there may be a couple of seconds of deviations, and these deviations may cause us to miscalculate demands considering the demand entrance frequency. Thus, frequent control of the inventory levels is necessary. The main advantage of autonomous implementation is less need for a user. Because the model works exactly hour by hour, we will not be missing any demand. So that, the need to control inventory levels will not be obvious. However, the autonomous system will be decreasing the control of the company on the product and this may not be desired by the company.

15.7 Benchmarking and Benefits

The performance metrics for the benchmarking are the operator's working hours in the production of engine brackets and the number of engine brackets produced in a shift. The validated model's output gives the number of production periods in the shift so that this can be compared with the current system results in the company. Since the main purpose of this project is to ensure efficient use of workforce, with our approach we are making the operator available at regular intervals to perform other tasks. In this way, we ensure that one-sixth of the operator's time is available for other tasks. Therefore, the expected benefits to the company are reducing the working hour of the operator in the production of engine bracket, elimination of possible results of faulty initiatives, efficient use of workforce and determination of production quantities according to a plan.

15.8 Conclusion

Examining the current system, production amounts of the engine brackets are determined with the initiative of the operator. Therefore, unnecessary engine bracket and storage, inefficient use of the workforce and time loss due to unplanned setups occur. Throughout the project, the main goal is to make the operator available periodically to perform other jobs. Utilizing the mathematical model that maximizes the production quantity of engine brackets, the last 10 minutes of each hour of the engine bracket production is saved for the assignment of the operator to other jobs while the car production is satisfied. Meaning that, 16.7% of each hour is considered as a break for the engine bracket production. Thus, reducing the number of engine bracket production periods, the current workforce is used efficiently. Providing a production plan through the interface to the operator, faulty initiatives are also prevented. In the future, in case of a change in the production quantities of the engine bracket quantities, the company is able to change the inventory levels manually on the interface.

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Appendix: Mathematical Model

Sets:
T = Period set
W = Engine bracket set
Parameters:
U_{it} = Number of engine bracket i required in period t (Weekly Plan)
D_{it} = Number of engine bracket i required in period t (Finalized Plan)
Z_i = Inventory limit for engine bracket i
M = Maximum number of engine brackets that can be produced in one period (hour)
L = Available working time in a period
TS = Setup time
TP = Production time of one unit of engine bracket
$Pcap$ = Engine bracket capacity of each package
$Ccap$ = Package capacity of each cart

MP_t = Big M parameter for engine bracket production in period t
$TPac$ = Package placement time to the inventory cabinets
TC = Travelling time between inventory area and production area with carts

Decision variables:

$$Y_{it} = \begin{cases} 1, \text{ if engine bracket i is produced in period t} \\ 0, \text{ if not} \end{cases}$$

C_{it} = Number of packages used for engine bracket type i in period t
EC_{it} = Number of carts used for engine bracket type i in period t for transportation to the inventory
P_{it} = Number of engine bracket i produced in period t
EX_t = Total extra time used in period t
I_{it} = Inventory level of engine bracket i at the end of period t

Model:

$$\max \sum_{t=1}^{T} \sum_{i=1}^{W} (P_{it} - MP_t \cdot EX_t)$$

s.t

$$\sum_{i=1}^{W} Y_{it} \leq |W| \quad \forall t \in T \tag{15.1}$$

$$I_{it} \leq Z_i \quad \forall i \in W, \forall t \in T \tag{15.2}$$

$$P_{it} \leq MY_{it} \quad \forall i \in W, \forall t \in T \tag{15.3}$$

$$I_{it-1} - U_{it} + P_{it} = I_{it} \quad \forall i \in W, t \in T \tag{15.4}$$

$$TS \sum_{i=1}^{W} Y_{it} + TP \sum_{i=1}^{W} P_{it} + TPac \sum_{i \in W} C_{it} + TC \sum_{i \in W} EC_{it} \leq L + 60 \cdot EX_t \quad \forall t \in T \tag{15.5}$$

$$Pcap \cdot C_{it} \geq P_{it} \quad \forall i \in W, t \in T \tag{15.6}$$

$$Ccap \cdot EC_{it} \geq C_{it} \quad \forall i \in W, t \in T \tag{15.7}$$

$$EX_t \leq 10 \quad \forall t \in T \tag{15.8}$$

$$I_{it} \geq 0, P_{it} \geq 0 \quad \forall i \in W, t \in T \tag{15.9}$$

$$Y_{it} \in \{0, 1\} \quad \forall i \in W, \forall t \in T \tag{15.10}$$

$$I_{it}, P_{it}, C_{it}, EC_{it} \text{ are integers } \forall i \in W, t \in T \tag{15.11}$$

Stratejik Dağıtım Ağı Tasarımı | 16

Norm Fasteners

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Özet

Bu proje sayesinde Norm Fasteners'ın Avrupa ve Türkiye'de kiralanan depolarının hacim ve sevkiyat verileri kullanılarak mesafe üzerinden lojistik maliyetlerini enazlayacak lokasyonların bulunmasına ve bu lokasyonlardan hizmet alacak müşterilerin belirlenmesine yönelik bir yaklaşım sunulması hedeflenmektedir. Şirketin stratejik düzeydeki depo açma kararını alırken kullanması için değişen koşullara adapte olabilen, kullanıcı dostu bir arayüz tasarlanmıştır. Depo konumları ve müşteri atamaları program kullanarak eniyi seviyede belirlenmiştir ve bu sayede şirkete Avrupa'da %4.12'lik, Türkiye'de %18'lik bir mesafe iyileştirmesi sağlanmıştır.

Anahtar Sözcükler: Lojistik, stratejik planlama, depo konumlandırma, mesafe enazlama, dağıtım ağı

Strategic Planning of Distribution Network Design

Abstract

The aim of this project is to provide an approach to find the optimal locations for warehouses that minimizes logistics costs over distance and identifies customers receiving service from these locations by using the shipment and volume data of current warehouses in Europe and Turkey. A user-friendly interface that can adapt to changing conditions has been designed for the company for strategic decision making while opening a warehouse. Warehouse locations and customer assignments were determined optimally via the program, thus providing the company a distance reduction of 4.12% in Europe and 18% in Turkey.

Keywords: Warehouse location, distance minimization, p- median, single sourcing

16.1 Company Information

Norm Fasteners was founded in 1973 in İzmir as one of the group companies of Norm Holding. More than 50,000 products are offered by Norm Fasteners and the main product groups are namely bolts, nuts, screws, ball joints, rivets, and special parts. There are nine production facilities in İzmir and Salihli with a closed area of over 100 thousand m^2. Many leading firms producing automobiles, household appliances, electronics, furniture, construction, and machinery are customers of Norm Fasteners. In 2021, international sales had a proportion of 56% of the total sales. Europe has the most extensive portion among the international sales of Norm Fasteners with 78.4% followed by North America with 13.2%. The company exports its products to a total of 35 countries. Shipments can either be sent directly to the customers or they can be sent via the warehouses Norm (2021).

16.2 System and Problem Description

16.2.1 Current System Analysis

Logistics department of Norm Fasteners is divided domestic and international markets. Inbound logistics deals with shipments from Norm Holding's factories to İzmir warehouse. Domestic logistics is in charge of the deliveries from the İzmir warehouse to the domestic customers. International logistics ship products from İzmir warehouse to both global customers and Norm warehouses in abroad. The goods can be transported by maritime, road, and air transportation. Logistics department assigns routes to the shipments, where maritime is the most preferable option and air transportation is the least preferable due to their prices.

16.2.2 Problem Definition and Its Scope

Current warehouse locations were selected based on the requests of customers. It is likely that the current placement of the warehouses is not optimal because the decisions regarding this settlement do not set their foundation on a proper methodology or mathematical model. The main focus of this project is to offer suggestions by considering the distance of sending shipments from İzmir facility to European warehouses and from warehouses to customers. By trying different scenarios, the model may suggest relocating or closing facilities. Since Norm Fasteners uses rental warehouses, their locations can be easily changed. In case of a relocation, new routes for that location is needed. The route selection is limited by two modes of transportation, which are maritime and road.

The scope of the project is limited to Europe and Turkey because 78.4% of the international shipments are sent to Europe and 44% of the total sales are distributed within Turkey. Thus Norm Fasteners decided to start the warehouse location optimization within these regions.

16.3 Proposed Solution

16.3.1 Proposed System

The core solution of the project is based on developing a model to locate the warehouses of Norm Fasteners by considering the distance limitations between warehouses and customers. The number of warehouses that have to be located is not specified by Norm Fasteners. Moreover, there is no budget constraint limiting the number of warehouses. Therefore, the model has been run multiple times with different numbers of warehouses, and the change in the total distance is observed. Each case has been presented to the company with the corresponding distance and cost values. Based on the analysis of proposed scenarios, the final decision on the number of warehouses will be determined by Norm Fasteners. Optimal locations for the warehouses are the ones minimizing the logistics cost over the total distance travelled. To find the exact locations of the warehouses, the entire continent of Europe should be divided into uninterrupted nodes, and warehouses should be located in some of these nodes. However, since there are plenty of cities in Europe and many potential places for warehouses, the alternative locations set will be too large. The completion time for the model would yield inefficiently; hence 12 commonly used ports in Europe and the given customer locations are added to the dataset of alternative locations.

16.3.2 Model Development

Our solution method consists of two consecutive steps which are preprocess and mathematical model. As the first step, the road distances are obtained from Bing Maps via Excel, dynamically while maritime distances are acquired from Searates (2021). To include the cost efficiency of maritime transportation to the model, we normalized the maritime distances by dividing it to 3.26. We obtained this value by proportioning the costs of road transportation to maritime. Therefore we can minimize the total logistics cost over total distance travelled. Then a pairwise minimum distance algoritm is applied to find the route of going from one node to another with the minimum distance traveled. The outputs of this process is used as inputs for the mathematical model. The optimum routes and the associated mode of transportations are determined in the preprocess while optimal warehouse locations, customer and warehouse assignments are determined by the mathematical model.

In the model, objective function is to minimize the distance. The objective function consists of two components which are the distances between İzmir warehouse and opened warehouses and the distances between the opened warehouses and their assigned customers. The route selection explicitly affects the objective function due to the varying distance values stemming from the selection of the transportation type. Although the aim is to minimize the total distance, the p-median constraint avoids the model to open warehouses in every customer node. To achieve this goal, integer programming (IP) is utilized. The decisions about whether to open a warehouse at a particular location or determine which shipment is delivered via which warehouse are attached to binary variables. To present the scenarios with different numbers of warehouses, the p-median problem is solved.

16.3.3 Mathematical Model

Parameters: The graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ is given

$$\begin{aligned}
\mathcal{N} &= \text{the set of all nodes} \\
\mathcal{A} &= \text{the set of all arcs} \\
\mathcal{L} &= \text{the set of alternative locations i.e. } \mathcal{L} \subseteq \mathcal{N} \\
\mathcal{K} &= \text{the set of shipments} \\
d(k) &= \text{Destination of shipment k} \\
V^k &= \text{Volume of shipment k} \\
p &= \text{the number of warehouses} \\
d_{ij} &= \text{minimum distance between node i and node j}
\end{aligned}$$

$MinCap =$ minimum volume a warehouse should be assigned to be opened

$MaxCap =$ Maximum volume a warehouse can be assigned

T_{izmir} : maximum distance between İzmir and a warehouse

$T_{warehouse}$: maximum distance between a warehouse and an assigned customer.

Decision Variables:

$$X_{ij}^k = \begin{cases} 1 & \text{if shipment k is carried from node i to node j} \\ 0 & \text{otherwise} \end{cases}$$

$$Z_i = \begin{cases} 1 & \text{if a warehouse is opened at alternative location i} \\ 0 & \text{otherwise} \end{cases}$$

$$S_i^k = \begin{cases} 1 & \text{if shipment k is assigned to warehouse at node i} \\ 0 & \text{otherwise} \end{cases}$$

Model:

$$\min \quad \sum_{k \in \mathcal{K}} \sum_{i:(i,j) \in \mathcal{A}} \sum_{j:(i,j) \in \mathcal{A}} X_{ij}^k d_{ij} V^k + \sum_{i \in \mathcal{L}} d_{izmiri} S_i^k V^k \tag{16.1}$$

$$\text{s.t.} \sum_{i \in \mathcal{N}} S_i^k = 1 \quad \forall k \in \mathcal{K} \tag{16.2}$$

$$S_i^k \leq \sum_{j:(i,j) \in \mathcal{A}} X_{ij}^k \qquad i \neq d(k) \quad \forall k \in \mathcal{K}, i \in \mathcal{L} \tag{16.3}$$

$$\sum_{i:(i,d(k)) \in \mathcal{A}} X_{id(k)}^k = 1 - S_{d(k)}^k \qquad \forall k \in \mathcal{K} \tag{16.4}$$

$$Z_i \geq S_i^k \qquad \forall k \in \mathcal{K} \quad \forall i \in \mathcal{L} \tag{16.5}$$

$$\sum_{i \in \mathcal{L}} Z_i = p \tag{16.6}$$

$$\sum_{k \in \mathcal{K}} S_i^k V^k \geq MinCap Z_i \qquad \forall i \in \mathcal{L} \tag{16.7}$$

$$\sum_{k \in \mathcal{K}} S_i^k V^k \leq MaxCap Z_i \qquad \forall i \in \mathcal{L} \tag{16.8}$$

$$\sum_{i:(i,j) \in \mathcal{A}} X_{ji}^k - \sum_{i:(i,j)^m \in \mathcal{A}} X_{ij}^k = S_j^k \qquad j \neq d(k) \quad \forall j \in \mathcal{N}, k \in K \tag{16.9}$$

$$d_{izmirj} Z_j \leq T_{izmir} \qquad \forall j \in \mathcal{L} \tag{16.10}$$

$$d_{id(k)} S_i^k \leq T_{warehouse} \qquad \forall i \in \mathcal{L}, k \in K \tag{16.11}$$

$$X_{ij}^k, S_i^k, Z_i \in \{0,1\} \qquad \forall k \in \mathcal{K}, \quad \forall i \in \mathcal{L} \tag{16.12}$$

The decision for the solver that is used is made according to the capabilities of the group members and the cost burden of the solver to the company. Thus, by considering the scope of the project and the capabilities of the software, the final decision was to use Excel Solver. The model is solved via Excel Solver and the same optimal solutions are obtained from CPLEX.

16.4 Verification and Validation

Verification step is necessary to check whether model works properly. The extreme values for the parameters d_{ij} (minimum distance between nodes i and j), p (number of warehouses), MinCap (minimum warehouse capacity), MaxCap (warehouse volume), V^k (volume of shipment k), are investigated to see whether results agree with the expectations or not. The model chose locations with least distance value, which complies with our expectations.

To validate our model, we forced the model to open 4 warehouses at their current locations to reflect the present situation. As an output, the model provided us with a theoretical benchmark that we can compare with our proposed optimal solution. The travel distances are obtained by our preprocess algorithm since Norm agrees with 3PL companies for its logistics processes and obtaining the real total distance travelled is not possible. Our academic advisor supported our methodology and we have discussed the output of our model with the company officials to ensure that it comply with the current setting. Therefore, we concluded that our model is valid.

16.5 Implementation and Integration

The main focus of the implementation plan is the system user interface that is designed. A software tool utilizing the developed mathematical model is

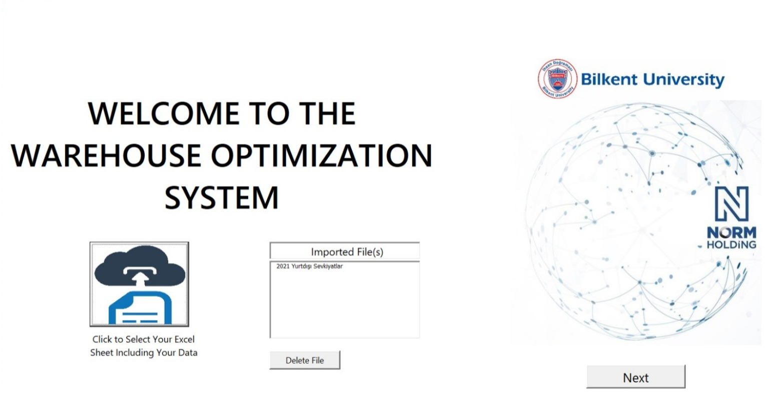


Figure 16.1: Homepage

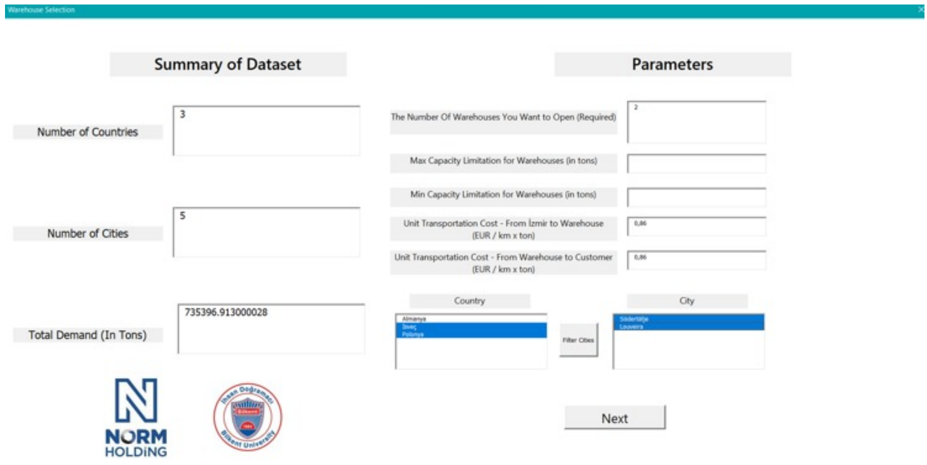


Figure 16.2: Summary page

delivered to Norm Fasteners, which is Excel VBA. This tool enables the company to update the parameters and obtain the new optimal solution for the existing situation. Also, by implementing such a tool, the usage of the project in the long term is encouraged. So, the company will be prepared for the variations of the customer demands, churned or new customers. Excel OpenSolver takes the customer locations, shipments, and volume from the file that Norm upload to the interface, as parameters. The number of warehouses, their capacity limitations if it is wanted, any fixed warehouse location, the maximum distance between warehouses, and the unit transportation cost are asked in the interface, then the model runs accordingly. The user interface has a home page where there is a "file upload" button and the user can upload more than one file which can be seen in Figure 16.1. These files' names are shown in the box next to the upload button.

