ISTANBUL TECHNICAL UNIVERSITY ★GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

INTEGRATION OF TIMETABLING AND CREW ASSIGNMENT IN LIGHT RAIL TRANSIT SYSTEMS

Ph.D. THESIS

Selmin DANIŞ ÖNCÜL

Department of Management Engineering

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

HAFİF RAYLI SİSTEMLERDE TARİFE OLUŞTURMA VE EKİP ATAMA PROBLEMLERİNİN BÜTÜNLEŞTİRİLMESİ

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Selmin DANIŞ ÖNCÜL
(507042009)

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Selmin Danış Öncül, **a Ph.D.** student of ITU **Graduate School of Science and Technology** student ID 507042009**.**, successfully defended the **dissertation** entitled "**INTEGRATION OF TIMETABLING AND CREW ASSIGNMENT IN LIGHT RAIL TRANSIT SYSTEMS**", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. Demet BAYRAKTAR** Istanbul Technical University	....
Jury Members :	**Prof. Dr. Cengiz KAHRAMAN** İstanbul Technical University	....
	Assoc. Prof. Dr. Mehmet Mutlu YENİSEY İstanbul Technical University	....
	Prof. Dr. Şakir ESNAF İstanbul University	....
	Prof. Dr. Selim ZAİM Marmara University	....

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To my uncle, who left us suddenly at a very early age,

FOREWORD

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Selmin DANIŞ ÖNCÜL
Management Engineering

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ABBREVIATIONS

ANN	**:** Artificial Neural Network
CPP	**:** Crew Planning Problem
GA	**:** Genetic Algorithm
LP	**:** Linear Programming
LRT	**:** Light Rail Transportation
MIP	**:** Mixed-Integer Programming
MILP	**:** Mixed-Integer Linear Programming
NP	**:** Non-deterministic Polynomial time
TTP	**:** Timetabling Problem

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INTEGRATION OF TIMETABLING AND CREW ASSIGNMENT IN LIGHT RAIL TRANSIT SYSTEMS

SUMMARY

The work presented in this thesis has the main aim to contribute to the field of light rail transportation by developing mathematical model for planning processes. Preparing timetables and crew assignment are the main tasks of planning process. The experimental validation of the models presented in this thesis has been solved using the CPLEX algorithm for real-life data.

This thesis is structured in five main chapters. In the first chapter, a brief introduction is made. Motivation of research, research scope, research objective, research question, research methodology and the structure of thesis study is explained.

The reason of focusing public transportation in the thesis study is its importance in terms of economic and environmental factors. Widely use of public passenger transportation is important for metropolitan in order to minimize traffic problems, pollution and congestion. Therefore, effective public transportation planning is one of the key issues for metropolitan. There is certain need for transporting many passengers with minimum number of trips in order to spent less energy resources such as fuel oil, electricity etc.

The most essential schedule of transportation systems is the timetable. Because of this reason, the train timetabling problem has received considerable attention recently in the literature. Due to complexity of problem, still many companies' operators prepare manual timetables which are feasible but not optimal. Resource assignment problem is basically the problem of allocating tasks to a set of identical resources. Specifically for transportation problems the resources are defined as crew and the assignment of crew to duties are made after the preparation of timetables. Timetabling problems are solved for long-periods and revised for shorter time periods if needed in real-life. Crew assignment problems are later solved according to fixed timetables. There is need of flexibility for preparing timetables and assignment of crew, which must be made consequently considering short-term constraints.

The research objective of this thesis study is to propose a novel model to solve the timetabling problem combining with crew assignment of a light rail transit system (LRT). Generally these two problems are solved separately in literature. The reason of focusing on light rail transit systems is its ability to provide an opportunity to move large number of people in high-density areas. This research is concentrated on only operational level timetabling and crew assignment problems. Moreover this research focused on only models and techniques used in passenger transportation which is completely different from freight transportations. Passenger demand data is also considered in this study.