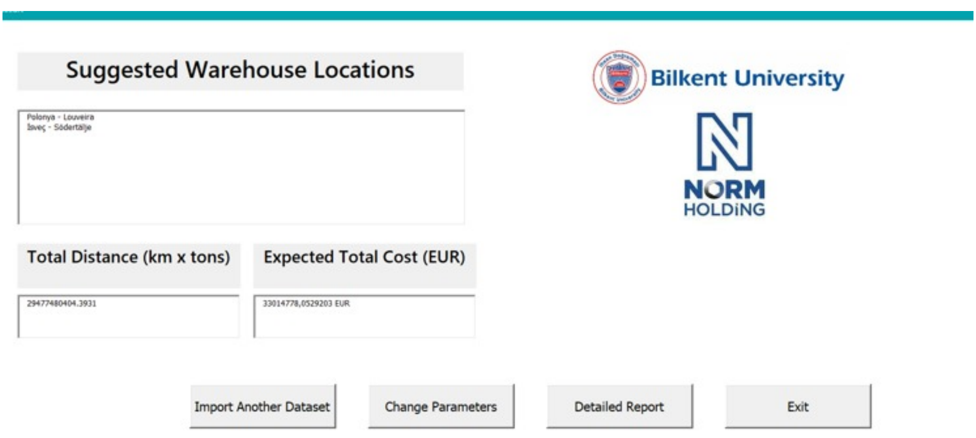
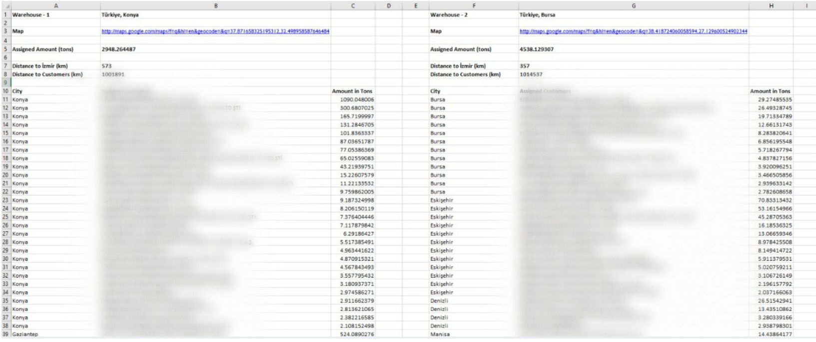


Figure 16.3: Result page



	A	B	C	F	G	H
1	Warehouse - 1	Türkiye, Konya		Warehouse - 2	Türkiye, Bursa	
2						
3	Map	http://maps.google.com/maps?f=q&hl=en&geocode=&q=37.87165832519531 2,32.498958587646484		Map	http://maps.google.com/maps?f=q&hl=en&geocode=&q=38.418724060058594,27.129600524902344	
4						
5	Assigned Amount (tons)	2948.264487		Assigned Amount (tons)	4538.129307	
6						
7	Distance to İzmir (km)	573		Distance to İzmir (km)	357	
8	Distance to Customers (km)	1001891		Distance to Customers (km)	1014537	
9						
10	City		Amount in Tons	City	Assigned Customers	Amount in Tons
11	Konya		1090.048006	Bursa		29.27485535
12	Konya		300.6807025	Bursa		26.49328745
13	Konya		165.7199997	Bursa		19.71334789
14	Konya		131.2846705	Bursa		12.66131743
15	Konya		101.8363337	Bursa		8.283820641
16	Konya		87.03651787	Bursa		6.856195548
17	Konya		77.05386369	Bursa		5.718267794
18	Konya		65.02559083	Bursa		4.837827156
19	Konya		43.21939751	Bursa		3.920096251
20	Konya		15.22607579	Bursa		3.466505856
21	Konya		11.22133532	Bursa		2.939633142
22	Konya		9.759862005	Bursa		2.782608658
23	Konya		9.187324998	Eskişehir		70.83313432
24	Konya		8.206150119	Eskişehir		53.16154966
25	Konya		7.376404446	Eskişehir		45.28705363
26	Konya		7.117879842	Eskişehir		16.18536325
27	Konya		6.29186427	Eskişehir		13.06659346
28	Konya		5.517385491	Eskişehir		8.978425508
29	Konya		4.963441622	Eskişehir		8.149414722
30	Konya		4.870915321	Eskişehir		5.911379531
31	Konya		4.567843493	Eskişehir		5.020759211
32	Konya		3.557795432	Eskişehir		3.106726149
33	Konya		3.180937371	Eskişehir		2.196157792
34	Konya		2.974586271	Eskişehir		2.037166063
35	Konya		2.911662379	Denizli		26.51542941
36	Konya		2.813621065	Denizli		13.43510862
37	Konya		2.382216585	Denizli		3.280339166
38	Konya		2.108152498	Denizli		2.938798301
39	Gaziantep		524.0890276	Manisa		14.43864177

Figure 16.4: Detailed report worksheet

There is also a "delete" button, if they want to remove one of these excel files. Additionally, we have a "next" button at the right bottom of the page. This button is used for starting the analysis of the dataset and it moves to the next page. On the second page, there is a brief summary of the dataset that shows the analysis of the data uploaded by the user. This summary shows the number of countries, cities, and the total demand in the uploaded file. On this page, we have an optional parameters section for the user to add information. These parameters are the number of warehouses, capacity limitations for warehouses, specific choice for the country or/and the city of the warehouses. The user can select the specifications from the boxes, where they want to open a warehouse. These parameters are used in the model, that can be seen in Figure 16.2. Then, the user can click the "next" button to run the model and change the page. After this page, the result page is opened where the suggested warehouse locations are shown on the map which can be seen in Figure 16.3. To show the map and locations, a Bing Maps add-in is used. Also, the user can see the names of these warehouse locations and the corresponding capacities in the boxes next to the map. Also, there is an "Export Results" button to show the customer-warehouse match with their corresponding capacities. If we click to the "Detailed Report", detailed information is created to a new Excel Workbook for company to work with, which can be seen in Figure 16.4.

16.6 Benefits to the Company

The program decides the warehoues locations and the corresponding routes. Therefore as an outcome, we obtain the distribution network design which contains the optimal locations of the warehouses, the customer assignments, amount of supplies of these warehouses, the routes and the corresponding mode of transportation. To measure the contribution of the proposed solution to the company, we performed benchmarking by comparing the objec-

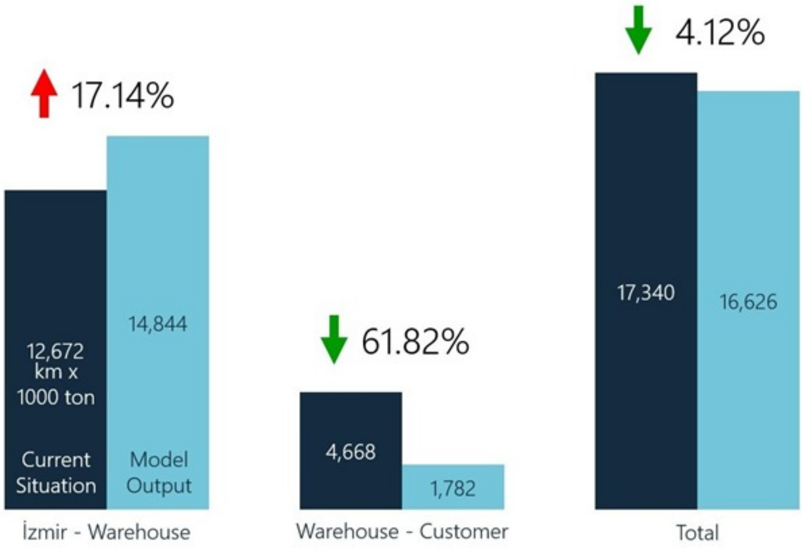


Figure 16.5: Distance savings in Europe

tives of the current situation with the proposed solution and the comparisons can be seen in Figure 16.5. In the first scenario, we fixed the current warehouses of the Norm Fasteners and obtained a total value of 17,340 km x ton by opening the current warehouses in Poznan, Poland; Bucharest, Romania; Essen, Germany and Meaux, France. The 4,668 km x ton of this value consists of distances between warehouses and the assigned customers. The remaining 12,672 km x ton is the total value between İzmir warehouse and the current warehouses.

In the second scenario, we have not fixed the current warehouses and let the model decide where to open the warehouses. Since Norm Fasteners possesses four current warehouses, we run the model for p=4 and we have not indicated any upper and lower bounds for the capacities of the warehouses. As a result, we obtained a total value of 16,626 km x ton by opening a warehouse at Hannover, Germany; Nürnberg, Germany; Paris, France and Bilbao, Spain. 1,782 km x ton is the value between warehouses and the assigned customers while 14,844 km x ton is the value between İzmir warehouse and the opened warehouses. When we further analyze the

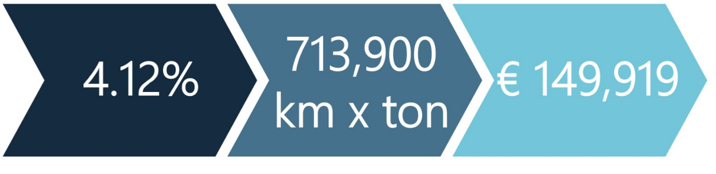


Figure 16.6: Cost improvement in Europe

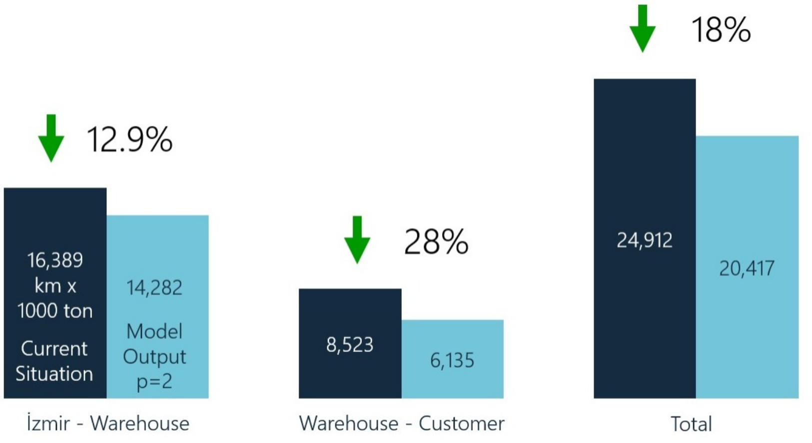


Figure 16.7: Distance comparison in Turkey

distance, we see a 61.82% reduction in the distance between warehouses and the assigned customers while we see a 17.14% deterioration in the distance between İzmir warehouse and the opened warehouses. Howevever, when we compared the objective function values, we observed a 4.12% reduction in the total distance. Norm provided us the average cost of transportation in Europe for the first quartile of 2022 as €0.21 per km x ton. Hence the 4.12% reduction on the total distance value refers to a €149,919 cost improvement. This improvement can be seen in Figure 16.6.

We also performed benchmarking with Turkey's data by comparing the objectives of two scenarios and the comparisons can be seen in Figure 16.7. In the first scenario, we fixed the current warehouses of the Norm Fasteners and obtained a total value of 24,912 km x ton by opening the current warehouses in Ankara and Kocaeli. The 8,523 km x ton of this value consists of distances between warehouses and the assigned customers. The remaining 16,389 km x ton is the total value between İzmir warehouse and the current warehouses. In the second scenario, we have not fixed the current warehouses and let the model decide where to open a warehouse. We run the model for p=2 and we have not indicated any upper and lower bounds for the capacities of the warehouses. As a result, we obtained a total value of 20,417 km x ton by opening a warehouse at Konya and Bursa. 6,135

Figure 16.8: Cost improvement in Turkey

km x ton is the value between warehouses and the assigned customers while 14,282 km x ton is the value between İzmir warehouse and the opened warehouses. When we further analyze the distance, we see a 28% reduction in the distance between warehouses and the assigned customers while we see a 12.9% reduction in the distance between İzmir warehouse and the opened warehouses. When we compared the objective function values, we observed a 18% reduction in the total distance. Norm provided us the average cost of transportation in Turkey for the first quartile of 2022 as 0.77 TL per km x ton. Thus the 18% reduction on the total distance value refers to a 3,461,150 TL cost improvement. This improvement can be seen in Figure 16.8.

16.7 Conclusion

As a result, we concluded the current warehouse locations are not optimal and our model is the strategical tool that finds the optimal locations which minimizes the total travel distances. Since we reduced the total cost of warehouses in Europe by €149,919 and the total cost of warehouses in Turkey by 3,461,150 TL the company officials were satisfied by the result. Due to the performance of the model, Norm decided to execute the output of the program. Initially they determined to start relocating the warehouses in Turkey accordingly.

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17 | Takım Atama ve Yıllık İzin Planlama

Demir Export

Proje Ekibi
Ezgi Akar, İdil Bayar, Caner Canlıer, Yiğit Çelik,
Beril Korkmaz, Simge Uzun, Gülin Yurter

Şirket Danışmanı
Haydar Çınar
Kıdemli Veri Bilimci

Akademik Danışman
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Endüstri Mühendisliği Bölümü

Özet

Demir Export Soma yeraltı kömür işletmesinde çalışan ekiplerin manuel olarak oluşturulması iş gücünün dengeli ve adil dağılımını olumsuz etkilerken, çalışanların yıllık izinlerinin manuel olarak düzenlenmesi de operasyonel verimliliği azaltmaktadır. Bu proje temelde iki farklı problemi çözme amacı taşımaktadır. Birinci problem şirketin çalışan takımlarını oluşturmak, ikinci problem ise bu çalışanların yıllık izinlerinin planlanmasıdır. Bu problemlerin çözümü için matematiksel modeller geliştirilmiş ve aynı zamanda kullanıcı dostu bir sistem oluşturulmuştur. Takım ataması problemi için önerilen çözümün sonuçları şimdiki sistemle karşılaştırılarak, yıllık izin planlaması modeli içinse sonuçlar şirket yetkililerinin onayıyla doğrulanmıştır. Geliştirilen sistemin şirkette dengeli takım ataması ve yıllık izin dağılımı sağlaması, çalışanların yıllık izin günlerinden memnuniyetlerini arttırması ve güncelleme kolaylığı sağlaması beklenmektedir.

Anahtar Sözcükler: Takım oluşturma, yıllık izin planlama, denge, adalet

Team Assignment and Annual Leave Scheduling

Abstract

In Demir Export Soma underground coal mine, manually forming the workers' teams and manually scheduling their annual leaves decrease the system's operational efficiency and responsiveness. Moreover, arranging the annual leaves of the workers manually decreases responsiveness towards operational efficiency. The aim of this project is to develop a decision support system with the help of an advanced algorithm that the company can utilize for forming the teams and scheduling the annual leaves. To solve these problems, two mathematical models are developed and applied with the help of a user interface. The team formation model is confirmed by comparing the company's current team assignments with the assignments made by the proposed model; and annual leave model's results are verified by the approval of company officials. The proposed system is expected provide balanced team assignments and annual leaves and ease of update to the company as well as increasing the workers' satisfactions with their annual leaves.

Keywords: Team formation, annual leave scheduling, balance, fairness

17.1 Company and Problem Description

Demir Export A.Ş., which is a mining company, was founded as a part of Koç Holding in 1957. "Soma Eynez I Yeraltı Kömür İşletmesi" (Soma), which belongs to Demir Export A.Ş. is an underground coal mine that has a source of 40.5 million tons of coal. In Soma, there are more than 1400 employees of 32 types, divided into four teams named A, B, C and D. All workers belong to one of the levels 1, 2, 3, and 4; 1 being the highest level Demir Export A.Ş. (2021). There are three shifts in a day. One of the teams has weekly day off while others work in different shifts in a given day. This situation requires a fair and balanced distribution of workers into teams, which means that company wants workers from different levels and different types in each team. Keeping team assignments and weekly off days in mind, the company allows workers to take annual leaves. Workers who have more than 6 years of experience have 24 days of annual leave right, whereas other workers have 18 days. The company assigns workers to teams manually, as well as manually scheduling the annual leaves. This scheduling is done by taking workers' preferences into consideration, which varies throughout the year. Currently, difference between number of workers from each level across teams are 21, 26, 53, 56 for levels 1, 2, 3 and 4 respectively, giving sum of pairwise differences as 156 as shown in Table 17.1. Also, the data

Table 17.1: Sum of pairwise differences across number of workers from different levels in teams in the current system

	Number of Workers				
Team	**Lvl.1**	**Lvl.2**	**Lvl.3**	**Lvl.4**	**Total**
A	43	26	46	49	164
B	38	32	53	46	169
C	40	26	42	59	167
D	44	30	37	67	178
Sum Pairwise	21	26	53	56	**156**

regarding annual leaves of workers and their reasons for using leaves for September 2021 are shown in Table 17.2.

Doing the team assignments and annual leave scheduling manually for a high number of workers causes the company loss of time. Therefore, updating the system when necessary is difficult, and the updates do not always give favorable outcomes for the company. It is observed that there is a lot of difference in worker levels across teams, which creates an unequal situation causing the company hire overtime workers which imposes an additional cost. Also, some workers' annual leaves cannot be satisfied and their preferences cannot be tracked as they specify their preferences verbally to their supervisors. Although the supervisors try to satisfy worker preferences as much as possible, it is difficult to do that without distributing the annual leaves into weeks throughout the year in an unbalanced way. In the current system there are unbalanced teams, unbalanced used annual leaves, and unfairness in workers' annual leaves. Number of workers from each level

Table 17.2: The analysis of numbers of workers that are working or not working in September 2021

Situation	**Mean**	**Min**	**Max**
Working	589.60	516	649
Weekend Holiday	212.60	176	304
Reported Leave	23.13	15	32
Unpaid Leave	5.93	3	10
Absent	1.53	1	3
Paid Leave	2.20	0	8
Administrative Leave	9.50	3	16
Workplace Accident	7.63	7	9
Annual Leave	58.47	34	79

in each team, number of workers with specific skills in each team, number of workers with satisfied annual leave preference and used annual leave difference across different weeks are the performance measures.

17.2 Proposed Methodology and Model

There are two observed problems in the system: team assignments and annual leave scheduling. The first one is a classical workforce planning problem and the second one is a classical scheduling problem; and the most common approach to such problems are building mathematical models with integer programming. So, the proposed methdology is to develop two separate mathematical models and solving each of them in order to get the optimal solutions. For the models, it is assumed in this project that the planning period is one year, there are 4 teams, there is ready and robust equipment and stable worker level through the planning period, as well as assuming that the exact annual leave preferences are taken from the workers at the beginning of the year. As 678 of 1400 workers and 21 of 32 worker types require team assignment, the scope of the project is limited with these numbers. For the team assignment model each worker should be assigned to a team, and in each team there should be prespecified number of workers from specific worker types. For the annual leaves scheduling model, the workers have 18 or 24 days of annual leave right in a year depending on their experience and at least 80% of the workers must be present to work. The objective in team assignment is minimizing the level difference across teams. For the annual leaves planning, having similar number of workers in different weeks of the year and increasing the satisfaction of workers from their annual leave days are aimed. The two models are shown below:

17.2.1 Team Assignment

In this model, $I = \{1, 2, \ldots, n\}$ denotes the set of workers, $J = \{1, 2, 3, 4\}$ the set of teams, $K = \{1, 2, \ldots, r\}$ different worker skills, and $S = \{1, 2, 3, 4\}$ set of worker levels. l_{is} is a binary parameter which is equal to 1 when worker i is at level s. The parameter thr_{jk} denotes the minimum requirement of workers from skillset k in team j. Also, $\sum_{i=1}^{k} m_i = M_k$, $\sum_{i=1}^{21} m_i = M_{21} = n$ and $M_0 = 0$. Absolute difference of worker numbers between teams j and t for level s is minimized in the model. Constraint 17.2 is for assigning each worker to a team, constraint 17.3 is for making sure there is enough workers from each skillset in each team, constraints 17.4 and 17.5 are linearization constraints for the objective function whereas constraint 17.6 shows non-negativity of the variables.The decision variables are

A_{jts} = Absolute difference of worker numbers between teams j

and t for level s, $j, t \in J(j > t), s \in S$,

$$x_{ij} = \begin{Bmatrix} 1, & \text{if worker } i \text{ is in team } j \\ 0, & \text{otherwise} \end{Bmatrix} \quad \text{for every } i \in I, j \in J,$$

and the model is

$$\min \quad \sum_{j=1}^{4} \sum_{t=1}^{4} \sum_{s=1}^{4} A_{jts}, \tag{17.1}$$

$$\text{s.t.} \quad \sum_{j=1}^{4} x_{ij} = 1 \quad \forall i \in I \tag{17.2}$$

$$\sum_{i=M_{k-1}+1}^{M_k} x_{ij} \geq thr_{jk} \quad \forall j \in J, \quad \forall k \in K \tag{17.3}$$

$$\sum_{i=1}^{n} (l_{is}x_{ij} - l_{is}x_{it}) \leq A_{jts} \quad \forall j, t \in J(j > t), \quad s \in S \tag{17.4}$$

$$\sum_{i=1}^{n} (l_{is}x_{ij} - l_{is}x_{it}) \geq -A_{jts} \quad \forall j, t \in J(j > t), \quad s \in S \tag{17.5}$$

$$x_{ij}, A_{jts} \geq 0 \quad \forall i \in I \quad \forall j, t \in J(j > t), \quad \in S. \tag{17.6}$$

17.2.2 Annual Leave Scheduling

In this model, number of days set $D = \{1, 2, ..., m\}$ in the planning horizon and number of weeks set $W = \{1, 2, \ldots, z\}$ in the planning horizon are used in addition to the sets in the previous model. The parameter $AL_i =$ gives the number of annual leaves used by worker i until current day, $N_j =$ is the number of workers in a team, $R_{jd} =$ is the net worker requirement for a team in a day and β is the percentage of workers required to work in a day. Also, the binary parameters are S_{id} which is equal to 1 if worker prefers to use annual leave in a day, y_{id} which is equal to 1 if the worker is scheduled to work in a day and t_{ij} which is equal to 1 if the worker is in a certain team. The objective function for this problem can either be satisfying workers' preferences, or distributing annual leaves to the year in a way that there are similar number of used leaves in each week. Combining the two objectives and giving each of them a weight, the model can be solved. As the importance of equally distributing annual leaves is more important than satisfying workers' preferences, it has the weight 0.67 while workers' preferences have the weight of 0.33, making α=0.33. In constraint 17.8 used annual leaves in a week is defined. Constraints 17.9 and 17.10 are for the linearization of objective function, constraint 17.11 limits the annual leaves that a worker can use, constraint 17.12 says a worker can use annual leave only if he is working, constraint 17.13 says that the worker skill requirements must be satisfied for each day, constraint 17.14 says percent requirement should be satisfied for each day and constraint 17.15 is non-negativity constraint. The decision variables are:

$$x_{id} = \left\{\begin{matrix} 1, & \text{if worker } i \text{ uses annual leave in day } d \\ 0, & \text{otherwise} \end{matrix}\right\} \quad \forall\, i \in I, d \in D$$

$$\begin{aligned} WO_w &= \text{Total number of annual leaves used in week } w,\ w \in W \\ P_{wq} &= \text{Absolute difference of used annual leave between weeks } w \\ &\quad \text{and } q,\ w, q \in W(w > q) \\ P_{max} &= \text{Maximum pairwise difference between two weeks} \end{aligned}$$

and the model is:

$$\min \quad \alpha \sum_{i=1}^{n} \sum_{d=1}^{m} S_{id} x_{id} - (1-\alpha) P_{max} \tag{17.7}$$

$$\text{s.t.} \quad \sum_{d=7(w-1)+1}^{7(w-1)+7} x_{id} = WO_w \quad \forall i \in I \quad \forall d \in D \quad \forall w \in W \tag{17.8}$$

$$WO_w - WO_q \leq P_{max} \quad \forall w, q \in W(w > q) \tag{17.9}$$

$$WO_w - WO_q \geq -P_{max} \quad \forall w, q \in W(w > q) \tag{17.10}$$

$$\sum_{d=1}^{m} x_{id} \leq 24 - AL_i \quad \forall i \in I \tag{17.11}$$

$$y_{id} \geq x_{id} \quad \forall i \in I \quad \forall d \in D \tag{17.12}$$

$$\sum_{i=1}^{n} t_{ij} x_{id} \leq N_j - R_{jd} \quad \forall j \in J \quad \forall d \in D \tag{17.13}$$

$$\sum_{i=1}^{n} t_{ij}(y_{id} - x_{id}) \geq \beta \sum_{i=1}^{n} t_{ij} y_{id} \quad \forall j \in J \quad \forall d \in D \tag{17.14}$$

$$x_{id}, WO_w, P_{wq} \geq 0 \quad \forall i \in I \quad \forall d \in D \quad \forall w, q \in W(w > q). \tag{17.15}$$

The two mathematical models that are solved with COIN-OR, which is the solver of Python's MIP package Túlio A. M. Toffolo (2021). While the team assignment model is solved with data provided by the company, the annual leave scheduling model is solved using dummy data as the company does not log the annual leave preferences of workers. The results for the two models are shown in Tables 17.2 and 17.4.

17.3 Validation

As the project involves two problems, two different ways of validation are used. For team assignment model, current system's data are available and can be compared to the results of proposed mathematical model. Table 17.1 shows that current system has sum of pairwise level differences across teams and levels as 156, whereas it is 14 in the proposed solution. If comparison criterion is chosen as sum of pairwise level differences across teams, it can be observed that the number decreases from 92 to 19. As stated in the previous section, the annual leave scheduling model is solved using several different dummy datasets, each of them having differences in worker preference with regards to the time of the year. The obtained results for one of these scenarios is shown in Table 17.4. In that case, average worker satisfaction is found to be 95.61% while the maximum pairwise difference across weeks is found to be 40. As there is no comparison criteria for this model, the results are shown to the person who has been doing the scheduling manually for the past year and his feedback and approval are obtained.

17.4 Integration and Implementation

By taking the total number of workers, worker levels and worker types, the team assignment model can be solved to give the optimal team assignments of workers. Taking these assignments as input to the annual leaves scheduling model and also taking the workers' annual leave preferences, required number of workers in teams and required worker percentage, the model can be solved to give a balanced distribution of annual leaves as well as the satisfaction level of workers. Through the user interface, the company is able to add/delete workers, change their levels, add/delete annual leave preference for any worker, change the requirements of the mathematical models, and solve the models for the new data. Additionally, through the interface, the

Table 17.3: Sum of pairwise differences across number of workers from different levels in teams in the proposed system

	Number of Workers				
Team	**Lvl.1**	**Lvl.2**	**Lvl.3**	**Lvl.4**	**Total**
A	41	28	44	55	168
B	42	29	45	55	171
C	41	28	44	56	169
D	41	29	45	55	170
Sum Pairwise	3	4	4	3	**14**

Table 17.4: Summary of the results of annual leave scheduling model

α=0.5	Results
Maximum Satisfaction	100.00 %
Minimum Satisfaction	82.14 %
Average Satisfaction	95.61 %
Workers with Fully Satisfied Preferences	46.02 %
Maximum Pairwise Diff.	40

company can see data and graphs for outputs of both models. The main pages of the interface are shown in Figures 17.1-17.3.

Figure 17.1: User interface home page

Figure 17.2: User interface team assignment page

17.5 Benefits to the Company

For the team assignment model, benchmarking is done by comparing the current team assignments with the team assignments done by the proposed model. The current system's data shown in Table 17.1 can be compared with the results of proposed model shown in Table 17.3. Sum of pairwise differences across levels and teams decreases from 156 to 14, which means

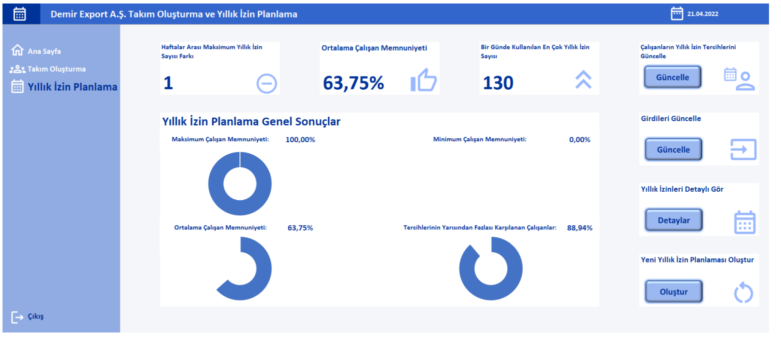

Figure 17.3: User interface annual leaves page

91.02% change. This result means that the workers are distributed to teams in a more balanced way. Number of workers in each team is close to each other, and number of workers from each level is also close to each other in each team. The proposed solution provides work efficiency to the company.

For annual leave scheduling, most workers are content with assigned annual leave days. The system also enables company to keep track of who uses annual leave and when as well as who wants to use annual leave and who can. The first one is something that the company has already been doing. However, the others are new to company. There were no data about worker preferences of annual days, and now the company will be able to see and analyze that data. Having approximately 96% of workers satisfied with their annual leaves, proposed system seems to provide company both an organized and beneficial way of scheduling the workers' annual leaves.

17.6 Conclusions

As the solution times are less than five minutes, the interface has easy to use, data are easy to update, the interface enables company to store past data in the interface and models give optimal solutions, all previously defined problems are adressed with proposed solution. Pilot applications are performed with Demir Export A.Ş. in Soma. The company mentioned that the proposed solution can also be applied to their other coalmines.

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Ürün Satış Tahmini ve Malzeme Tedarik Planlaması | 18

Arçelik Elektronik İşletmesi

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Özet

Şirket televizyonlarının satış talebini tahmin etme yöntemine sahiptir, ancak yöntemin uzun vadedeki (3-12 ay) doğruluğunu arttırmak istemektedir. Mevsimsel ve proje bazlı farklılıklar, hatalı tahminlere yol açmakta, satılamayan stoklar ve üretimde darboğazlar ortaya çıkmaktadır. Projenin amacı mevcut tahmin yöntemini değerlendirmek, farklı tahmin yöntemleriyle karşılaştırmak ve en başarılı istatistiksel sonucu veren yöntemi seçmektir. Bu amaçla yürürlükteki sistemin ve farklı tahminleme yöntemlerinin analizi yapılmıştır. Birçok tahmin yöntemi değerlendirilmiş ve en başarılı yöntem geliştirilmiştir. Belirlenen iş paketleri üzerinden çalışmanın çıktıları raporda sunulmuştur.

Anahtar Sözcükler: Tahmin yöntemleri, televizyon, sezonsallık, trend.

Long-Term Product Sales and Material Planning Forecasting

Abstract

The firm has a method of forecasting the sales demand of televisions, but their method has inaccaptable accuracy in the long term (3-12 months). Seasonal and project-based differences are causing errors in the calculations and result in inaccurate predictions, unsold stocks, and bottlenecks in production in the factory. This project aims to evaluate the current system and propose a more accurate long term sales and material planning forecasting method. Literature review has been conducted. Project outcomes and deliverables are presented.

Keywords: Forecast, television, seasonality, trend.

18.1 Company Information

Arçelik Çerkezköy Electronics Plant established in 2018 aiming to invest into innovative and user-oriented products towards TV technology by producing future televisions. It is designed and operated with digital and robotic technologies. The plant was built with a total investment of 500 million TRY, and 65% of its production is exported to 48 countries. Manufacturing takes place on a single integrated line, equipped with 107 robots that support human resources with digital technologies and, employs 700 people from the region. The plant is responding to expectations with a focus on innovation, quality and speed with a production capacity of daily 12 thousand, annually 3.2 million televisions.

18.2 Current System Analysis

Arçelik Electronics Plant in Çerkezköy manufactures televisions for 4 subbrands of Arçelik, cash registers, and circuit cards of white goods. Proposed project will be focused on televisions only, as the television category is a dynamic and fast evolving one among other categories that needs demand forecasts as accurate as possible. Because of the long lead times in raw materials, the production plans have to be updated very frequently which is not a favorable production strategy. Current sales forecasting strategy is taking this year's and previous year's last 4 month's weighted average. Production decisions are based on a tracking system called Total Visibility Report (TVR). Each week, the demand amount calculated by the Sales Department is taken from SAP ERP (enterprise resource planning), and TVR is generated. TVR contains essential data on demand, total production requirement, and confirmed production. TVR projects at most 8 weeks of production plans, the remaining period is left uncertain. Minor changes are handled in the weekly TVR updates. Due to TVR having low visibility, Arçelik aims to determine the demand for the rest of the year without backlogging or ending up with extra in hand inventory so that they can give order on the right amount to international suppliers.

18.3 Problem Definition

Arçelik's request is to find a forecasting algorithm regarding four important variables: country of exportation, screen dimensions, brand of TV and chassis of TV. These variables are important in terms of finding the most suitable forecasting methods for each segmentation. With this project, they can eliminate the "maximum 3 months of reliable forecast" limitation and prolong that period, resulting in better demand meeting and material requirement planning. The current method is not responsive to changes in demand as it simply takes the average of the same 4 months of the current and previous year. The formulation resembles the Moving Averages (MA) method known to be used with constant demand, which has a slight trend or seasonality. MA often overlooks complex relationships in the data and does not respond to fluctuations such as cycles and seasonal impacts. This calculation would only be sustainable only if each year followed a very similar pattern. A more sophisticated formulation for different television models is needed.

The current method is to take the average of the salesforce composites submitted the same 4 months of current and previous year Let D_t denote demand at time t for every s < t. Let $\widehat{D}_{t|s}$ be the forecast of D_t at time s using all information known up to and including time s. $\widehat{D}_{t+h|t}$ is called h-step ahead forecast of demand at time t. Then

$$\widehat{D}_{t+1|t} = \frac{D_t + D_{t-1} + D_{t-2} + D_{t-3} + D_{t-12} + D_{t-12-1} + D_{t-12-2} + D_{t-12-3}}{8}.$$

18.4 Proposed Solution

To determine the best forecasting method most appropriate while handling the data, we tested four different methods with the same data set. The selection was made among the most commonly used time series forecasting methods that would also be complementary to each other: ARIMA, exponential smoothing, double exponential smoothing, Holt-Winters. Each of these methods focuses on a different characteristic of a time series. The flow chart of the conceptual model is shown in Figure 18.1.

- **Exponential Smoothing:** Deals with analysis of stationary time series where there is no trend or seasonality (Nahmias, 2005)

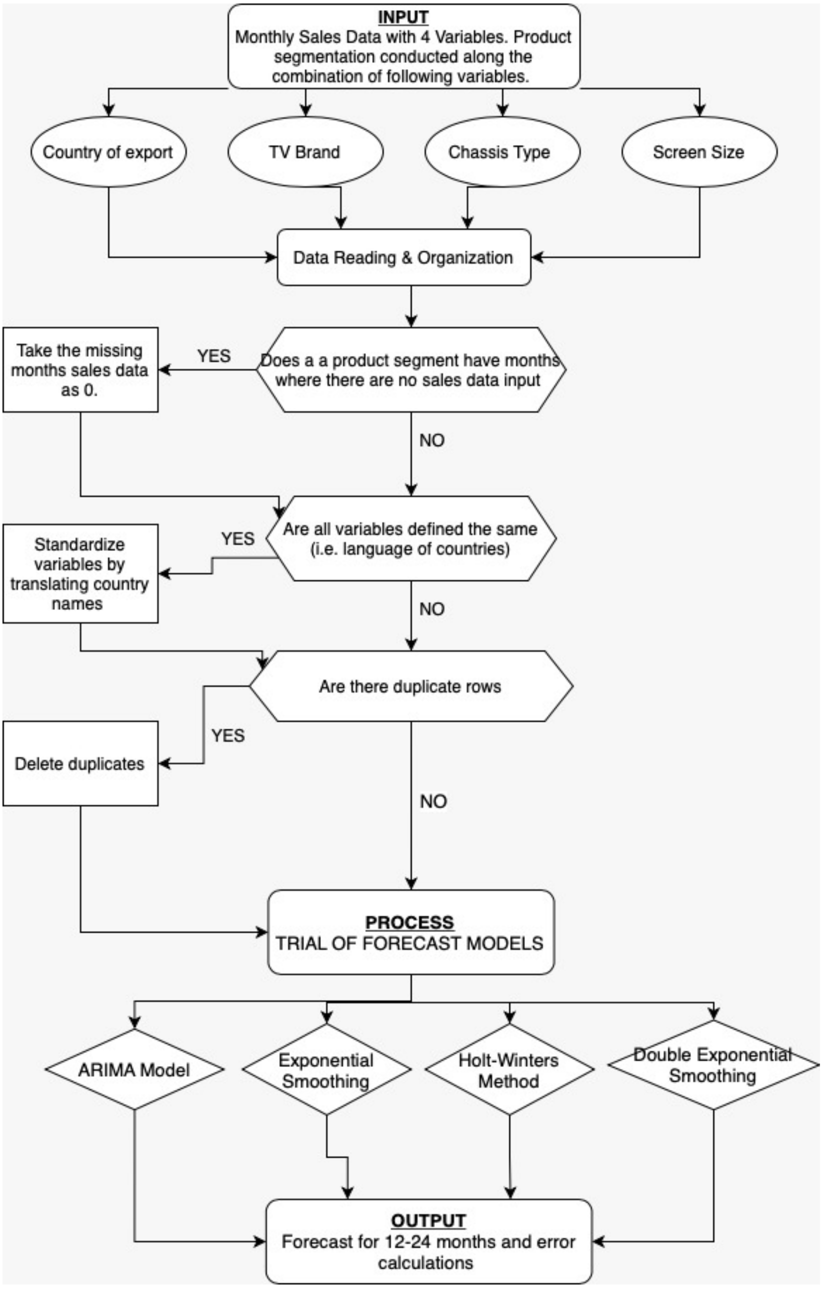

Figure 18.1: Data cleansing, classification, and forecasting steps

- **Double Exponential Smoothing:** Trend based method designed to track time series (Hyndman and Athanasopoulos, 2021)

- **Holt-Winters' Method:** Designed for seasonal series with or without trend (PennState, 2021)

- **ARIMA:** Aims to describe drift with differencing and autocorrelations by taking trend and seasonality into account (Paliari et al., 2021)

Since the methods are all different, trials allow us to understand the data set and its characteristics better. The percentage error figures were calculated by dividing the prediction method's sales value with the actual sales value, then comparing the error. These calculations were done by the implementations of models in R. Evaluating the output in each model with a focus on largest segments of data, the one that gives the smallest error will be chosen as the solution model and used for forecasting the entire data.

18.5 Validation

Cross-validation overcomes overfitting problems by simulating the dataset dividing it into two parts: training data and test data. The test set consists of a single set of observations while the training set consists of all the prior observations that were used to forecast, in other words the test set. The data supplied to us were the monthly production numbers of each television model in the past 30 months. We obtained newer data during the progress of the project and developed our models' accuracy with more data.

Both the current method of Arçelik and the methods we implemented were tested under Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE)values: MSE is the average squared distance between the observed and predicted demand. Because of randomness or because the estimator does not account for information that could generate a more accurate estimate, MSE is almost always strictly positive. The impact of larger errors is amplified by squaring. Larger errors are penalized disproportionately more than smaller faults in these calculations. To observe less errors in a model, this attribute is critical (Hyndman and Athanasopoulos, 2021):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(D_i - F_i)^2$$

where n is the number of observations, D_i denotes demand at observation i and F_i is the forecasted value at observation i.

MAPE is calculated using the absolute error in each period divided by the observed values that are evident for that period. Then, averaging those fixed percentages, MAPE result is reached. This approach is useful when the size or size of a prediction variable is significant in evaluating the accuracy of a prediction (Khair et al., 2017):

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \frac{|D_i - F_i|}{D_i}$$

where n is the number of observations, D_i denotes demand at observation i and F_i is the forecasted value at observation i.

One of the ways we validated our code and models was through comparing error rates of the existing method and our methods. We know the method of forecasting that Arçelik is currently using, SARIMA, and have calculated their error percentages with regards to 24 months of training data and 6 months of testing forecast outputs. We then applied our code to the data set and calculated our own error rates. For a majority of the cases, we observed lower MSEscores for the output of our code. Apart from this basic method, below are two other perspectives to validation that we explored for our models.

- Face Validity: In the dataset we have some designated TV models that were produced not for the market but designated buyers such as corporate customers. This means that a company ordered a loaded batch of that product for one time. The model predicts those products as if the next year's demand will be 0 too but it might not be since these are rare and extreme occurrences. This situation does not spoil the overall performance of the system because we analyze each product independent from each other.