In second chapter, in order to reach our objective, a detailed literature review is carried out related to train timetabling and crew assignment problems. The train timetabling problems in the literature are classified into two main categories as periodic and non-periodic train timetabling problems. The constraints of train time-tabling problem are classified as soft and hard constraints. The physical constraints can be station capacities, minimum headway, connections, minimum run time between stations and minimum stop time at each station. The assumptions of a typical time-tabling problem are trains have to be run every day of a given horizon, a train is allowed to stop in any intermediate station, number of trains departing and arriving passengers assumed equal on daily basis. Performance measurement parameters of time-tabling problems are categorised as delay-based, waiting cost based, punctuality based, number of passenger transported based, train idle time based, weighted sum of violations based and total travel time based parameters. The objective function of crew assignment problems are generally about minimizing costs, maximizing availability and maximum reliability. Common assumptions are minimum two day off-period for personnel and meal breaks. The variables used in crew assignment problems are shifts, driving and non-driving periods, duty numbers, rest days and rest hours. The performance measures are average number of cover crews and average deviation from the target profile. Academic researches combining timetabling and crew assignment problem are also discussed. The solution methods such as heuristics, integer programming, tabu search, neural networks, simulation and genetic algorithms are also discussed as well.

In third chapter, the mathematical models of the timetabling and crew assignment problems are developed. Extensive interviews have been carried out with authorized experts whom are working at a transportation company in Istanbul in order to build a comprehensive mathematical model. The model involves objectives of minimizing number of passengers waiting at stations and the number of trains on trip. Dwell times, headway times, capacity of vehicles and cycle times have been taken into consideration as the constraints of the model.

On the other hand, considering the outputs of the timetabling problem solution, a mathematical model is built for assignment of machinists to trips. Up to researchers' knowledge, integrating the results of timetabling results directly with machinist assignment model is studied rarely in literature. Weekly planning period from Monday to Sunday, at most six working days, at most one working shift in the same day, balanced workload among machinists, common shift hours for machinists, obligatory rest period between consecutive trips, minimum and maximum working hours for machinists, fixed-number of machinists, availability of all machinists at the beginning of a shift are the basic issues taken into consideration in the model building process.

Constraints such as assigning a machinist at most to one shift in a day, workload balance, maximum weekly working hour, maximum working days a week, not taking two consecutive trips are considered. The off-day and shift preferences, start and finish hours of trips, total extra work hours from previous week are also considered as input parameters. Objective function is minimizing linear combination of several costs such as, penalty cost of not considering machinists' off-day preferences and shift preferences, penalty cost of unbalanced workload and fixed cost of total number of machinists in a day.

First output of the model is start and finish hours of each trip for each shift and day of the week. The second output is the information whether a trip is made or not. This information is also used as input parameters for machinist assignment model. Hence, in the proposed model, firstly a timetable is developed; according to timetabling model outputs, machinist assignment model is developed. Then, the second model yields whether a machinist is working at a specific day, shift and trip and also total working hour of a machinist at a specific day and shift as the values of decision variables.

Using the results of this study, timetables are prepared dynamically on shift basis, as the output of the first proposed model and the crew is directly assigned to trips after solution of the second proposed model. The proposed crew assignment model directly integrates trips with machinists and give chance to bypass duty generation step and provides more flexibility to regenerate machinist assignment tables for short and midterm planning periods.

Also in third chapter, the mixed-integer programming approach and motivation of using this method is discussed. Train scheduling is an optimization problem that has been argued to be NP-hard problem in the literature and mixed integer programming is up today one of the most widely used techniques for dealing with hard optimization problems. Also, there are several studies that used mixed-integer programming at timetabling and crew assignment problems in literature. That’s why, the mathematical models are built using mixed-integer programming (MIP) method and solved by CPLEX algorithm. But the proposed model in this research is not NP-hard, as it is focused on short-midterm and single line timetabling and crew assignment.

In fourth chapter, the validation of the model is explained. Validation is made by comparing model results with real-life application. In order to validate the model, the passenger data of a 20 km LRT line in İstanbul is used. LRT is important and at early stage of its development both for İstanbul and Turkey. The line has seventeen stations and passenger data taken for March 2008. The demand data is included in the model based on minute intervals and the run frequency of the model is made on shift base. Other data taken from the transportation company are: inflow of passenger for each station, time distances between stations, headway time of line, minimum dwell time of station, number of trains and capacity of trains. It is concluded that, the number of trains on trip at timetable resulted by the model is lower than the actual timetable. Moreover, there is significant difference between model results and real-life data at the number of passengers waiting at stations criteria, according to single factor ANOVA test results at significance level of 0.05.