- Operational Validity: Pilot studies with Arçelik officials to run the code and analyze the output of it were conducted. The performance indicators for the pilot study were the MSE score as before as it is the error measurement method we applied throughout our studies.

18.6 Integration and Implementation

Initially, after exploring the different forecasting models, we decided that the television models features of trend and seasonality vary. Thus, we were not able to standardize it to a single forecast model. We utilized all the forecasting models in Rusing different functions for exponential smoothing, double exponential smoothing, ARIMA and holt-winters' methods such as `auto.arima`. The code reads the data of television models from the Excel files submitted to us by Arçelik and runs different forecasting models explained above. Our obtained data were for 30 months. The first 24 months of data were labeled as training data, while the next 6 months were labeled as test data. Training data were used to forecast the next 6 months and the forecasted values are compared with test data. MSE of each forecast method is found and compared with each other. The model with minimum MSE value is chosen to be the forecast model of that specific television model. The models automatically calculate the best values for paramaters, α, β, γ and choose the value which minimizes the MSE score the most. Thereby, the model does not run on any constant parameter value but on the training set dynamically updates itself for each TV model's demand. We managed to build a flexible method to investigate the best forecasting model whichever the characteristics of the data were. We preferred to work with MSE as the deviation from the real value is reflected more significantly in this method. Large deviations' effect on the MSE score will be higher so we would avoid any result which has a high MSE score and be sure that the real data and predicted one is actually close. The basic flow of the code process is shown in Figure 18.2. The code inputs an Excel file that we aggregated with the data handed since 2019. Excel file and its aggregation principle is shared with Arçelik. In the future, the requested output can be obtained with any Excel file that inputs the correct form of data.

18.7 Benefits to the Company

Expectations of the company stated in the kick-off meeting are as follows:

- Develop a forecasting method for 3-12 months ahead
- Improve the accuracy of materials planning for project change periods as a result of more accurate forecasting

In the current system, the production and shift planning teams are dealing with too much uncertainty while doing their jobs because the data that is provided to them concerning the future sales by the Sales and Marketing team is often unreliable. This is why the production and shift planning team often encounter shortages and overstocks. This is an added expense to the company and a huge burden. By implementing our proposed algorithm and solution, the company will be able to lower this expense since the results will yield a lower frequency of overstocks and shortages. This will also help the company to plan more efficiently especially in their plans of over 3 months. They will be able to forecast the future sales more efficiently especially in the longer run and therefore plan the production beforehand saving time and money. The decision support system that we build scans all forecasting methods mentioned above and chooses the best according to the MAPE values of tests. Table 18.1 shows the difference of the current system and the

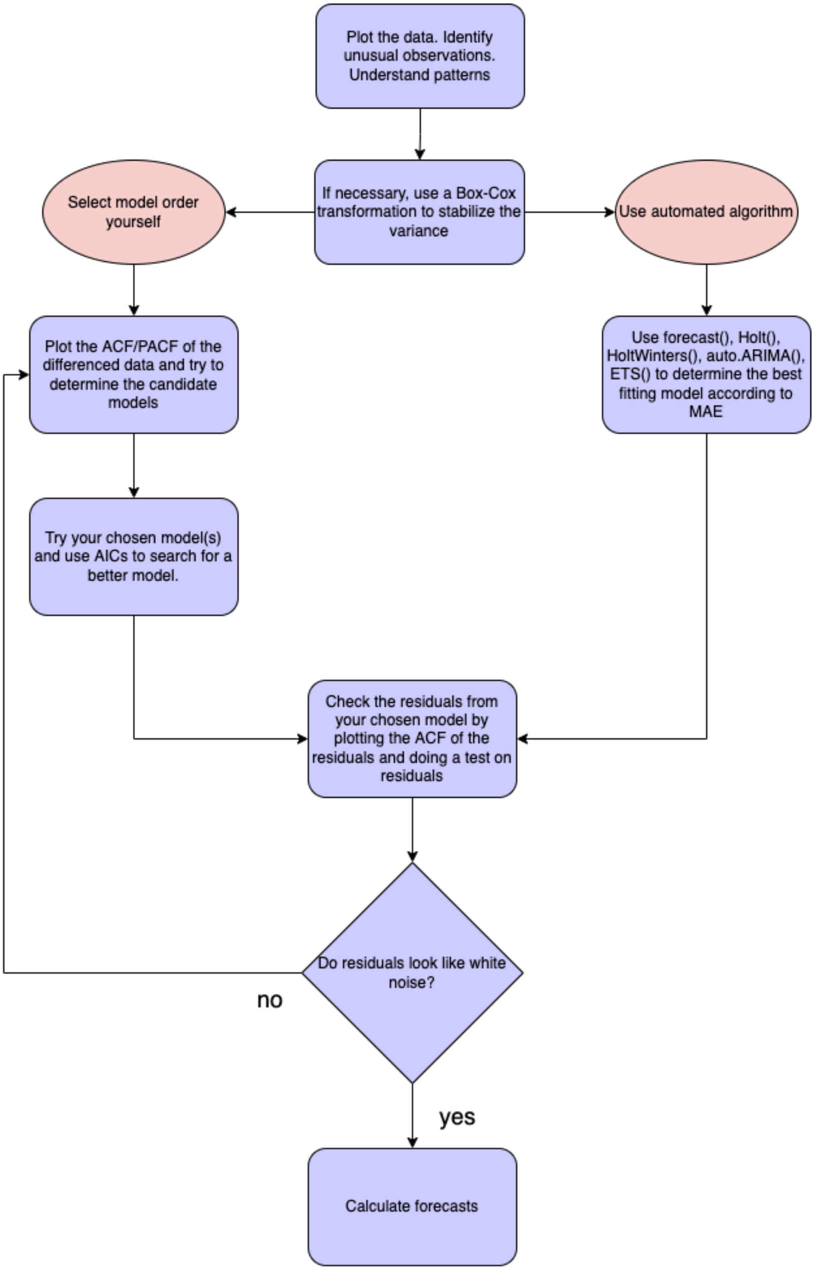

Figure 18.2: Flow chart of conceptual model

newly build system for the top selling 10 television models. Out of 10 models in 7 models, our forecasts are more close to actual demand in the test data. The current forecasting methods used by the company are open to human errors. By creating an algorithm which we started doing based on statistical models and previous data, we aim to minimize the human errors in the forecasting process. We believe that by using statistics and data analysis, we improved the current method of forecasting with testing different methods for different television models. Current method was only using SARIMA for every television model disregarding the exclusive characteristics of more than 300 models.

MSE

	AF-43-GRUNDIG	AF-32-GRUNDIG	AF-50-GRUNDIG	AF-55-GRUNDIG	AF-49-GRUNDIG	AF-65-GRUNDIG	NX-55-ARCELIK	NX-49-ARCELIK	YK-32-ARCELIK	NX-55-BEKO
	76%	13%	10%	43%	45%	149%	230%	13%	23061%	489%
	26%	36%	57%	29%	120%	174%	351%	75%	23061%	700%
	238%	38%	162%	58%	206%	332%	125%	94%	23061%	381%
	73%	17%	9%	26%	288%	483%	28%	42%	23061%	1%
	54%	32%	10%	3%	734%	807%	1966%	75%	23061%	5440%
	18%	30%	472%	0%	56%	928%	3421%	56%	23061%	13499%
	5%	3%	169%	16%	67%	84%	409%	62%	23061%	537%
	40%	46%	89%	15%	78%	163%	2647%	67%	23061%	378%
	57%	55%	213%	30%	29%	262%	19129%	71%	23061%	1000%
	490586%	430637%	1254530%	368932%	104191%	233861%	9899%	75%	23061%	1157%
	490586%	430637%	100%	368932%	104191%	233811%	249881%	78%	23061%	149485%
	Averages									
ARELT Error	89251%	78322%	114165%	67099%	19091%	42823%	26190%	64%	23061%	15733%
Arçelik Error	92428%	83844%	83905%	61803%	37621%	27250%	38966%	180198%	205857%	17956%
	YES	YES	NO	NO	YES	NO	YES	YES	YES	YES

Table 18.1: Comparison for our methodology and current Arçelik method for the most selling ten television models

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19 | Veri Odaklı İş Planlaması ile Verimli Marka Başvuru Değerlendirmesi

Türk Patent ve Marka Kurumu

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Endüstri Mühendisliği Bölümü

Özet

Türk Patent ve Marka Kurumu (TÜRKPATENT) Marka Dairesi, iş yükü birikimi problemi ile karşı karşıya kalmaktadır. Bu problemin sonucu olarak başvurulara cevap verme süresi uzamakta ve vaat edilen cevap verme süresine uyulmamaktadır. Marka başvuruları, şekil inceleme ve başvuru değerlendirme aşamalarından oluşmaktadır ve darboğaz olarak başvuru değerlendirme süreci belirlenmiştir. TÜRKPATENT, gelen her başvuru değerlendirme işini, üzerindeki iş sayısı en az olan çalışana atamaktatır. Önerilen çözüm şekli her iş için başvuru değerlendirme süresini makine öğrenmesi ile tahmin edip tamsayı programlaması ile gecikmiş iş sayısını en aza inderecek bir sistemdir. Simülasyon yolu ile elde ettiğimiz sonuçlara göre tavsiye edilen sistem, mevcut sisteme göre geciken iş sayısı %50 daha az olup çalışanlar arasındaki iş yükü dengesizliğini %5'in altında tutmuştur.

Anahtar Sözcükler: Makine öğrenmesi, tahminleme modeli, iş atama problemi, tamsayı programlaması.

Data-driven Business Planning for Efficient Trademark Application Evaluation

Abstract

Turkish Patent and Trademark Office (TÜRKPATENT) Trademark Bureau is suffering from workload accumulation problem. As a result, the response time for trademark applications are increased and the promised deadline to the customers is not met. The trademark applications are done in two steps: format evaluation and application evaluation, which is the bottleneck of the process. The proposed solution is to predict the completion times of application evaluations with machine learning and to assign jobs with integer programming in order decrease the number of tardy jobs. According to the simulation results, the proposed system has 50% less tardy jobs while keeping the work count balance between employees under 5%.

Keywords: Machine learning, prediction model, job assignment problem, integer programming.

19.1 Company and System Descriptions

19.1.1 Company Description

Turkish Patent and Trademark Office (TÜRKPATENT), formerly known as Turkish Patent Institute, was established under the Ministry of Industry and Technology as a non-profit government agency in 1994. The office performs the registration of patents, utility models, brands, geographical signs, traditional product names and designs in accordance with the provisions of the relevant legislation and the protection of these rights. Their vision is to be an agency that contributes to the advancement of intellectual property (IP) and the capacity of innovation, and influences the national and international policies governing IP.

19.1.2 System Description

In TÜRKPATENT, trademark applications enter a two-step process: the format evaluation and the application evaluation. The application's appropriateness is evaluated in the first process, while a similarity search is done for the appropriate applications in the second process. In the format evaluation process, the variability of job completion times by different employees is lower than in the application evaluation process. There are 58 employees currently active in the office. Completed trademark applications increased 7000+ from 2019 to 2020, and the average completion time for the trademark applications decreased from ∼34 days to ∼27 days (see Figure 19.1).

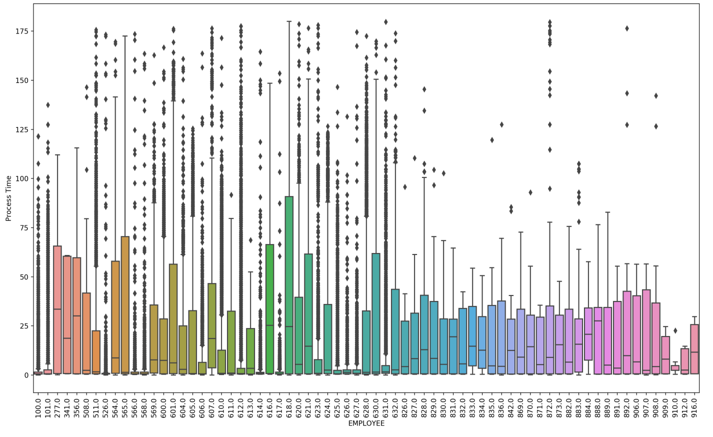

Figure 19.1: Boxplot of Completion Times by Employees

The current job assignment systematic reckons the instant job balance between active employees by assigning each arriving job to the employee with the least job count.

19.2 Problem Definition

As the number of applications increased while the employee count remained the same over the years, a work accumulation problem occurred in TÜRKPATENT. As mentioned, the trademark application process takes longer than the format evaluation process, hence, the bottleneck for the whole system is this process. There are two significant problems with the current job assignment systematic: the variability between employees is ignored, and the job balance is satisfied instantly rather than gradually.

19.3 Solution Approach

The proposed system predicts the variability and offers a trade-off between the number of tardy jobs and the job count balance between the employees.

19.3.1 Conceptual Model

The preprocessing is done according to job arrival data for 2019, 2020 and 2021. Hence, we obtained a prediction function for job completion times in days. When a job arrives, firstly, predictions are made. Then it is added to the batch of the day. The assignment is systematically based on mixed-integer programming is triggered based on a schedule. The systematic allocates jobs in the batch over the horizon of five days while regarding the job count balance and minimizing the number of tardy jobs. Jobs allocated on the first day are assigned to the corresponding employees. This process is repeated daily. The conceptual model can be seen in Figure 19.2.

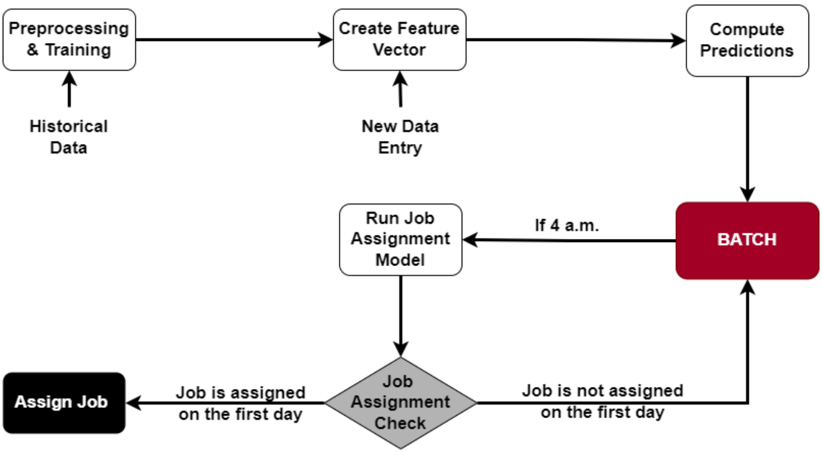

Figure 19.2: Conceptual Model Flow Chart

19.3.2 Mathematical Models

In the proposed solution strategy, there are two mathematical models: a prediction model and a job assignment model.

Prediction Model:

For preprocessing, we constructed the feature matrix, which contains the predictor variables. In the feature matrix, we have "Common Words" (most frequent words in trademarks), NICE Codes (universal convention for sectoral classification of trademarks), employee IDs, day of the week, year and holiday as binary variables, and job count of employees and average job completion time as integer variables. There are 245 total variables in the feature matrix. Subsequently, we tried five machine learning methods to form our prediction model, which are; Linear Regression (Regularized) (Ram, 2021), Artificial Neural Network (ANN) Model (Khalid et al., 2017), Classification Tree, AdaBoost Regression Tree and Random Forest Regression (Anurag, 2018). Additionally, we have an ensemble method combining ANN, Random Forest Regression and AdaBoost Regression Tree.

Job Assignment Model:

The main objective of the model is to minimize the number of tardy jobs. Note that tardiness is computed based on the predicted job completion times. The model ensures that

- each job in the batch is assigned to exactly one employee,
- an employee can have more than one job,
- at least 20% and at most 30% of the jobs are assigned on the first day,

- the ratio between the maximum and the minimum number of jobs on employees should be less than or equal to the balance coefficient.

The balance coefficient starts at 1.05. To guarantee feasibility due to balancing condition, model updates balance coefficient in increments of 0.05.

The job assignment model allocates the jobs for the next five days. Rather than balancing the job counts on employees in the first day, we allow for gradual improvement on the balance. You can see the sets, parameters, decision variables and the model in Table 19.1.

Software

Prediction: For the prediction part, five different models were build that gave completion times in unit 'day'. We formed linear regression model, random forest, classification tree, AdaBoost regression tree and Artificial Neural Network model for the total 2019 and 2020 data sets. The Regularized Linear Regression model was made by using scikit-learn Linear Regression module. ANN model was formed via tensorflow Keras module. The ANN model was formed with 3 hidden layers and 1000, 400, 100 nodes in each. ReLu activation function was used in hidden layers. AdaBoost Regression Tree again uses "sklearn.tree" library and "DecisionTreeRegressor" functionality. Adaptive Boosting algorithm uses "sklearn.ensemble" library and "AdaBoostRegressor" functionality. The Random Forest model was generated through the sklearn.ensemble library's "RandomForestRegressor" functionality.
Job Assignment: For the job assignment, we initially used Gurobi Optimizer on Python. Due to licencing issues, we coded our model using Google OR-Tools and Pywraplp on Python. Then, the job assignment and the prediction model are combined on Python to create the solution pipeline.

19.4 Verification and Validation

19.4.1 Verification

The prediction model was verified using three methods: Continuity testing, theoretic justification, and feature selection. Firstly, we increased/decreased continuous features to observe how our prediction functions behave against changes in continuous parameters. Secondly, we plotted histogram of prediction errors and concluded that they were normally distributed. Lastly, using Wrappers methods, we performed feature selection to acquire a refined model that performs the best w.r.t. accuracy with the least number of features; see Figure 19.3. Pruning unnecessary features helps reduce noise. We experimented with small and large values for each parameter within reasonable ranges to verify our assignment model. How the model performs

Table 19.1: Mathematical Job Assignment Model

Sets and Parameters	
I: Active employee count	$T = 5$: Planning horizon in days
J: Job count in the batch	BC: Balance coefficient
CI_i: Initial job count of employee i, $\forall i \in I$	
R_j: Remaining time of job j at day 0, $\forall j \in J$	
P_{ij}: Predicted completion days of job j by employee i, $\forall i \in I, \forall j \in J$	
Decision Variables	
C_i^t: Job count on employee i at day t, $i \in I,\ t \in T$	
C_{max}: Maximum job count on employees	
C_{min}: Minimum job count on employees	
$x_{ij}^t = 1$, if job j is assigned to employee i at day t; 0, otherwise, $i \in I,\ j \in J,\ t \in T$	
CT_j: Predicted completion days of job j starting at time 0, $j \in J$	
A_j: Tardiness of job j, $j \in J$	
$z_j = 1$, if job j is tardy; 0, otherwise, $j \in J$	
Model	

$$
\begin{aligned}
\min\ & \textstyle\sum_{j \in J} z_j \\
\text{s.t. } & \textstyle\sum_{i \in I} \sum_{t \in T} x_{ij}^t = 1, \quad \forall j \in J \\
& J * 0.2 \leq \textstyle\sum_{i \in I} \sum_{j \in J} x_{ij}^0 \\
& J * 0.3 \geq \textstyle\sum_{i \in I} \sum_{j \in J} x_{ij}^0 \\
& CT_j = \textstyle\sum_{i \in I} (P_{ij} x_{ij}^0 + ((P_{ij} + 1) x_{ij}^1) + ((P_{ij} + 2) x_{ij}^2) + \\
& \qquad ((P_{ij} + 3) x_{ij}^3) + ((P_{ij} + 4) x_{ij}^4)), \quad \forall j \in J \\
& A_j \geq CT_j - R_j, \quad \forall j \in J \\
& A_j \leq (CT_j - R_j) + (M(1 - z_j)), \quad \forall j \in J \\
& A_j \leq M z_j, \quad \forall j \in J \\
& C_i^0 = CI_i + \textstyle\sum_{j \in J} x_{ij}^0, \quad \forall i \in I \\
& C_i^t = C_i^{t-1} + \textstyle\sum_{j \in J} x_{ij}^t, \quad \forall i \in I, \forall t \in T \setminus \{0\} \\
& C_{max} \geq C_i^4, \quad C_{min} \leq C_i^4, \quad C_{max} \leq BC * C_{min}, \quad \forall i \in I \\
& C_{max} \geq 0,\ C_{min} \geq 0,\ C_i^t \geq 0,\ CT_j \geq 0,\ A_j \geq 0, \\
& x_{ij}^t \in \{0,1\},\ z_j \in \{0,1\}, \quad \forall i \in I,\ \forall j \in J,\ \forall t \in T
\end{aligned}
$$

in extreme points and often encountered points are examined. For the feasibility of the problem, balance coefficients are iteratively decreased until there is no improvement left in the scope of the assignment problem.

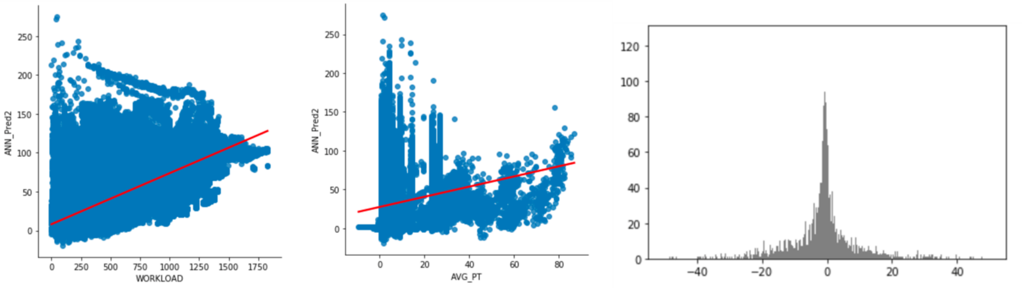

Figure 19.3: Job Count Feature (left), Avg_PT Feature Verifications (middle), and prediction error histogram

19.4.2 Validation

Prediction Validation

R-square, Mean Absolute Error (MAE), Mean Absolute Relative Error (MARE) and Root Mean Square Error (RMSE) values for our refined prediction model containing the aforementioned feature can be seen in Tables 19.2 and 19.3. The metrics are reported on training (70%), validation (15%), and test (15%) sets each. From the individual models, the random forest model reported the best test set accuracy however the overfitting problem can also be seen. The ANN model was the best in terms of robustness. To be able to benefit from the best of all models we utilized ensemble learning. The ensemble model we build with ANN, AdaBoost Regression Tree and Random Forest reported a 89% test accuracy.

	R-Square	MAE	MARE	RMSE
Linear Regression	0,52276	14,87232	4,20094	21,87834
	0,51480	14,84741	4,02400	21,97564
	0,53433	14,84869	4,04313	21,79642
ANN	0,83520	7,65884	1,67111	12,85666
	0,80107	8,19338	1,80037	14,07110
	0,80738	8,19962	1,79635	14,01848
Classification Tree	0,99970	0,61119	0,26926	0,54568
	0,79159	5,47499	0,94664	14,57447
AdaBoost Regression Tree	0,98952	1,63599	0,54834	3,24231
	0,89505	4,65581	0,98744	10,34764
Random Forest Regressor	0,98661	1,62341	0,34898	3,66483
	0,90271	4,34744	0,96720	9,96277
ANN, AdaBoost & Random Forest	0,96711	3,49611	0,84051	5,74365
	0,89177	5,43711	1,22492	10,50798

Table 19.2: Performance metrics of prediction models

		2019				2020			
		R-Square	MAE	MARE	RMSE	R-Square	MAE	MARE	RMSE
Linear Regression	Training Set	0,49295	20,28401	7,77739	29,70015	0,52276	14,87232	4,20094	21,87834
	Validation Set	0,48951	20,24016	7,59580	29,62513	0,51480	14,84741	4,02400	21,97564
	Test Set	0,45075	20,47892	7,98088	30,03042	0,53433	14,84869	4,04313	21,79642
ANN	Training Set	0,64372	14,88356	4,67081	24,89583	0,83520	7,65884	1,67111	12,85666
	Validation Set	0,61423	15,33998	4,71686	25,75299	0,80107	8,19338	1,80037	14,07110
	Test Set	0,61639	15,35019	4,75207	25,75377	0,80738	8,19962	1,79635	14,01848

Training Set Validation Set Test Set

Table 19.3: Comparison of 2019 and 2020 performances

Job Assignment Validation

In order to validate the assignment model, we utilized historical data. Boundries of two approaches are the same since they have the same constraint. Since our model assigns jobs for the next five days and only actually assigns the first day, we also validated TURKPATENT's algorithm (assigning jobs one by one to each employee in an order) this way. TURKPATENT's current algorithm had been run in both daily and by assigning five days in order to compare to our model.

19.5 Integration and Implementation

We have collaborated intensely with TURKPATENT Information Technologies (IT) department and Trademark bureaus and we decided on the integration process of the project with the current operations of TURKPATENT through a mock-up of the planned interface. We cooperated with the We cooperated with the IT department on pulling the daily data of the newly received trademark applications from their database. See Figure 19.4 for the detailed implementation process.

The integration with the database is used in the following manner: At 6 P.M., we pull data using the API and run the prediction model using incoming new job data (averages at 6000 new instances everyday). Following the predictions and using the output as model parameters, at approximately 4 A.M. the assignment model run and the results are displayed in our GUI at approximately 7 A.M.. See Figures 19.5-19.7 for GUI pages.

19.6 Benchmarking and Benefits

19.6.1 Pilot Study by Simulation

The main objective of the simulation is to create a system that can provide a comparison of the model we developed and the model that is currently

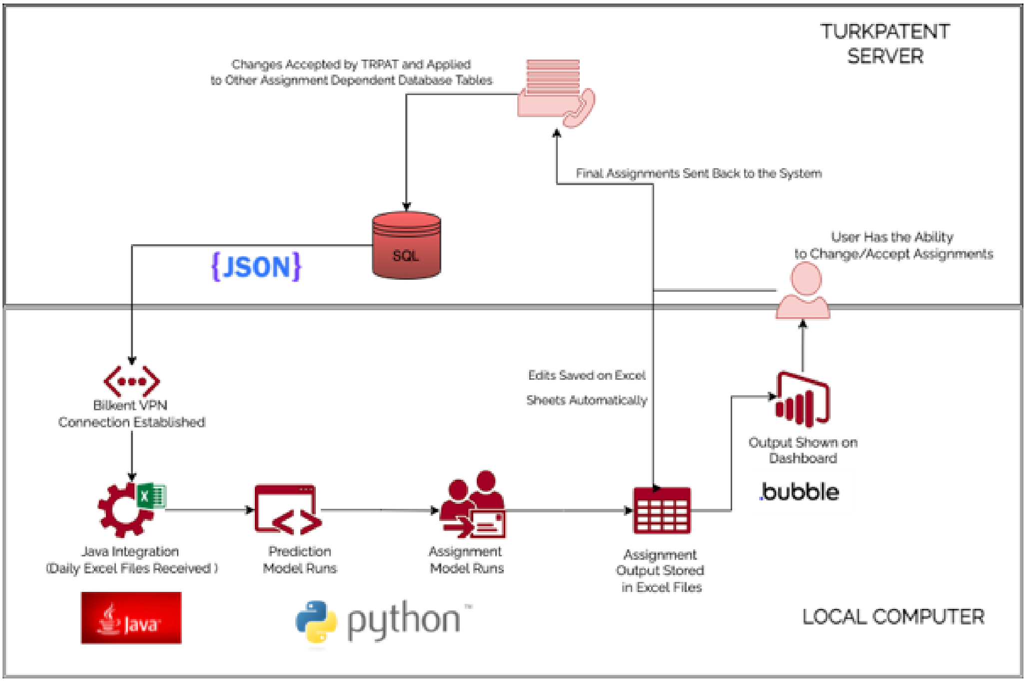

Figure 19.4: Implementation pipeline flow chart

running. We created a simulation algorithm in Python to benchmark the proposed and the existing system. Our simulation can test corner cases for the system and mimic the current system. While simulating the plan, our

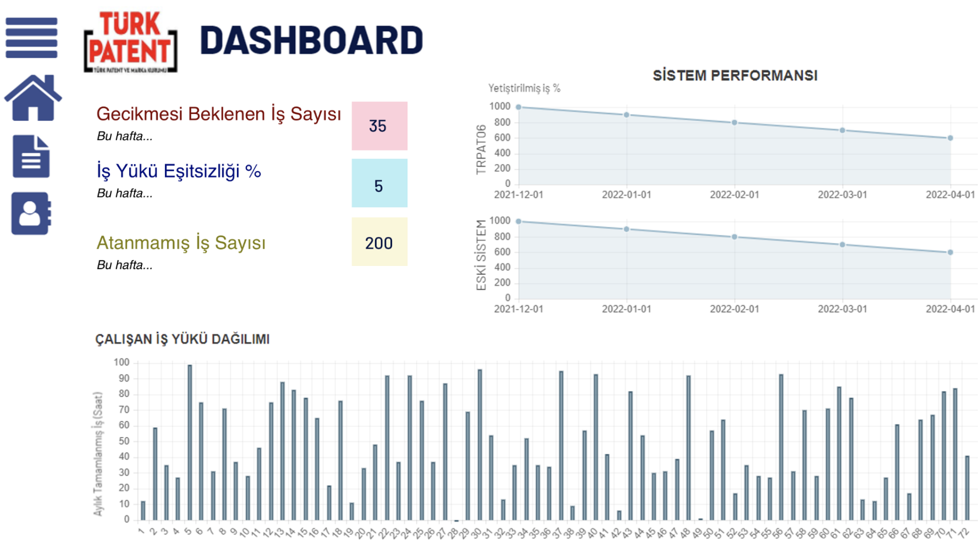

Figure 19.5: The dashboard page for the model, showing some key performance indicators for the company

Figure 19.6: This page is for checking and changing the model assignments and the page to view the assignments.

fundamental measure is the tardiness and the number of tardy jobs. We aimed to construct a confidence interval for two models to analyze the system comprehensively. In the simulation model, we simulated the job arrivals starting from January 1, 2020. The arrival jobs were assigned to random features for "NICE Codes" and "Common Words." To create appropriate

Figure 19.7: The page for checking individual workers' workload and number of defined jobs. Filtering tools are available for ease of users.

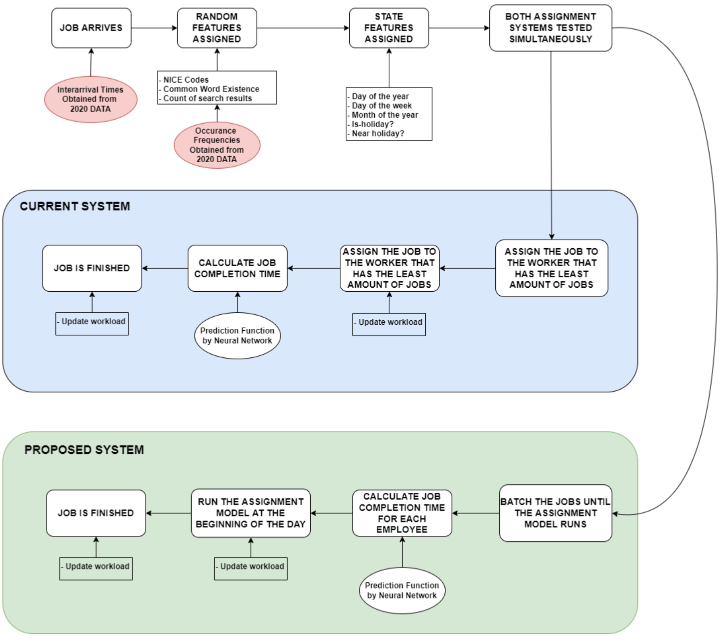

Figure 19.8: Simulation Model Flow Chart

simulation data, we fitted distributions of the random features from the historical data for 2020. Date and employee features are updated daily. On day 0, the employees have a different number of jobs. Note that there are two sets of initially identical employees for each system. The states of the identical employees differ in the run spans according to assignments.

The simulation starts with the daily job arrivals. For each system, identical jobs arrive. Jobs are added to the batch for the proposed system. Then, the job's predicted completion times are calculated for employees. Having obtained the employee features, the predictions are made. All of the jobs in the current system are assigned. The jobs allocated on the first day are assigned and removed from the batch for the proposed system. The completed jobs are disposed of from the system. The simulation runs were done in daily iterations while keeping track of arriving jobs, job completions, and resulting employee states. See Figure 19.8 for the flow chart of the simulation. We have tried different R-squared scores since we cannot know the actual score of the prediction in 2022. We have been attempting R-squared scores as low as 0.650 and as high as 0.903 to understand the impact of our system in possible scenarios. Similarly, we have tried different initial and daily job counts to understand our solution's resiliency in different possible scenarios. We cannot know the actual tardy percentages for the current system since it is highly dependent on the trademark ecosystem.

	# of Days	# of Emp.	Total # of Jobs	Prediction Accuracy (R-squared)	Final Balance Coefficient for the Proposed System	# of Tardy Jobs (Existing System)	# of Tardy Jobs (Proposed System)	# of Tardy Jobs (Proposed w/o prediction)
RUN 1	7	5	240	0.836	<1.05	58 (24.16%)	33 (13.75%)	35 (14.58%)
RUN 2	10	10	453	0.725	<1.05	109 (24.06%)	25 (5.52%)	84 (18.54%)
RUN 3	10	10	594	0.793	<1.05	73 (12.29%)	16 (2.69%)	26 (4.38%)
RUN 4	10	10	644	0.903	<1.05	38 (5.90%)	6 (0.93%)	39 (6.06%)
RUN 5	10	10	755	0.922	<1.05	308 (40.79%)	82 (10.86%)	158 (20.93%)
RUN 6	10	10	758	0.837	<1.05	204 (26.91%)	41 (5.54%)	101 (13.32%)
RUN 7	10	10	763	0.881	<1.05	145 (19.00%)	42 (5.50%)	77 (10.09%)
RUN 8	10	10	784	0.65	<1.05	91 (11.61%)	6 (0.77%)	42 (5.36%)
RUN 9	10	10	780	0.84	<1.05	142 (18.21%)	34 (4.36%)	74 (9.49%)
RUN 10	30	10	5271	0.757	<1.05	2611 (49.54%)	1723 (32.69%)	2565 (48.66%)

Table 19.4: Simulation Runs for Benchmarking the Systems

19.6.2 Simulation Results

The proposed system is the best in terms of the number of tardy jobs despite the increase in the tardiness percentage, i.e., a high number of initial jobs. The proposed system is still the best regarding the number of tardy jobs with low R-squared scores. The proposed system yields the lowest (best) number of tardy jobs in every run. The current system yields the highest (worst) number of tardy jobs in every run; see Table 19.4.

19.6.3 Benefits to the Office

We expect a 50% decrease in the number of tardy jobs in trademark applications. This increase will result in better customer service and faster response times for the office. In order have the same impact with a strategic decision, the company should employ 3 new employees to the bureau, which is a TRY ~500.000 investment annually. The solution is scalable to other processes in the office, especially in the patent bureau. Additionally, the office is expected to have a better employee utilization while keeping the workload discrepancy under 5%.

19.7 Conclusion

For the proposed solution, various machine learning algorithms and operations research are utilized to decrease tardy jobs in TÜRKPATENT. The solution is expected to reduce the number of tardy jobs by 50% while keeping the job count discrepancy between employees under 5%. This solution could improve customer service and decrease the response time for trademark applications. Utilizing machine learning and operations research, the proposed solution is expected to ease the backlog problem that TÜRK-PATENT Trademark Bureau. This solution method is applicable for other service sectors, such as medicine, which could have a societal impact.

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Yardımcı Sanayilerde Kalıp Atama Optimizasyonu ve Karar Destek Sistemi | 20

Arçelik Buzdolabı İşletmesi

Proje Ekibi
Ezgi Al, Begüm Çevik, Alp Göğüsgeren, Zeynep Göze Gürkan, Atakan Mumcuoğlu, Selen Saygun, Sedef Sızmaz

Şirket Danışmanı
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Özet

Şirkette otomatik kalıp atama sistemi bulunmaması, karar alma işlemlerini olumsuz etkilemektedir. Raporda, Arçelik'in mevcut sistemi analiz edilmiş, yeni karar destek sistemi tasarlanmıştır. Çok amaçlı matematiksel model yazılarak atanmayan kalıpların sayısının, fazla mesai kullanımının ve kademeli yardımcı sanayi hareketinin en aza indirilmesi ve öncelikli yardımcı sanayilere yapılan atamaların en çoklanması amaçlanmıştır. Şirket verileriyle matematiksel modelin doğruluğu ve geçerliliği test edilmiş ve hazırlanan modelin ideal sonucu verdiği gözlemlenmiştir. Matematiksel modelde değişiklik yapılmasını sağlayan bir kullanıcı arayüzü geliştirilmiş, şirkete kalıp atama süreçlerinde kullanılmak üzere bir karar-destek sistemi sunulmuştur.

Anahtar Sözcükler: Kalıp Atama Optimizasyonu, Karar Destek Sistemi, Çok Amaçlı Model.

Mold Assignment Optimization and Decision Support System in Suppliers

Abstract

In the Arçelik Refrigerator Factory, the lack of an automated mold assignment system affects the decision-making operations. This report summarizes our findings regarding the analysis of the current structure and proposes a methodology for an improved system. A mathematical model is developed for effective mold assignment, verified and validated using sample data. The report presents a decision support system consisting of Python, Excel and VBA that provides an automated decision-making process according to the company's requests.

Keywords: Mold Assignment Optimization, Decision Support System, Multiobjective Model.

20.1 Company Information

Arçelik A.Ş. was founded in 1955. Initially, the product segment was only dishwashers. In the past years, the main actions taken by the company authorities were focused on enlarging its main market share nationwide. Thus, the product segment was expanded to vacuum cleaners, refrigerators, cooking appliances, drying machines, and dishwashers. Currently, the company has a market share of 63% nationwide and 7% worldwide, and 42% of the manufactured goods are sold in Turkey while the rest are exported.

20.2 System and Problem Descriptions

20.2.1 System Analysis

About 60-65% of refrigerator parts are made out of plastic and produced by plastic mold injection through supplier firms and delivered to Eskişehir plant. When a plastic part enters the production system, industrial engineers assign its injection mold to a supplier. As the preparation processes of the molds are time consuming, changes in supplier assignments are not preferred to prevent delays in the production schedules of refrigerators. Unless there occurs an extraordinary circumstance, initial assignments are retained.

Each plastic part is classified by several parameters: mold ID number, plastic part name, number of molds used in production, required press tonnage for production, mold cavity number, cycle time, monthly production amount, additional requirements, and grouping number. While assigning molds, each firm's remaining available capacities of press tonnage machines are viewed. It should be noted that the capacity requirement of a mold

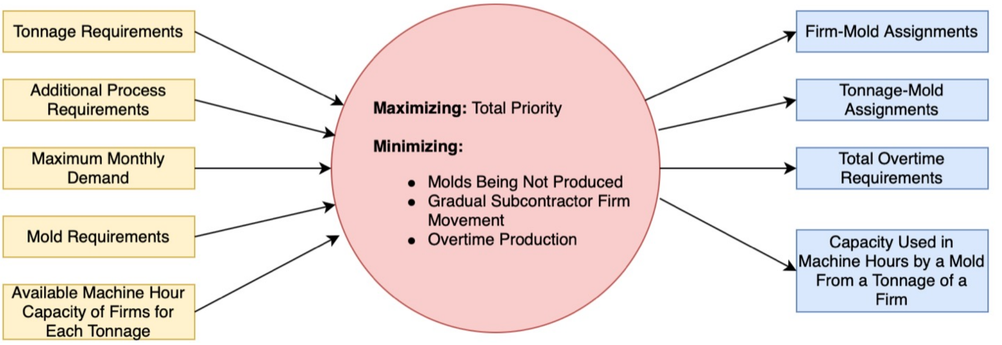

Figure 20.1: Problem definition visualization

can be satisfied by the required tonnage and one level higher tonnage machine. The required machine hour capacity to meet the demanded production amount is calculated. The positive values indicate the availability of the press machines, while negative values indicate lacking machine capacity.