Sensitivity analysis is also performed by changing parameter values such as train capacity and also weights of objective function. All the results are analysed and compared with the results which were already prepared by timetabling experts.

When the results are analysed, it can be seen that the assigned number of machinists per day is significantly lower at the model results compared to real-life assignments. Moreover, the average efficiency rate of machinists is increased at model run results. In conclusion, we can say that, the proposed model not only solve the crew assignment problem with better results, but also provides flexibility to revise existing assignments according to the changing constraints which also effect the timetables. So, sensitivity to short-term demand changes can be satisfied.

In fifth chapter, the results of the study and future research proposals are discussed. The contribution of study is satisfied by directly integrating trips with machinists and giving chance to bypass duty generation step and providing more flexibility to regenerate machinist assignment tables for short and midterm planning periods.

HAFİF RAYLI SİSTEMLERDE TARİFE OLUŞTURMA VE PERSONEL ATAMANIN ENTEGRASYONU

ÖZET

Bu tezde sunulan çalışmanın temel amacı, planlama sürecinde matematiksel bir model geliştirerek hafif-raylı sistem taşımacığındaki planlama sürecine katkıda bulunmaktır. Tarifelerin hazırlanması ve ekip atamalarının yapılması planlama sürecinin ana adımları arasında yer alır. Bu tezde sunulan modellerin deneysel geçerlemesi gerçek hayat verisi ile CPLEX algoritması kullanılarak gerçekleştirilmiştir.

Tez beş ana bölümden oluşmaktadır. İlk bölümde genel bir giriş yapılmıştır. Araştırmanın motivasyonu, araştırmanın kapsamı, araştırmanın amacı, araştırma sorusu, araştırma metodolojisi ve tezin yapısı açıklanmıştır.

Tez çalışmasında toplu taşımaya odaklanılmasının sebebi ekonomik ve çevresel açıdan konunun önemli olmasından kaynaklanmaktadır. Trafik probleminin, kirliliğin ve kalabalığın azaltılabilmesi için metropollerde toplu yolcu taşımacılığının yaygın şekilde kullanılması önem arzetmektedir. Öte yandan etkin toplu ulaşım planlaması metropollerin en önemli sorunlarından biridir. Yakıt, elektrik gibi enerji kaynaklarını daha az harcamak için çok sayıda yolcuyu en az sefer sayısı ile taşıma ihtiyacı vardır. Ulaşım sistemlerinin en zaruri çizelgesi ise tarifelerdir. Bu sebeple, tren tarife problemi yakın geçmişte literatürde büyük ilgi görmüştür. Problemin karmaşıklığı sebebiyle hala pek çok şirkette operatörler manuel olarak uygun fakat optimal olmayan tarifeler hazırlamaktadırlar.Kaynak atama ise temel olarak bir grup benzer kaynağa görevleri yerleştirme problemidir. Ulaştırma problemleri için kaynaklar ekip olarak tanımlanır ve ekibin görevlere atanması tarifelerin hazırlanmasından sonra yapılır. Gerçek hayatta tarife problemleri uzun dönem için çözülür ve daha kısa dönemler için revize edilir. Ekip atama problemleri ise daha sonra sabit tarifelere göre çözülür. Tarifelerin oluşturulmasını ve ekiplerin atanmasını kısa dönemli kısıtları dikkate alarak yapacak esnekliğe ihtiyaç vardır.

Bu tez çalışmasının amacı hafif-raylı sistem tarife problemini ekip atama problemi ile birleştiren yeni bir model önerisinde bulunmaktır. Genellikle bu iki problem ayrı çözülmektedir. Tarife problemleri uzun dönem için çözülmekte ve ihtiyaç duyulduğu takdirde kısa dönem için revize edilmektedir.Hafif raylı sistemlere odaklanılmasının nedeni, geniş sayıda insanı yüksek yoğunluklu bölgelerde hareket ettirme olanağını sağlayabilmesidir. Bu araştırma yanlızca işlemsel düzeyde tarife hazırlama ve ekip atama problemine odaklanmıştır. Ayrıca bu araştırma yük taşımacılığından tamamen farklı olan yolcu taşıma problemindeki model ve tekniklere odaklanmıştır. Bu çalışmada yolcu talep verisi dikkate alınmıştır.