Some molds have additional requirements and they must be assigned to the firms that fulfill these requirements. While assigning the molds to the suppliers and their press machines, overtime can occur in some situations. Grouped parts, namely a combination of multiple parts sharing the same grouping number, should be produced by a single firm. When grouped parts are separated, a cost is incurred called the gradual supplier movement cost. In order to minimize this cost, it is important to make an assignment with the minimum possible separation of grouped parts. Prioritization of the firms is a linear scale that rates all companies out of 100 in terms of their technical and industrial qualifications. It is prefered to assign the molds to the firms with higher prioritization levels.

20.2.2 Problem Definition

Press tonnage requirements of molds, additional process requirements such as painting, hot stamping etc., maximum possible monthly demand of each mold, mold requirements, which are cycle time and number of mold cavities and available capacity of firms from each tonnage in machine hour unit, are the inputs of the system. It is aimed to obtain firm-mold assignments maximizing the total priority, minimizing instances in which not all molds are assigned, minimizing number of separate grouped parts and minimizing total overtime production. All of the processes are subject to capacity and capability restrictions. The processes are visualized in Figure 20.1.

All plastic part-supplier assignments in the Arçelik Eskişehir plant are managed manually. The manual assignment method followed through Excel is not efficient as it is not possible to directly choose the optimal assignment relying only on the experiences of the engineers. As the company does not have a decision tool that provides an optimal capacity planning, the assignment processes require long manual calculations. Although engineers spend an excessive amount of time on making the assignments, they still cannot decide on optimal pairings. The precision of calculations also decreases when manual methods are used. The company requires the use of another decision tool that considers all related constraints and provides improved alternative solutions by maintaining necessary requirements.

20.3 Proposed Solution Approach

20.3.1 Model Development

Extensions of the Classical Assignment Problemwere investigated while preparing the model for the mold assignment problem of Arçelik. Ross and Soland (1975) proposed Generalized Assignment Problem (GAP), where there are capacity restrictions on the agents, in this case supplier firms, that perform the tasks required for a mold. Similar to the Classical Assignment Problem, the constraints of GAP ensure that a mold is assigned to a single firm. However, the capabilities of the suppliers cannot be represented with the depth of GAP. Thus, to propose a better representative model, Multiple Resource Generalized Assignment Problem (MRGAP) was considered. Introduced by Gavish and Pirkul (1991), a constraint of supplier firms having multiple operations such as ho stamping, painting, standard-/complex grouping is included. For GAP and MRGAP, we gained a perspective on how to develop the model regarding Arçelik's Mold Assignment Problem since the concept of assignment for the problem has similarities. On the other hand, these problems take objective as minimizing the costs. Our model includes cost minimization but it is not the primary objective. The primary objective being maximizing the priorities of the firms, a Goal-Programming Model by Özçelik and Saraç (2017) was analyzed. A multiobjective model is constructed consisting of minimizing number of unassigned molds, the number of separated grouped parts, and overtime usage for the tonnage machines while maximizing total priority. To manage multiobjective optimization problem, the "Epsilon-Constraint Method" was applied. The Epsilon constraints were obtained by solving the minimization models separately. Then the results of these models were reflected as constraints in the model that the total priority is maximized. With the obtained results, the constraints were added to reflect these limitations subject to the parameters from sample data. The model parameters and decision variables are presented in Table 20.1.

Sets

I : Set of molds, $i \in I = \{1..49\}$	J : Set of firms, $j \in J = \{1..14\}$
K : Set of tonnages, $k \in K = \{1..24\}$	G : Set of groups, $g \in G = \{1..6\}$

Parameters	
$b_{ij} = \begin{cases} 1, & \text{if firm } j \text{ satisfies the all of the additional requirements for mold } i \\ 0, & \text{otherwise} \end{cases}$	
p_i = tonnage requirement of mold i mapped to its corresponding index	
d_i = maximum monthly demand for mold i	
t_i = cycle time for mold i	
n_i = number of mold cavity for mold i	
Mhr_i = demand for mold i in terms of machine hours	
w_j = priority of firm j	
Cap_{jk} = capacity of machine tonnage k in firm j	
O_{jk} = overtime capacity of machine with tonnage k in firm j in machine hours	
$a_{ig} = \begin{cases} 1, & \text{if mold } i \text{ belongs to group } g \\ 0, & \text{otherwise} \end{cases}$	
$h_{ig} = \begin{cases} 1, & \text{if mold } i \text{ is the maximum tonnage mold in group } g \\ 0, & \text{otherwise} \end{cases}$	
u = overtime cost	v = group separating cost per part
c = cost of not producing a mold	setup=setup cost for machines

Decision Variables
$y_{ij} = \begin{cases} 1, & \text{if mold } i \text{ is assigned to firm } j \\ 0, & \text{otherwise} \end{cases}$
$x_{ijk} = \begin{cases} 1, & \text{if mold } i \text{ is assigned to firm } j \text{ to tonnage } k \\ 0, & \text{otherwise} \end{cases}$
$z_{gj} = \begin{cases} 1, & \text{if the maximum tonnage mold of group } g \text{ is assigned to firm } j \\ 0, & \text{otherwise} \end{cases}$
o_{jk} = total amount of overtime of firm j in tonnage k in machine hours
m_{gj} = the number of molds in group g assigned to firm j
T_{ijk} = capacity used in machine hours by mold i in firm j from tonnage k
f_g = the number of molds in group g assigned to primary firm
$q_i = \begin{cases} 1, & \text{if mold i cannot be assigned to any firm} \\ 0, & \text{otherwise} \end{cases}$

Table 20.1: Sets, parameters and decision variables of the model

Model:

$$\max \quad \sum_{i\in I}\sum_{j\in J} y_{ij} \times w_j \tag{20.1}$$

s.t.

$$y_{ij} \leq b_{ij} \quad \forall i \in I, j \in J \tag{20.2}$$

$$\sum_{j\in J} y_{ij} + q_i = 1 \quad \forall i \in I \tag{20.3}$$

$$\sum_{i\in I} q_i \leq 0 \tag{20.4}$$

$$\sum_{i\in I} T_{ijk} \leq Cap_{jk} + o_{jk} \quad \forall j \in J, k \in K \tag{20.5}$$

$$\sum_{k=p_i}^{p_i+1} T_{ijk} = Mhr_i \times y_{ij} \quad \forall i \in I, j \in J \tag{20.6}$$

$$\sum_{j\in J}\sum_{k=p_i}^{p_i+1} T_{ijk} \leq \sum_{j\in J}\sum_{k=p_i}^{p_i+1} Cap_{jk} + o_{jk} \quad \forall i \in I \tag{20.7}$$

$$o_{jk} \leq O_{jk} \quad \forall j \in J, k \in K \tag{20.8}$$

$$\sum_{k\in K} T_{ijk} \leq M \times y_{ij} \quad \forall i \in I, j \in J \tag{20.9}$$

$$T_{ijk} \leq M \times x_{ijk} \quad \forall i \in I, j \in J, k \in K \tag{20.10}$$

$$\sum_{j\in J}\sum_{k\in K} o_{jk} \leq 0.34 \tag{20.11}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} x_{ijk} \leq 49 \quad \forall j \in J, g \in G \tag{20.12}$$

$$\sum_{i\in I} a_{ig} \times y_{ij} = m_{gj} \quad \forall g \in G, j \in J \tag{20.13}$$

$$\sum_{i\in I} h_{ig} \times y_{ij} = z_{gj} \quad \forall g \in G, j \in J \tag{20.14}$$

$$f_g \geq m_{gj} - M(1 - z_{gj}) \quad \forall g \in G, j \in J \tag{20.15}$$

$$f_g \leq m_{gj} + M(1 - z_{gj}) \quad \forall g \in G, j \in J \tag{20.16}$$

$$\sum_{g\in G}\sum_{j\in J} m_{g,j} - \sum_{g\in G} f_g \leq 1 \tag{20.17}$$

$$y_{ij} \in \{0,1\} \quad \forall j \in J, k \in K \tag{20.18}$$

$$x_{ijk} \in \{0,1\} \quad \forall i \in I, j \in J, k \in K \tag{20.19}$$

$$o_{jk} \geq 0 \quad \forall j \in J, k \in K \tag{20.20}$$

$$q_i \in \{0,1\} \quad \forall i \in I \tag{20.21}$$
$$f_g \geq 0 \quad \forall g \in G \tag{20.22}$$
$$m_{gj} \geq 0 \quad \forall g \in Gj, \in J \tag{20.23}$$
$$z_{gj} \in \{0,1\} \quad \forall g \in Gj, \in J \tag{20.24}$$
$$T_{ijk} \geq 0 \quad \forall i \in I, j \in J, k \in K \tag{20.25}$$

20.3.2 Solution Method

To implement the proposed model for assignment that the company can use, we preferredPython programming language. The Python code calls upon four functions which we model the assignment problem with the same constraints but different objectives that work in order; firstly the unassignment minimization, secondly the group separation minimization, then overtime minimization and finally the priority assignment maximization. Each function calls the objective value of the preceding functions into itself as Epsilon constraints and the final model (priority maximization) gives a solution with the best objective while adhering to the previous objectives' solutions.

After an Excel file containing the parameters of the model is uploaded, the code asks for the name of the file and a number for the alternative results having different mold-supplier assignments under the same limitations as inputs. As a result, our mathematical model is outputting a new Excel file with the date and time in its name, which shows where each mold is assigned to, which molds are unassigned and how much capacity is left for each machine in each firm. The assigned molds are shown in Figure 20.2. We also wanted to give the company flexibility of predetermining the values or constraints for some of the variables and provide a result accordingly. In anExcel Workbook, we used VBA to create a User Form in which the company can decide to assign a mold to a certain supplier, force a mold

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
2	0	0	0	0	0	0	0	0	0	1	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	1	0
4	0	0	0	0	0	0	0	0	0	0	0	1	0	0
5	0	0	0	0	0	0	1	0	0	0	0	0	0	0
6	0	0	0	0	0	0	1	0	0	0	0	0	0	0
7	0	0	0	0	0	0	1	0	0	0	0	0	0	0
8	0	0	0	0	0	0	1	0	0	0	0	0	0	0
9	0	0	0	0	0	1	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	1	0	0
11	0	0	0	0	0	0	1	0	0	0	0	0	0	0
12	0	0	0	0	0	0	1	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	1	0
15	0	0	0	0	0	0	1	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	1	0	0
17	0	0	0	0	0	0	1	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	1	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	1	0
20	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Figure 20.2: Assigned molds

to be assigned strictly or put a limit or a minimum to overtime variables (Figures 20.3-20.5). The constraints filled out in the User Form have been processed to the model as inputs. The only way that the current model could find an infeasible solution is when the constraints inputted by the company make the problem infeasible. In order to tackle this problem as much as possible we wrote another function that makes a logical check on each constraint before calling the functions of the model and prints out error messages as well as what the errors are when it catches them and stops the code. If there are no foreseeable errors the code works as it normally would.

20.4 Validation of the Approach

In order to validate the model, real-life data are requested to see whether the developed decision support system can make meaningful assignments that

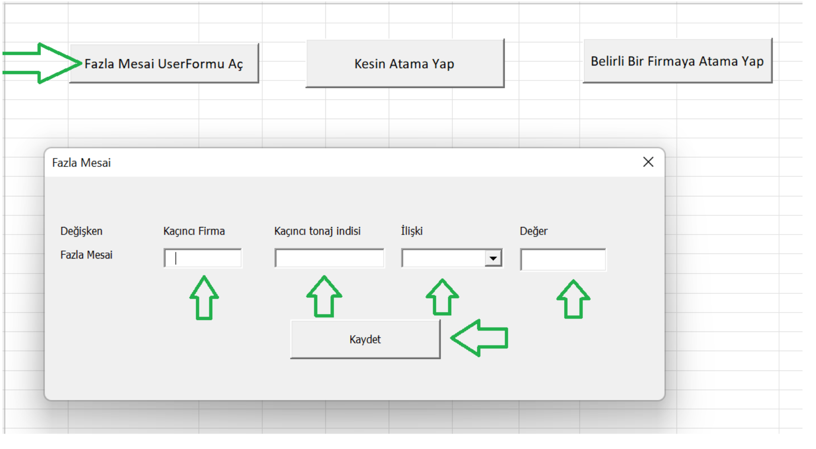

Figure 20.3: User Form for overtime

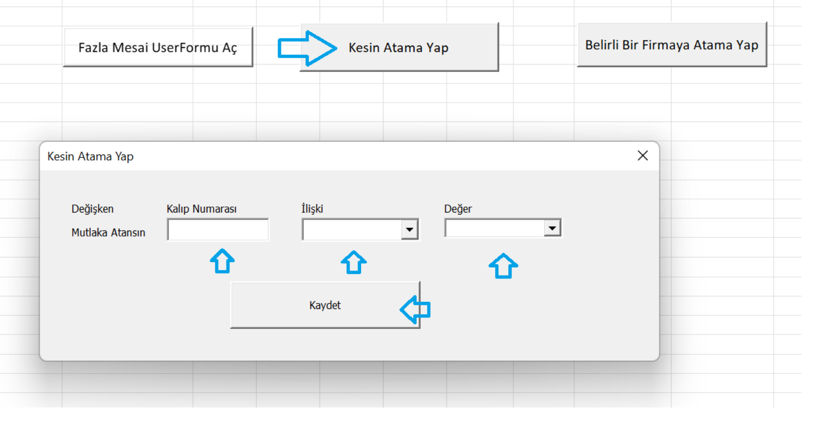

Figure 20.4: User Form for strict assigments

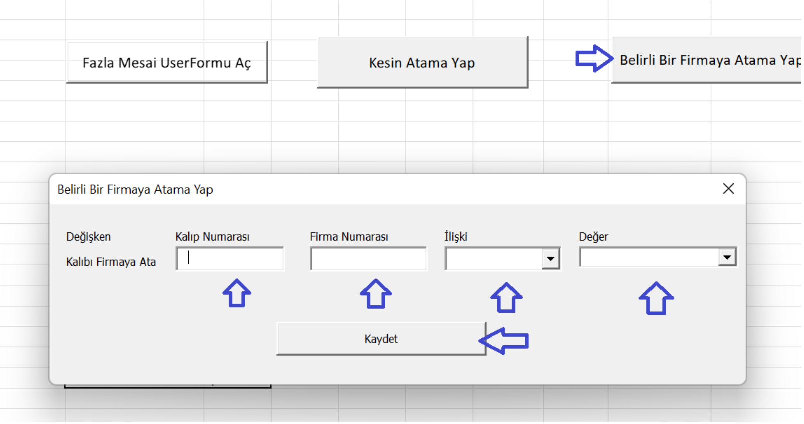

Figure 20.5: User Form for specific supplier-mold matches

can be used by the company. The data provided by the company included 24 manual mold assignments. It is observed that using the mathematical model developed, a meaningful assignment result can be obtained. However, there are several differences in the results of manual assignment which are mainly based on prioritization. In the manual assignment method, the molds are assigned to their required tonnage and it is preferred not to separate the grouped parts even if it means that the firm has a low priority level. When the reasonability of these sorts of assignment differences were consulted to Arçelik, we received positive feedback about the validity and applicability of the system. The primary objective values, which is the total prioritization, were compared to conclude the validation. The objective function value of the proposed solution is 2250. On the other hand, the results of the manual method were obtained as 1965. This shows that the developed model provides a 14% better result compared to the manual assignment.

20.5 Integration and Implementation

In order to provide the firm a user-friendly decision support system, we supported our mathematical model by Python, Excel and VBA. Being one of the most commonly used programming languages, the model's current use and future implementations into a bigger system would be more feasible with Python. We usedPuLP which is a free Python library with the ability to call upon different free or commercial solvers that can solvemixed integer problems. Another library that we utilized is Pandas, which helps to manipulate the data and automatically generates the model parameters for use. We wrote the code on Google Colab which is a web-based Python interface from Google which no download is required as the code works online which made it easier for both us and the company to test and use the system. Since Excel is commonly used by Arçelik, it is decided as the main tool to ease the implementation and adaptation processes. Also, VBA is utilized to create user-friendly User Forms.

We created sample tables for parameters using Excel for the company to insert the problem parameters into the Python code correctly. For our system to work properly, the initial parameter information in the Excel file must follow the predetermined format that is currently used by the company.

Our aforementioned User Form in the input Excel file can be updated by the company and they can arrange overtime amounts for a certain tonnage or change the assignment status of any mold or adjust mold-supplier matches. The User Form should be filled out with the parameters or decision variables that do not make the problem infeasible and not satisfied with the current result yet. After the input Excel file has been updated, the code must be run once more. As a result, the company obtains new outputs with predetermined values or constraints. By using this decision support system it is ensured that the molds are assigned to the most prioritized available company within the restrictions and requirements of Arçelik's expectations.

20.6 Benefits to the Company

The benefits of the proposed mathematical model were measured on four elements: prioritization, overtime usage, capacity, and group separation. When the calculated priority of the manual assignment of the company and the prioritization objective of the proposed solution approach were compared, a total of 14.5% increase has been observed. For the overtime comparison of both methods, it is observed that the model performs better since it is able to successfully assign molds without using any unnecessary overtime hours and leaving out any molds unassigned. According to the analysis made, increasing fill rates are observed in the firms having higher priority values with the assignments of the model, whereas several assignments were being made to low-priority firms in the manual system previously. Despite the 14.5% increase in the primary objective of prioritization the model separates two grouped parts from their primary firms whereas the manual method of the company does not separate any parts from their primary assignments. Considering the importance of the prioritization objective, the model computed that maximizing the total priority is preferred over separating two parts from their primary assignments. The transaction of increasing the total prioritization rather than separating two parts from their initial groups has been determined to be favorable by the model.

As a result of implementing the suggested system, the company is now able to standardize its mold assignment processes. With the system prepared, the company can make the assignments with higher priority values and in a shorter time instead of doing everything in Excel manually. The assignment process is almost completely free of human intervention with the designed system but the engineers will be able to select from several different assignment scenarios based on their experiences. Additionally, as the output is in the form of an Excel file, engineers will also be able to assign a mold to a specific firm, force a mold to be assigned and restrict the overtime usage of a particular firm. Considering the long computations of the industrial engineers, the model both improves the timespan of the assignments and the objective value of the primary objective. The company will save a considerable amount of time with the implementation of this decision support system in their system.

20.7 Conclusion

In this project, a multiobjective mathematical model is developed, which targets to minimize the number of not assigned molds, the number of separated grouped parts and overtime usage for the tonnage machines and maximize the total priority. "Epsilon-Constraint Method" has served for the fulfillment of this aim and the developed model is implemented into a Python code as the company requested. For allowing the users to interact with the system after they see the assignment results, a User Form is prepared in which the users can specify their specific requests regarding the assignments. As a result of the validation step conducted, it is observed that the developed system provides a 14% better result compared to the manual assignment. The origin of this improvement is interpreted as the holistic search the mathematical model carries, unlike the manual assignment.

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21 | Yarı Mamül Üretim ve Kadro Çizelgeleme Sistemi

Eti Gıda

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Özet

Bu rapor, Eti Bisküvi Fabrikası tarafından verilen üretim ve kadro çizelgeleme projesine ilişkin bilgileri içermektedir. Şirket, GAMS kullanarak yarı mamul ürünler için bir ana üretim planı oluşturan ve üretimi denetlemek için 10 adet farklı tesiste çalışan makinelere mavi yakalı işçi atayan bir program oluşturulmasını istiyor. Bu raporda her tesis için yazılan matematik modeller ile ilgili bilgiler ve bu programın entegre edilmesi yer almaktadır.

Anahtar Sözcükler: Üretim Çizelgeleme, Karar Destek Sistemi, Kadro Planlama.

Production Planning of Semi-Finished Goods and Worker Assignment

Abstract

This report includes information on the project given by Eti Biscuit Factory. The company asks us to create a program using GAMS that creates a master production plan for the semi-finished products and assigns a blue-collar worker to the operating machines to supervise the production in 10 different facilities. This report includes information about the mathematical models written for each facility and the integration of this program.

Keywords: Production Scheduling, Decision Supporting System, Worker Assignment.

21.1 Company Information

Eti produces biscuits, crackers, chocolate, cake, milk, and frozen products. The biscuit factory has two main facilities: an old building (Eski Bina) and a G block. In the old building, there are seven areas where semi-finished goods are produced. These areas are Suruphane, 4. Hat Krema, TFT, Kavrulmus Hindistan Cevizi, Granul and Drop. There are also 3 areas where different semi-finished goods are produced in G block, which is the other facility of the biscuit factory. These are Wiener, Caraster, and Fruit Jelly.

21.2 Current System Analysis

In the current system, production planning of the semi-finished goods for biscuits is made manually according to the amount of product shown in the master production schedule. Stock keeping unit (SKU) requests entered the master production schedule are updated weekly. Factory of the biscuits works 24 hours a day and there are 3 shifts in the form of 00:45-08:44, 08:45-16:44, 16:45-00:44. According to the demands, the number of SKUs and how many tons of which kind of biscuits should be produced on a day and shift basis are scheduled weekly. Considering SKU quantities, a certain ratio indicates how much of each semi-finished good should be produced. When this ratio is multiplied by the planned SKU amount on a shift basis, the semi-finished good amount to be produced in that shift is obtained. However, there are different constraints for the semi-finished goods produced in the facilities such as shelf life, stock capacity, setup times and production quantities. Considering these constraints and based on the number of SKUs, production planning of the semi-finished goods is prepared according to the previous experience of the production planner. In addition, after semi-finished good quantities are determined on a shift basis, different numbers of factory floor workers are assigned to each facility. The assignment of the workers to the facilities is not related to any mathematical background, it is determined according to past experiences.

The production planner prepares a master production schedule for semi-finished goods and assigns the factory floor workers to facilities weekly, as well as revises the existing master production schedule when a change in the semi-finished good amount or a change in the shift occurs due to a change in demand. In the current situation, as the production plan of semi-finished goods is made manually, the possible problems faced by the company are as follows; problems in the supply of raw materials, semi-finished goods may not be used after an amount of time due to shelf-life constraints, and there is a need for revision of the master productions schedule sometimes. According to the company, revisions are made 3 times a week due to some reasons such as demand changes, line failures, and problems in staff balance. However, Eti does not have a production plan that can update itself in case revision is needed. Our problem is similar to that of Çölova (2006), who also is an industrial advisor.

21.2.1 Major Constraints

- The shelf life of some of the semi-finished goods is relatively short, and a delay in the production can result in loss of some of those products.

- Some of the production facilities use machines that require certain batch sizes to work. Thus, decisions must be made by considering the batch sizes.

- While some semi-finished goods can be stored, some cannot due to high perishability; which means that a smooth production line should be formed.

- There are storing capacities for some of the semi-finished goods.

- Machines require setups, which create a burden to our optimization plans.

- Some machines can be used on multiple semi-finished goods while some are only reserved for one. Machine flexibility is not very high.

- For some materials, the road that they are carried to another machine may only transfer one product at a time, which would mean that some machines may be forced to wait until some other product is finished.

- Machines must be supervised by the required number of factory floor workers.

- Total number of factory floor workers is limited.

- Machine capacities may also cause some problems in finding the optimal solution to the production plan.

- Some products have safety stock values.

21.3 Proposed Solution Strategy

21.3.1 Objectives

The objective of the project is to create a mathematical model that decides on the amount and the order of each product to be produced in each shift while creating a balanced workload for the factory floor workers supervising the production on site. It is required that the main production program is running nonstop with the minimal wasted workforce (idle time minimization). Figure 21.1 shows the conceptual model.

In the pursuit of the optimal solution, the number of wasted products, wasted workforce, problems encountered in raw material supply, and the number of revisions to the master production schedule should all be minimized.

21.3.2 Solution Method

After considering the problem as a whole, we chose to create separate models for each building during the modeling phase and then combine all the models to create a single model for the whole factory. To do this, we created a base model which consists of simple production and inventory equations.

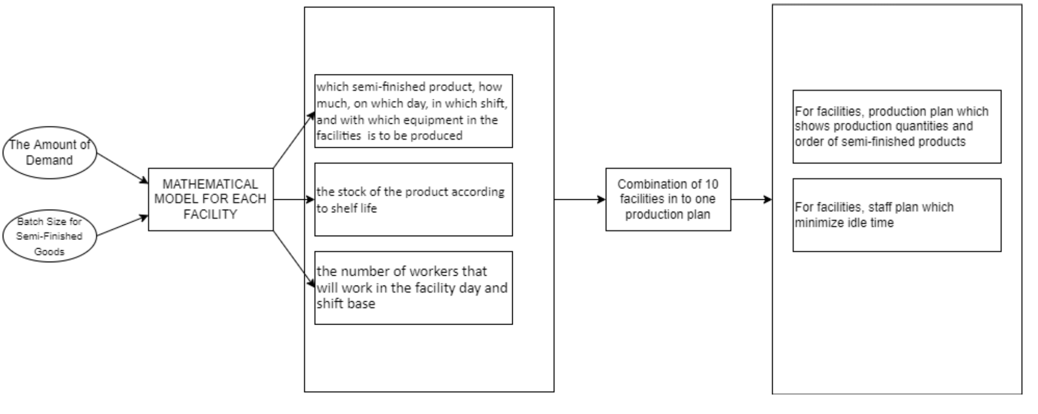

Figure 21.1: Conceptual model

We started constructing a mathematical model for 4th Hat Krema. By developing our basic model with additions such as how many products are produced in the 4th Hat Krema building, how many machines are available, which product can be produced in which machine, the hierarchy of products, stock constraints of products, shelf-life constraints of products, setup constraints of machines, and worker assignment constraints related to production, we constructed our mathematical model. The mathematical model of one of the facilities can be found in the Appendix.

After constructing a mathematical model for 4th Hat Krema, we implemented our mathematical programming model to GAMS and solved it using the CPLEX solver. We were able to solve the problem instantly, which is a satisfactory result in terms of time efficiency. We obtained an output for the number of products to be produced for each semi-finished good for a specific day and a specific shift and the number of workers for a specific day and a shift.

Then, we moved to the other buildings and since each of the buildings has different specifications for the production of the semi-finished goods, we constantly modified our base model.

As soon as the modeling of the buildings was finished, we transferred our models to the GAMS.Then, we solved the models via GAMS and started analyzing corresponding output. Thus, we had the opportunity to immediately see the errors caused by our models or parameters, and to correct the building models without collecting them under a single model.

After successfully constructing the models for all buildings one by one, we have obtained a single model including 10 buildings by naming and rearranging the constraints, parameters, and decision variables of each model in the appropriate format at the stage of combining the models.

The complexity of the model created increased the level of computer hardware required to achieve the solution. As a matter of fact, as we combined our models, we obtained solutions by uploading our model to external servers to control the working functions. Afterward, during the meetings with Eti, we solved the 10-building model we created using Eti's servers, and we obtained these solutions within the desired time frames.

21.4 Validation

To validate our model, we used a sample data given by Eti. This data included a production and a worker assignment plan of a regular week. This manual feasible plan was ran in our model.Our model also found same feasible solution. Afterward, We ran our model using the same parameters data and came at new production plan and worker assignment.After getting production plan and worker assignment, we compared these outputs with ETI's current production plan as well as worker assignment. While comparing, we first checked whether any demand was missed or not, since Eti does not want any backlog. After that, we checked whether the model obeyed the major constraints stated above.

- For each facility requiring setup, we checked if the machines were used correctly.
- We checked if the workers were assigned properly.
- The products with very little shelf-life were used within the allowable time.
- The inventory capacities were not breached.
- The total number of assigned workers was not above the number of available workers.

For the given data, our model has satisfied all of the constraints, however, we also wanted supervisors in Eti to check and point out if any of the constraints were overlooked. Additionally, in our meetings with Eti, they mentioned some additional constraints that were not given to us initially. We revised our model as Eti gave feedback regarding the current solution. We kept improving our model so that it would be fully adapted to the way the factory works. We have aimed to observe whether the models we have constructed are working as intended or not.

Verifying models for each facility does not mean that they will also function properly when they are combined and solved as a singular model. Thus, the verification has been applied to the finalized single model as well.

21.5 User Interface and Implementation

We will provide an interface to Eti using Excel.The company has told us that they use SAP to extract the data to Excel and use the Excel sheet to create their production plan and worker assignment. We will again use this method to extract the demand of the semi-finished goods to Excel and then use Excel VBA to reformat the data so that it would be in proper form for GAMS to read the input. Then, the GAMS code is going to run using the newly acquired data and once an optimal solution is found, the outputs will be put into Excel and the tables for the production plan and the worker assignment will be created. If the GAMS code fail to find any feasible solutions, this will be due to the given demand, and GAMS will say which product in which shift has infeasible demand. This will be reported back to the production planners to revise their demand. Eti has

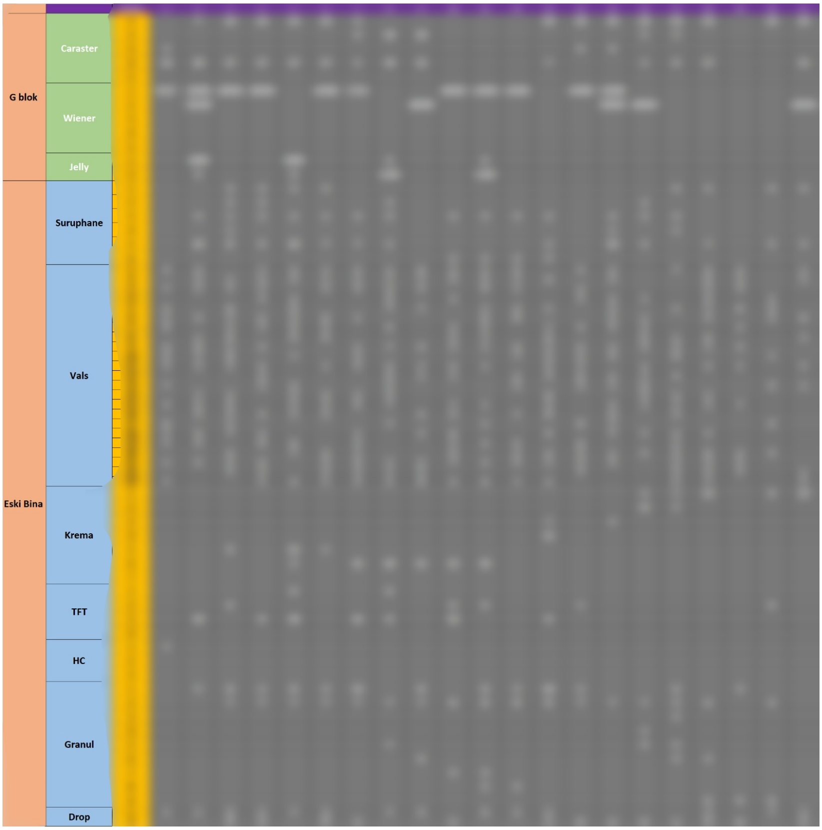

Figure 21.2: Production schedule

told us that this happens frequently, and they receive this feedback from the production crew. This way, we will help them discover the problems during the production planning phase, rather than during the production. Figures 21.2 and 21.3 show two samples of the tables. The tables are not complete, since our computers are not suited for this large-size mathematical model; however, we can use Eti's server under their provision.

In the implementation phase, once Eti is satisfied with our solution, we will share our codes with them for repeated use. We will create a manual for them for every part of the solution stated above and assist them while

Figure 21.3: Worker assignment

there are getting comfortable with it. We are expecting Eti to first use the solution as a help to their current system; however, as they get more comfortable, we expect them to use our solution for every production week.

21.6 Benefits to the Company

Since Eti prepares and revises production plans for the semi-finished goods manually, making these production plans via the DSS tool saves production planners time. In the current system, quantity and order decisions of the semi-finished goods are made based on the production planners' current experience, resulting in an idle time of factory floor workers. Thus, through the decision support system (DSS) tool, the production planning system minimizes the expected idle time of the factory floor workers. We aimed to minimize the time spent while making the production plan as much as possible since the project's main aim is to save time and effort. Last but not least, by implementing the proposed solution, workers can contribute effectively to production during their shifts. For this reason, the number of inventory held will vary compared to the current system, taking into account the shelf life.

Eti provided a one-week semi-finished goods production plan, including worker assignments. Using the same data of this week, our program decreased the expected idle time of the factory floor workers for one week. Our model's solution demonstrated around 13% improvement. Thanks to this improvement, more balanced worker assignment can be done with fewer workers according to this solution.

Talking about the long-term impact, Eti can generate a semi-finished good production plan in an automized manner. Considering the ease of use and decrease in time spent, planners will be able to detect infeasibility and possible bottlenecks and work on fixing them more effectively.

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Appendix: Mathematical Model

Decision Variables:

P_{agvn} : production amount in batches of product a in day g on shift v in machine n,

I_{agv} : inventory amount of product a in day g on shift v,

Y_{gv} : number of workers assigned to day g shift v,

$$f_{gv} = \begin{cases} 1, & \text{if any of the machine is working on day } g \text{ in shift } v \\ 0, & \text{otherwise,} \end{cases}$$

T_{gv} : number of produced semi-products that will be trashed due to end of their shelf-lives,

$$w_{agvn} = \begin{cases} 1, & \text{if machine } n \text{ is working on product } a \text{ on day } g \text{ in shift } v \\ 0, & \text{otherwise,} \end{cases}$$

where $a \in \{1, \ldots, 5\}$, $g \in \{1, \ldots, 7\}$, $v \in \{1, \ldots, 3\}$, $n \in \{1, \ldots, 3\}$.

Parameters:

A_{gv} : assigned number of workers to one shift by the company,
BS_a : batch size of product a,
cap_a : inventory capacity of product a.
D_{agv} : demand of product a in day g shift v,
G_a : maximum production allowed in one shift in one machine.

Model:

$$\min \rho_a + \rho_b + \rho_c \tag{21.1}$$

$$\text{s.t. } BS_a \sum_{n=1}^{3} P_{agvn} + I_{ag(v-1)} - D_{agv} = I_{agv} + T_{agv}, \ \forall a, g, v \tag{21.2}$$

$$I_{a11} = 0, \forall a \tag{21.3}$$

$$I_{agv} \leq cap_a, \forall a, g, v \tag{21.4}$$

$$P_{agvn} \leq G_a w_{agvn}, \forall a, g, v, n \tag{21.5}$$

$$(\sum_{a=1}^{5} \sum_{n=1}^{3} w_{agvn}) \leq 3 f_{gv}, \forall g, v \tag{21.6}$$

$$2(\sum_{a=1}^{5} \sum_{n=1}^{3} w_{agvn}) + 7 f_{gv} \leq Y_{gv}, \forall g, v \tag{21.7}$$

$$I_{agv} - \sum_{g \in S_a} d_{agv} \leq M z_g$$

$$I_{agv} - \sum_{g \in S_a} d_{agv} - T_{agv} \leq M(1 - z_g) \tag{21.8}$$

$$T_{agv} \leq M z_g$$

$$\rho_a \geq Y_{g1}, \forall g$$

$$\rho_b \geq Y_{g2}, \forall g$$

$$\rho_c \geq Y_{g3}, \forall g$$
$$P_{agvn} \geq 0, I_{agv} \geq 0, Y_{gv} \geq 0 \text{ and all integer}, w_{agvn} \in \{0, 1\}, \forall a, g, v, n$$

where

(21.1) we aim to minimize the sum of the maximum number of workers assigned to each shift,

(21.2) is the production-inventory-demand equality,

(21.3) is the initial inventory, which can be set for other values depending on the company's input,

(21.4) is the inventory capacity per product,

(21.5) is the production capacities per shift,

(21.6) and (21.7) are the worker assignment constraints,

(21.8) is the shelf-life constraint, where S_a in the shelf-life of product a. If the inventory in a given shift is above the total demand in the upcoming shifts until the shelf-life is up, then the unused products are assumed to be trash.

The constraints and sets differ from facility to facility; however the structure is very similar for buildings with single machine processing is required for all the products. Also, some products do not follow the same rules as others. For example, some products have no shelf-life, so the working models ignore them in shelf-life assessment.

22 | Yedek Parça Talep Tahminlemesi için Karar Destek Sistemi Tasarımı

Arçelik Kurutma Makinası İşletmesi

Proje Ekibi
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Özet

Projenin amacı, şirket için yedek parça talep tahminleme sistemi oluşturmaktır. Yazılım araçlarıyla doğru ve tutarlı tahmin yapan modeller geliştirmek hedeflenmiştir. Literatürde yedek parça talep modelleri taranmıştır. Her yedek parça için siparişlerdeki mevsimsellik ve aralıklı talep dikkate alınarak 12 farklı tahmin yöntemi arasından en uygun yöntem seçilmiştir. Mevcut ve geliştirdiğimiz tahmin sistemleri karşılaştırılmıştır. Talep edilen parça sayısının yüzden büyük ve sıfır olduğu parçaların talep tahminlerinde sırasıyla %15.16 ve %64.81 iyileştirme gerçekleşmiştir.

Anahtar Sözcükler: Aralıklı talep, malzeme planlaması, mevsimsellik, tahmin yöntemleri, yedek parça talebi

A Decision Support System for Spare Part Demand Forecasts

Abstract

The main purpose of this project is to create a forecasting system for spare parts that would serve Arçelik Tumble Dryer Plant for many years. We aimed to present a sustainable and consistent solution by developing forecasting models with the support of software tools. A literature review is conducted to find different approaches on spare part demand and to build our model effectively. For each spare part, the optimal forecasting method is selected among 12 different forecasting methods determined by literature review considering the high seasonality and intermittency in demands. This project also includes the analysis of the existing system of the company, problem definition, project plan and outcome. According to the forecast results obtained for parts with a demand greater than 100 and 0, improvements of 15.16% and 64.81% were realized, respectively.

Keywords: Intermittent demand, material planning, seasonality, forecasting methods, spare part demand

22.1 Company and Engineering Problem

Arçelik A.Ş is a Turkey-based household appliances manufacturer company founded in 1955. The company has a total of 12 brands including Arçelik, Beko, Grundig, Blomberg, ElektraBregenz, Arctic, Leisure, Flavel, Defy, Altus, Dawlance, and Voltas Beko. Arçelik has a product portfolio covering 6 different areas: built-in and freestanding major appliances, small household appliances, heating ventilation-AC, consumer electronics, kitchen furniture, and components. Arçelik Tumble Dryer Production Facility in Tekirdağ is one of the nine production facilities of Arçelik in Turkey and is the scope of our project. Since tumble dryers have the highest seasonality rate among all product groups of Arçelik, sales volumes and spare part demands have a volatile nature through the different periods of the year. The intermittent nature of the spare parts and the variability between non-zero demand values cause the Material Planning Department to have difficulties in forecasting. After service is requested from Arçelik Tumble Dryer Facility (make-to-order), Arçelik has a limited time to repair the product or provide the spare part. Thus, the make-to-stock method is used for the outdated parts due to intermittency in demand, which results in approximately 15% forecast accuracy. This project aims to provide forecasts for spare part demands on a monthly and yearly basis, aiming to achieve a higher percentage of demand fulfillment by providing better forecast accuracy rates.