İkinci bölümde amacımıza ulaşmak için, tren tarifeleri ve ekip atama ile ilgili detaylı bir literatür çalışması yapılmıştır. Tren tarife problemleri literatürde periyodik ve periyodik olmayan tren tarife problemleri olarak iki ana kategoride

sınıflandırılmıştır. Tren tarife problemlerinin kısıtları esneyebilir ve katı kısıtlar olmak üzere sınıflandırılmaktadır. Tren tarife problemlerinin fiziksel kısıtları istasyon kapasitesi, iki taşıt arasındaki minimum süre, bağlantılar, istasyonlar arası minimum çalışma süresi, ve her istasyondaki minimum duruş süresi olabilir. Tipik bir tren tarife problemindeki varsayımlar: trenlerin belirlenen zaman diliminde her gün sefer yapması gerektiği, trenlerin herhangi bir ara istasyonda durabileceği ve günlük bazda trene binen ve trenden ayrılan yolcu sayısı eşit kabul edilir. Tren tarife problemlerinin performans ölçüm parametreleri: gecikme, bekleme maliyeti, dakiklik, taşınan yolcu sayısı, tren boş zamanı, sapmaların ağırlıklı toplamı ve toplam seyahat zamanı temelli olarak sınıflandırılır. Ekip atama problemlerinin amaç fonksiyonları genelde maliyetlerin minimum kılınması, hazır bulunma ve güvenilirliğin maksimum kılınmasıdır. Ortak varsayımlar, personel için minimum iki günlük izin günü ve öğün aralarıdır. Ekip atama problemlerinde kullanılan değişkenler; vardiyalar, sürüş yapılan ve yapılmayan zaman dilimleri, görev numaraları, dinlenme günleri ve saatleridir. Performans ölçütleri ise ortalama kullanılan personel ve hedef profilden ortalama sapmadır. Tarife hazırlama ve ekip atama problemlerini birleştiren akademik çalışmalar tartışılmıştır. Tablolarda sezgisel yaklaşım, tamsayılı programlama, tabu arama, yapay sinir ağları, benzetim ve genetik algoritma gibi çözüm yöntemleri kategorize edilmiştir.

Üçüncü bölümde, tarife oluşturma ve ekip atama problemleri için ayrı ayrı matematiksel model önerisinde bulunulmuştur. Kapsamlı bir matematiksel model oluşturmak için İstanbul'da ulaştırma şirketinde çalışan yetkili uzmanlarla yoğun görüşmeler yapılmıştır. Model, istasyonlarda bekleyen yolcu sayısının ve sefer yapan tren sayısının azaltılması hedeflerini içermektedir. Duruş süreleri, ilerleme süreleri, araçların kapasitesi ve çevrim süreleri modelin kısıtları olarak ele alınmaktadır.

Diğer taraftan tarife probleminin çözümünün çıktıları kullanılarak makinistlerin seferlere atanması için ikinci bir matematiksel model önerisinde bulunulmuştur. Araştırmacının bilgisine göre, literatürde, tarife sonuçlarını direkt olarak makinist atama modeli ile bütünleştiren nadir çalışma bulunmaktadır. Modelin temel varsayımları; haftalık planlama periyodunun Pazartesi gününden Pazar gününe olması, en fazla altı çalışma günü olması, aynı günde en fazla tek vardiya çalışılması, makinistler arasında dengelenmiş iş yükü, makinistler için ortak vardiya saatleri, ard arda seferler arası zorunlu dinlenme periyodu, makinistler için minimum ve maksimum çalışma saatleri, sabit makinist sayısı, vardiya başında tüm makinistlerin hazır olması şeklinde belirlenmiştir.

Ekip atama modeli olan ikinci modelde, bir makinistin en fazla bir vardiyada çalışması, iş yükü dengelemesi, haftalık maksimum çalışma saati, üst üste iki kez sefere atanamama gibi kısıtlar dikkate alınmıştır. Çalışılmayan gün ve vardiya tercihleri, seferlerin başlangıç ve bitiş saatleri, makinistlerin önceki haftaki ekstra çalışma saatleri girdi parametreleri olarak kullanılmaktadır. Amaç fonksiyonu, makinistlerin tatil günü tercihlerinin ve vardiya tercihlerinin dikkate alınmamasının ceza maliyeti, dengelenmemiş iş yükünün ceza maliyeti ve günde çalışan toplam makinist sayısının maliyeti gibi maliyetlerin lineer birleşiminin minimize edilmesidir.