22.2 Proposed Model and System

To develop the model, many articles were researched to clearly understand the problem and suggest a solution approach. According to Van der Auweraer et al. (2019) the spare part demand usually consists of intermittent data. Along with other related articles, information about statistical analysis, spare parts forecasting, intermittent demand, various forecasting methods, seasonal forecasting, explanatory variables, and data analysis for forecasting is gained. As a result of the research, the determined 12 methods for our model are (formulas for the models are given in Appendix):

- Moving Average
- Simple Exponential Smoothing
- The Holt's Method (Double Exponential Smoothing)
- The Holt-Winters' Method (Triple Exponential Smoothing)
- The Croston's Method
- Syntetos and Boylan Approximation (SBA)
- Teunter-Syntetos-Babai Forecasting Method (TSB)
- Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal Auto-Regressive Integrated Moving Average (SARIMA)
- Seasonal Trend Loess Model (STL) (Decomposition)
- Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS)
- The Theta Model
- Multiple Aggregation Prediction Algorithm (MAPA)

Our research has also shown that for error measurement calculations of forecasting outdated parts, MASE would be the most useful. If a forecast is successful, the MASE score of the forecast will be smaller than 1. For reference, naive forecasts give the MASE score of 1. If the chosen forecast method gives the MASE level greater than 1, we will consider that score as invalid, and that method as not appropriate. The smaller the MASE level, the more accurate the forecast becomes.

As stated earlier, there are two types of spare parts: active and outdated. Since the company has approved that the spare parts with no demand observed in the last 4 years are considered as outdated, these spare parts are eliminated from the monthly forecasts. All the predetermined forecasting methods are applied to the rest of the spare parts. The demand data are split into test and train data to determine the best applicable forecasting method for the spare parts. With the help of this split, error measurements are obtained, and the forecasting method with the minimum valid error measurement is chosen for that specific spare part to apply the monthly forecast. If the error measurement is invalid for all methods, yearly forecasting is applied to the specific spare part. Figure 22.1 shows the flow chart of the constructed forecasting model. R programming was utilized to apply

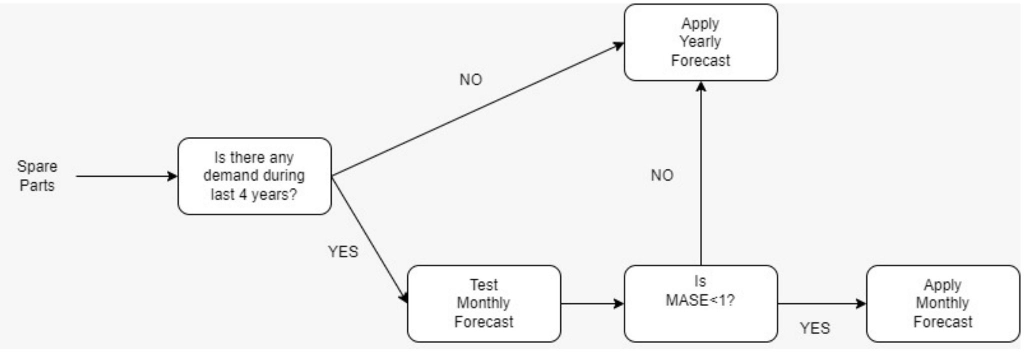

Figure 22.1: Forecasting model

our solution method and obtain the error measurements. In virtue of the comprehensive forecasting packages in the R programming, the forecasting results were obtained and compared automatically for all spare parts.

22.3 Validation of the Approach

The initial output provides forecast results for 2022 to the company based on the optimal forecast method on a monthly or yearly basis. We aimed to compare the forecasts with real data and check whether our code gives reasonable outputs in the real system. The most crucial boundary for the model is that the MASE results must be in a reasonable interval of 0-1. Therefore, if MASE is invalid, the spare parts forecasts are made yearly to decrease the error measurement method. As shown in Figure 22.2, when we applied the twelve forecasting methods to the specific spare part, we observed that the MASE was larger than 1 in all of them. Thus, it turned out that it was not appropriate to apply a monthly forecast to this spare part, and we decided to apply a yearly forecast. When this process is applied to all parts, parts are separated monthly and yearly by validating.

MASE_Croston	MASE_holt	MASE_ses	MASE_HW	MASE_SBA	MASE_TSB	MASE_ARIMA
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1.4192552	2.0603372	1.4720072	1.8686782	1.4361557	1.4642081	1.4723622

MASE_TBATS	MASE_STL	MASE_STLF	MASE_THETA	MASE_MAPA	MASE_MA	MASE_MF
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1.1948056	1.1311978	1.1325536	1.8655628	1.4716147	1.6533818	1.4723622

Figure 22.2: MASE levels of a part that will be yearly forecasted

According to the derived outputs, 3603 spare parts of 5093 spare parts have finite MASE results. 79.4% of 3603 parts, which makes 2861 parts, have MASE levels smaller than or equal to 1. These parts are separated to be forecasted monthly. The remaining 20.6%, 742 parts have MASE levels greater than 1, separated for yearly forecasting. Moreover, the 1490 spare parts of the 5093 which have infinite MASE results are also forecasted yearly. After all, 56.2% of all spare parts, 2861 parts, are forecasted monthly, and the remaining 43.8%, 2232 parts, including the parts having infinite MASE levels, are forecasted yearly.

When new inputs are added to the decision support system, the system will apply all forecasting methods and calculate the MASE levels. Thus, the consistency of the results with real data will be tested dynamically.

22.4 Integration and Implementation

The developed R codes can be used while generating both monthly and yearly forecasts. The R based decision support system shows:

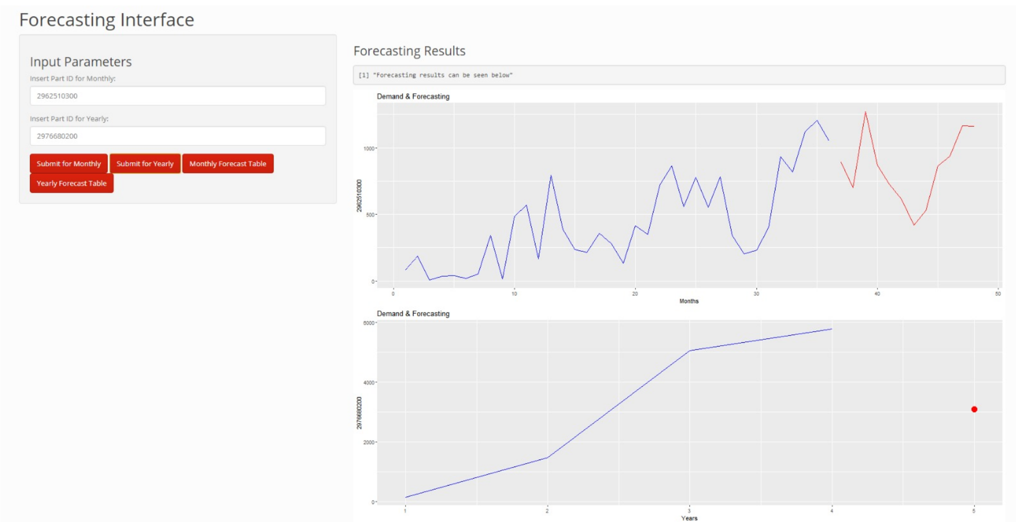

Figure 22.3: Interface output containing graphs and forecast values of a monthly forecast for a spare part

2964840200	2985400200	2970101500	2963670100	9003610100	2962510300	2964840100	2987300200	2970101400	2963670200	2971900100	2957500900	2961190200	2974870100	2985400100
2862.07	1923.98	428.37	1082.19	237.59	893.77	7991.62	4093.86	1243.33	1556.87	501.96	544.36	1022.64	429.84	667.52
2862.07	1923.98	428.37	1077.59	229.28	699.87	13101.16	4165.30	1441.49	1619.90	616.42	535.27	690.99	427.54	667.52
2862.07	1923.98	428.37	1072.99	220.98	1272.43	7585.08	3699.73	722.68	1760.53	516.60	554.25	717.86	421.79	667.52
2862.07	1923.98	428.37	1068.39	212.67	866.12	6271.00	3606.81	752.45	900.95	430.52	748.22	776.00	420.36	667.52
2862.07	1923.98	428.37	1063.79	204.37	724.91	6071.94	3270.11	564.69	1130.10	376.01	658.65	715.18	426.20	667.52
2862.07	1923.98	428.37	1059.19	196.06	613.22	4718.93	2893.75	558.92	1080.47	298.43	445.28	670.98	427.13	667.52
2862.07	1923.98	428.37	1054.59	187.76	417.45	3394.88	2476.81	569.03	836.66	265.68	592.51	613.32	429.62	667.52
2862.07	1923.98	428.37	1049.98	179.46	529.14	5355.32	3044.63	605.90	1311.09	356.00	849.89	611.38	429.17	667.52
2862.07	1923.98	428.37	1045.38	171.15	865.48	7228.87	3764.91	778.42	1437.36	333.16	1011.95	949.13	426.07	667.52
2862.07	1923.98	428.37	1040.78	162.85	938.65	6815.47	4386.87	1435.80	1272.01	632.62	654.33	1097.08	430.86	667.52
2862.07	1923.98	428.37	1036.18	154.54	1167.16	8118.12	5499.45	1769.19	2003.15	793.08	675.07	1067.23	427.53	667.52
2862.07	1923.98	428.37	1031.58	146.24	1160.10	9082.03	3819.91	911.59	1247.69	503.79	1014.74	887.44	426.92	667.52

2976736701	2976734201	2990605300	2957500900	2976680200	2990602900	2990603600	2963282402	2970101400	2985400400	2970101500	2987300200	2976680600	2969847902	2990604400
89.00	1690.00	583.00	4658.58	3083.58	151.68	137.83	3088.36	8011.59	3364.49	4724.65	48608.10	3575.35	654.05	169.00

Figure 22.4: Preview of the interface output of monthly forecast table

- Monthly forecast results for parts individually both on table and on graph (Figure 22.3)
- Yearly forecast results for parts individually both on the table and on graph
- Monthly forecast table containing all parts (Figure 22.4)
- Yearly forecast table containing all parts (Figure 22.4)

An excel output containing forecast results and error measurements is provided when the forecasting codes are run. The installation of the R program and its packages will be done in an online meeting conducted with the IT department of the facility. Our forecasting system will be available on the computers of the material planning department workers. After installation, the company will be able to use the user-friendly forecasting system. They will need to upload the "data.xlsx" demand file and simply click "Run". The system picks the required knowledge from the environment. Therefore, running the codes once is enough to see the forecasting results of the same data multiple times on the interface. However, if a change is desired in the data, the forecasting codes should be run again with the new data. In addition, the data files and the codes are required to be in the same directory.

The company is advised to run the forecasting system monthly for spare parts that require monthly forecasts and yearly for spare parts that require yearly forecasts.

22.5 Benefits to the Company

While calculating the improvements in forecasting, a sample of 1364 parts determined by the company was taken into consideration for March 2022.

- Our forecasting model has given a closer estimate for 750 parts out of 1364, so the percentage of the number of parts improved is 54%.

- We have made two comparisons, one for parts with demand greater than zero and the other for parts with zero demand.

  1. We have conducted a MAPE comparison for the parts with positive demand (823 parts) for both Arçelik's original and our forecast. The results show that Arçelik's MAPE is 73.65%, while our MAPE is 78.25%. However, where the demands are higher than 100, our MAPE results are better than Arçelik, which is 51.38% whereas Arçelik's MAPE is 66.54%. Besides, we get a better MAPE value than Arçelik in parts whose demand is greater than 250, 500, 750, and 1000 where the difference between Arçelik's and our MAPE values are 28.73, 32.18, 51.78, and 84.92, respectively.

     On a part basis, the results show that 237 out of 823 parts we provide a better forecast value, while Arçelik provides better for 493 parts. For the remaining 93 parts, both sides give the same forecast value.

     Mean Absolute Percentage Error (MAPE)
     $MAPE$=1/n$\sum_i^n (|A_i - F_i|)/A_i$
     where;
     A_i= The actual value
     F_i= The forecast value
     n=Total number of observations

  2. For the parts with zero demand (541 parts), the existing error measurement methods could not be performed, and a comparison of forecasts could not be made. Thus, we aimed to obtain distance-based accuracy results using a new method that divides the smaller forecast into the greater forecast. A scale is settled based on this ratio to prevent invalid error measurements. The results have shown that we have improved 64.81% on average in forecasting these parts. On a part basis, we obtained a 94.82% success rate by getting a better forecast value than Arçelik in 513 out of 541 parts for parts with zero demand.

     Measure used for 0-demand = $1/n \sum_i^n \min(F_1, F_2)/(\max(F_1, F_2)$
     where;
     F_1= Forecast value of ARYED
     F_2= Forecast value of ARÇELİK
     n=Total number of observations

22.6 Conclusion

At the start of the project, Arçelik clearly indicated that the aim of the project is to increase their forecast accuracy, especially for the spare parts with intermittent demand, because the forecasts have a prominent place in reducing product replacements, which occurred when the time limitations were exceeded in spare parts' procurement. Thus, the company expects to increase customer satisfaction and decrease stock costs resulting from inaccurate forecasting. For this reason, we developed a dynamic forecasting model. The model is utilizing 12 different forecasting techniques, and it decides the demand characteristics of a spare part (trendy, seasonal, intermittent, etc.) by comparing them according to MASE results and gives forecasts with the chosen best method.

To see the accuracy of our results, we compared our forecasts by forecasts of Arçelik for March 2022. The comparison results clearly demonstrated that our forecasting system gives results with higher accuracy for both intermittent and continuous spare parts. Also, an interface was developed to illustrate the graphs and forecasts of the spare parts that wanted to be analyzed specifically. Briefly, we sincerely believe that the system will satisfy the company's spare part management expectations at an acceptable rate. Lastly, as there are no limitations in improvements, the company can improve the system by adding new forecasting techniques or increasing the level of artificial intelligence used in the system.

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Appendix: Mathematical Models

Simple Exponential Smoothing Forecast is $F_t = F_{t-1} + \alpha(X_{t-1} - F_{t-1})$ where

$$\begin{aligned} X_t &= \text{Actual demand at time period t} \\ F_t &= \text{Forecast at time period t} \\ \alpha &= \text{Smoothing constant where } 0 < \alpha < 1 \end{aligned}$$

Holt's Method (Double Exponential Smoothing)
Level: $L_t = \alpha(X_t) + (1-\alpha)(L_{t-1} + T_{t-1})$
Trend: $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$

Forecast: $F_t(k) = L_t + kT_t$
where;
X_t=Actual demand at time period t
L_t=Demand level at time period t
T_t=Trend at period t
F_t=Forecast at period t
k=Component constant
α, β=Smoothing constants where $0 < \alpha, \beta < 1$

The Holt-Winters' Method (Triple Exponential Smoothing)

Level: $L_t = \alpha(X_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1})$
Trend: $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$
Seasonal: $S_t = \gamma(X_t - L_t) + (1-\gamma)S_{t-s}$
Forecast: $F_{t+k} = L_t + kT_t + S_{t+k-s}$
where;
X_t=Actual demand at period t
L_t=Demand level at time period t
T_t=Trend at time period t
S_t=Demand seasonality at time period t
F_t=Forecast at time period t
k=Component constant
s=Seasonal time period
α, β, γ=Smoothing constants where $0 < \alpha, \beta, \gamma < 1$

The Croston's Method

If $d_t > 0$;
Demand Level: $a_{t+1} = \alpha d_t + (1-\alpha)a_t$
Periodicity: $p_{t+1} = \alpha q + (1-\alpha)p_t$
Forecast: $f_{t+1} = a_t/p_t$
If $d_t = 0$;
Demand Level: $a_t = a_{t+1}$
Periodicity: $p_t = a - p_{t+1}$
Forecast: $f_{t+1} = f_t$
where;
d_t=Actual demand at time period t
a_t=Demand level at time period t
p_t=Demand periodicity at time period t
f_t=Forecast at time period t
α=Smoothing constant where $0 < \alpha < 1$

Syntetos-Boylan Approximation (SBA)

If $z_t = 0$;
$z'_t = z't - 1$
$p'_t = p't - 1$

Otherwise;
$z'_t = \alpha z'_t + (1 - \alpha)z'_{t-1}$
$p'_t = \alpha p'_t + (1 - \alpha)p'_{t-1}$
$Y'_t = (1 - \alpha/2)z'_t/p'_t$
where;
z_t=Actual demand at time period t
z'_t=Time between two positive demand
p_t=Demand size forecast for next period (Periodicity)
p'_t=Demand interval forecast
Y'_t=Average demand per time period t
α=Smoothing constant where $0 < \alpha < 1$
Teunter-Syntetos-Babai (TSB) Method
If $D_t = 0$;
$z'_t = z't - 1$
$D'_t = D'_{t-1} + \beta(0 - D'_{t-1})$
Otherwise;
$z'_t = z'_{t-1} + \alpha(z'_t = z'_{t-1})$
$D'_t = D'_{t-1} + \beta(1 - D'_{t-1})$
$Y'_t = D'_t z'_t$
where;
D'_t=Estimate of the probability of a demand occurrence at the end of time period t
z_t=Actual demand at time period t
z'_t=Time between two positive demand
Y'_t=Average demand per time period t
α, β=Smoothing constants where $0 < \alpha, \beta < 1$
Auto Regressive Integrated Moving Average (ARIMA)
$ARIMA(p, d, q)$=$y{*}_t$=$\mu + \sum i = 1^p \phi_i y * t - i + \sum i = 1^q \theta_i \epsilon_{t-i} + \epsilon_t$
where;
p=Non-seasonal Auto Regression (AR) order
d=Non-seasonal differencing
q=Non-seasonal Moving Average (MA) order
ϕ, θ, ϵ=Smoothing constants where $0 < \phi, \theta, \epsilon < 1$
μ=Average demand
$y{*}_t$=Forecast at time period t
Non-Seasonal Components:
AR=$\sum i = 1^p \phi_i y * t - i$
MA=$\sum i = 1^q \theta_i \epsilon_{t-i} + \epsilon_t$
Seasonal Auto Regressive Integrated Moving Average (SARIMA)
$SARIMA(P, D, Q)_S$=$\Phi(B^S)\phi(B)(x_t - \mu) = \Theta(B^S)\theta(B)w_t$
where;

P=Seasonal Auto Regression (AR) order
D=Seasonal differencing
Q=Seasonal Moving Average (MA) order
S=Time span of repeating seasonal pattern
$\Phi, \phi, \Theta, \theta$=Smoothing constants where $0 < \Phi, \phi, \Theta, \theta < 1$
x_t=Estimation of demand at time period t
w_t=Error value at time period t
μ=Average demand
B=SARIMA Constant
Seasonal Components:
AR=$\Phi(B^S)$=$1 - \Phi_1(B^S) - ... - 1 - \Phi_P(B^{PS})$
MA=$\Theta(B^S)$=$1 + \Theta_1 B^S + ... + \Theta_Q B^{QS}$
Mean Absolute Scaled Error (MASE)
$MASE$=$(\sum_{j=1}^{J} |e_j|)/(1/(\text{T-1}))(\sum_{t=2}^{T} |Y_t - Y_{t-1}|)$
where;
e_j= $Y_t - F_t$
Y_t = Actual values of demand in period t
F_t = Forecast values of demand for period t
T = Training set of periods
J = Total forecast period

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