Tarife modelinin ilk çıktısı her sefer ve her vardiya için başlangıç ve bitiş saatleridir. İkinci çıktısı bir seferin yapılıp yapılmayacağı bilgisidir. Bu çıktılar makinist atama problemi için girdi parametreleridir. Makinist atama modelinin çalışma sonuçları bir makinistin belirli bir gün, vardiya ve seferde çalışıp çalışmadığı ve belirli bir gün ve vardiyadaki toplam çalışma saatidir. Bu bilgiler aynı zamanda makinist atama problemine girdi parametrelerini oluşturacaktır. Bu sebeple, önerilen modelde önce tarife oluşturulmuş, tarife modelinin çıktılarına göre makinist atama modeli geliştirilmiştir.

Bu çalışmanın sonuçları kullanılarak, tarifeler vardiya temelli bir şekilde dinamik olarak oluşturulabilir ve ekip ikinci modelin çözümünden sonra direkt olarak seferlere atanabilir. Önerilen ekip atama modeli direkt olarak makinistleri seferlerle bütünleştirmekte ve kısa ve orta dönemli planlama periyotlarında makinist atama tablolarının tekrar oluşturulması için esneklik sağlamaktadır.

Ayrıca üçüncü bölümde karışık tamsayılı programlama yaklaşımı ve bu yöntemin kullanılma gerekçeleri açıklanmıştır. Tren çizelgeleme literatürde NP-zor problem olarak geçmektedir ve karışık tamsayılı programlama günümüze kadar zor optimizasyon problemlerinde en yaygın kullanılan teknik olmuştur. Ayrıca literatürde karışık tamsayılı programlamayı tarife ve ekip atama problemlerinde kullanan çeşitli çalışmalar mevcuttur. Bu sebeple, matematiksel modeller karışık tamsayılı programlama modeli olarak geliştirilmiş ve CPLEX algoritması kullanarak çözülmüştür. Ancak bu çalışmadaki önerilen model kısa-orta dönem planlamaya odaklandığı ve tek hat için tarife ve ekip atama yaptığından NP-zor problem değildir.

Dördüncü bölümde modelin geçerlemesi açıklanmıştır. Model sonuçları gerçek hayat uygulaması ile karşılaştırılarak model geçerlenmiştir. Modeli onaylamak için İstanbul'daki 20 km’lik bir hafif raylı sistem hattının yolcu verileri kullanılmıştır. Hafif raylı sistemler İstanbul ve Türkiye için önemli taşıma sistemleridir ve gelişiminin erken safhalarındadır. Hattın 17 istasyonu vardır ve Mart 2008 yolcu verileri kullanılmıştır. Talep verisi modele dakika aralıkları ile dahil edilmiş ve modeli çalıştırma sıklığı vardiya temelli olarak belirlenmiştir. Firmadan alınan diğer bilgiler; her istasyona gelen yolcu sayısı, istasyonlar arasındaki zaman mesafesi, hattın taşıt aralığı, her istasyonda minimum duruş süresi, tren sayısı ve tren kapasitesidir. Bu çalışmada önerilen modellerin çözümü ile belirlenen, seferdeki tren sayısı gerçek hayatta sefer yapan tren sayısından daha azdır. Ayrıca ANOVA test sonucuna göre, 0.05 anlamlılık düzeyinde istasyonda bekleyen yolcu sayıları kriterine göre model sonuçları ile gerçek hayat verileri arasında belirgin şekilde fark olduğu tespit edilmiştir. Tren kapasitesi, amaç fonksiyonun ağırlığı gibi parametrelerin değerleri değiştirilerek duyarlılık analizi yapılmıştır. Tüm çıktılar analiz edilmiş ve daha önce tarife uzmanları tarafından hazırlanan sonuçlarla kıyaslanmıştır. Sonuçlar analiz edildiğinde günlük atanan makinist sayısının gerçek hayatta atanana göre anlamlı şekilde daha az olduğu görülmektedir. Ayrıca model sonuçlarında makinistlerin ortalama verimlilik oranının yükseldiği görülmüştür. Sonuç olarak, önerilen model sadece ekip atama problemini daha iyi sonuçlarla çözmekle kalmayıp, mevcut atamaları değişen kısıtlara göre esnek bir şekilde güncelleyebilme esnekliğini sağlamaktadır. Dolayısı ile kısa dönem talep değişimlerine karşı duyarlılık sağlanabilmektedir.

Beşinci bölümde, çalışmanın sonuçları ve gelecekteki araştırma önerileri tartışılmıştır. Çalışmanın katkısı; tarife oluşturma sürecini ekip atama süreci ile bütünleştirerek değişikliklere karşı esneklik sağlamasıdır. Ayrıca önerilen modelde, problem alanına özgü varsayımlar, parametreler, kısıtlar, değişkenler ve amaç fonksiyon kullanılarak literatüre katma değer sağlanmıştır. Yönetsel anlamda da, modelin GAMS programı kullanarak çalıştırılması ve optimum tarifelerin otomatik şekilde planlamacıların hizmetine sunulması sağlanmıştır.

1. INTRODUCTION

The purpose of this thesis is to examine and solve the timetabling problem for light rail transportation systems together with crew assignment problem. This chapter presents a brief introduction and also explains the structure and objective of the thesis study. At this chapter research scope, research objective, research question and research methodology are explained.

1.1 Motivation of the Research

Energy consumption problem is one of the most important problems of the countries, which are dependent to other countries with rich natural resources such as petrol, electricity, fuel oil and natural gas. Therefore, every country, company or individual person is responsible for their carbon footprint. This makes companies more sensitive about environmental issues such as fuel consumption. Especially for metropolitans, one of the main consumers of energy resources is the transportation vehicles. So, it is important to direct people to use public transportation. Moreover, it is important to plan the capacity of public transportation and quality of service at reasonable cost, in order to prevent problems caused by individual means of transport such as pollution, congestion and social discrimination (Abbas-Turki et al., 2003). The quality of service is directly related with efficient planning. Instead of manual planning, companies must develop scientific approach to planning problems.

That’s why; the need for efficient scheduling has greatly increased in recent decades. In many companies, scheduling is still made manually by human. But, human beings are not very well equipped to control or optimize large and complex systems and the relations between actions and effects are very difficult to assess (Stoop and Wiers, 1996). Scheduling research has had an increasing impact on practical problems, and a range of scheduling techniques have made their way into real-world application development (Smith, 2003). Scheduling is applied in many areas such as production, transportation, preventive maintenance, supply chain, projects and education.

Timetabling is a common form of a scheduling problem and can manifest itself in several different forms. The first generation of computer timetabling programs in the early 1960's were, largely an attempt to reduce the associated administration work (Burke et al., 1994). Timetabling problems can be found in many areas, such as sports league, educational, transport and employee timetabling (Tan, 2003).

On the other hand, crew assignment problems are analysed in the literature since 1980s. However, there are a few researches that solve timetabling and crew assignment problem at the same time. Especially, for transportation industry, scheduling and crew allocation problems should be taken into consideration for short-term planners, in order to support decisions of the planners.

1.2 Overview of the Research

1.2.1 Research scope

This research is focusing on public transportation mainly, the light rail transportation systems. The reason of focusing on light rail transit systems is its ability to provide an opportunity to move large number of people in high-density areas.

Light Rail Transit systems have emerged as an attractive form of public transport both in industrialized as well as developing countries (Faruqi and Smith, 1997). Widely used public passenger transportation is important for metropolitan in order to minimize traffic problems, pollution and congestion.

In comparison with a metro or urban railway, light rail system is cheaper to build and operate, but at a lower commercial speed. However, it maintains a visible presence of surface public transport, offer better penetration of urban areas, enjoy better security, and generate less noise. Light rail can cater passenger flows economically and effectively between 2,000 and 20,000 passengers/hour, which is usually be found in cities with populations between 200,000 and 1,000,000.

On the other hand, if we want to compare light rail transit with highways:

- LRT has the ability to maintain high travel speeds when it is operated in an exclusive guide way.

- LRT is less intrusive than highways.
- LRT vehicles are typically quieter than buses because electric versus diesel power is used.
- LRT vehicles are higher capacity, more comfortable and more appealing than buses.

Considering the advantages of light rail transit systems listed above, it can be concluded that LRT systems can be preferred as a good transportation alternative where environmental sensitivity is high. LRT systems decrease dependency to petrol and decrease the carbon footprint.

1.2.2 Research objective

The most essential schedule of transportation systems is the timetable (Komaya, 1991). Constructing a timetable is part of the overall transit planning process, a choice of service frequency for each route, and allocations of vehicles and crews to routes (Palma and Lindsey, 2001). For example, a train timetable defines the planned arrival and departure times of trains to/from yards, terminals and sidings, and train scheduling plays a vital role in managing and operating complex railroad systems (Zhou and Zhong, 2007).Timetabling and crew scheduling are major planning problems for railway companies at operational and short-term level (Huisman et al., 2005).

This research is concentrated on only operational level timetabling and crew assignment problems. Moreover, this research is focused on passenger transportation considering passenger demand which is different from freight transportation.

The research objective of this thesis study is to propose a novel model to solve the timetabling problem combining with crew assignment of a light rail transit system. The objective of the proposed model is to minimize the number of passengers waiting and the number of trains under the operational and physical constraints of light rail transit system.

1.2.3 Research question

The tasks of public transportation are to meet the increasing demands of all kinds of passengers by high quality of service based on limited number of vehicles (Feizhou et al., 2003). The aim of train timetable problem is to determine arrival and departure times at each station so that no collisions happen between different trains and the resources can be utilized effectively. Due to uncertainty of real systems, train timetables have to be made under the uncertain environment in most circumstances (Yang et al., 2009).

On the other hand, the studies made for personnel scheduling are generally based on fixed schedule assumption and make resource scheduling accordingly (Liao and Kao, 1997; Chu and Chan, 1998; Alfares, 1999; Gomes et al., 2006; Felici and Mecoli, 2007; Deblaere et al., 2007). These personnel scheduling problems involve the allocation of staff to timeslots and possibly locations.

Up to now, these two problems are solved separately. Generally, timetabling problems are solved for long-periods and revised for shorter time-periods if needed. Timetabling problem is itself very hard to solve, as there are many variables and constraints. Crew assignment problems are later solved according to fixed timetables. But in real-life there is need of flexibility for timetables and crew assignments to tasks, which must be made consequently considering short-term constraints.

In this thesis study, the timetabling problem is solved sequentially with resource assignment problem. This study is *a frontier attempt for the application at passenger transportation area for operational level timetabling*. The constraints and demand structure is different and specific to this problem area, such as minimum technical frequency constraint because of signalization system.

1.2.4 Research methodology

In order to reach this objective and research question, the following methodology is developed. The major steps taken into consideration are:

- Model parameters specific to light rail transit are defined.
- Objective function and constraints are defined.
- Model is developed, solved, validated and verified.
- The results are analysed.

The proposed research includes the following steps:

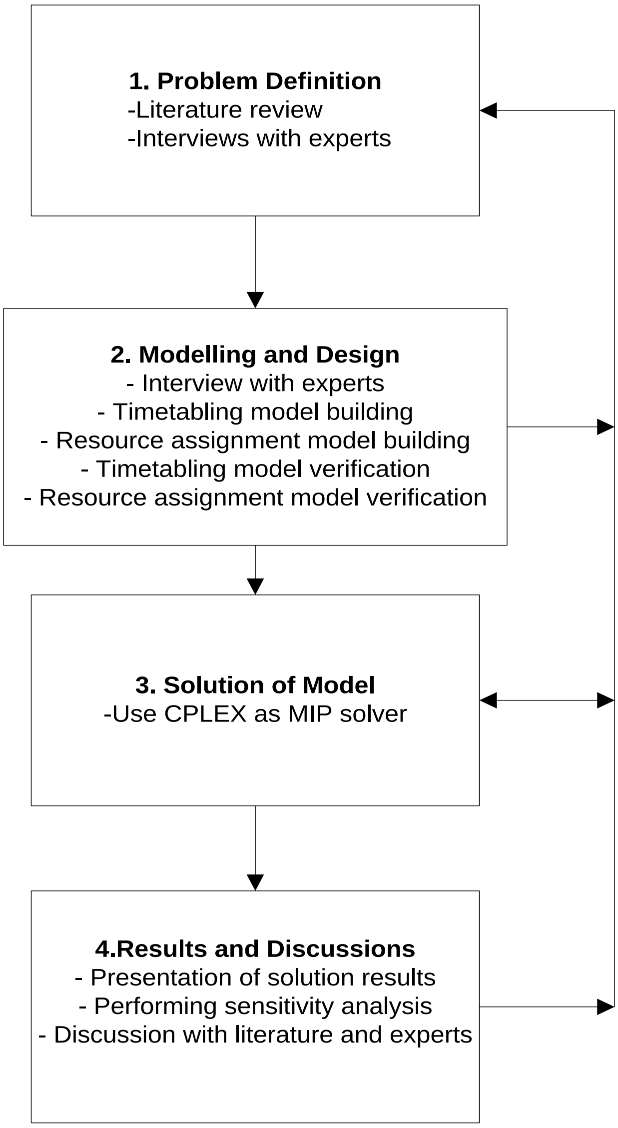

Figure 1-1 : Schematic view of research methodology.

Problem Definition

In the first stage of this research, the literature in the context of timetabling problem was reviewed and a research area was determined as the problem of light rail transit time-tabling with personnel scheduling. The reason of concentrating on public transportation is its importance for crowded cities. After discussing with the experts and reviewing the literature, it's determined that a few of the studies were concentrated on solution of timetabling and personnel scheduling problems concurrently. Hence, the research question is set accordingly and the problem is defined as developing light rail transit time-table schedules considering operational and personnel constraints and demand data within an effective model.

Modelling and Design

In the modelling and design stage, the research problem is analysed in detail within the given scope based on detailed literature study. The key constraints and objectives of the model are identified and a set of assumptions are made as well. Most of the assumptions are specific to this study such as minimum headway time, minimum dwell times, measurement of demand data at certain intervals, machinist rest time between trips, working at most one shift in a day and balanced workload among machinists.

The study focuses on the operational-term timetabling of light rail transit considering double track, n lines with a number of intermediate stations in between. The operational and physical constraints are defined to reflect the real world applications.

The purpose of this thesis study is set as, developing optimal timetables and personnel schedules for light rail transit by means of utilizing a novel mathematical model. Hence, the system is composed of two sub-problems as the timetable problem and personnel scheduling problem. The contribution of study is, to integrate two planning problems via common output and input variables such as, start and finish time of each trip and variable for tracking whether a trip is made or not at a specific, day and shift.

Solution of Model

In the solution stage, an optimal timetable is obtained for each shift. The goal is to find an efficient timetable which minimizes the number of passengers waiting at stations and the number of trains under system constraints. The timetable includes trip arrival and departure hours, trip durations, number of trains required, duty numbers and machinist numbers. The results of the first model run are inputs to crew assignment problem such as arrival and departure times of trips, binary parameter if there is a trip at a specific day and shift. The output of the machinist assignment problem is assignment of machinists to trips and shifts and day. According to researchers knowledge at literature there is no similar study which focused on LRT transportation and also tried to solve timetabling and crew assignment problem at the same time.

Results and Discussions

Finally, validation and verification of the proposed system is discussed by comparisons of the data attained from realizations of real-life applications. Sensitivity analyses are made by changing parameters such as weights of objectives, trip durations. In order to validate the model, the passenger data of a LRT line with 17 stations in Istanbul for March 2008 is used. LRT is important and at early stage of its development both for Istanbul and Turkey. The run period of the model is shift based.

1.3 Structure of the Thesis Study

In this report light rail transit systems are examined for modelling and solving the timetabling and crew assignment problems. Chapter 2 discusses previous studies on timetabling and crew assignment problems. In Chapter 3, the structure of the system and assumptions are presented and a mathematical model is proposed for solution of timetabling and crew assignment problem. Also, the formulation of mixed-integer programming is explained. Chapter 4 presents the application of the study to real-life timetabling and crew assignment problem at a line of LRT system of Istanbul. Finally, at Chapter 5 further research plan of thesis study is explained. The flow of the thesis is summarized at Figure 1-2.

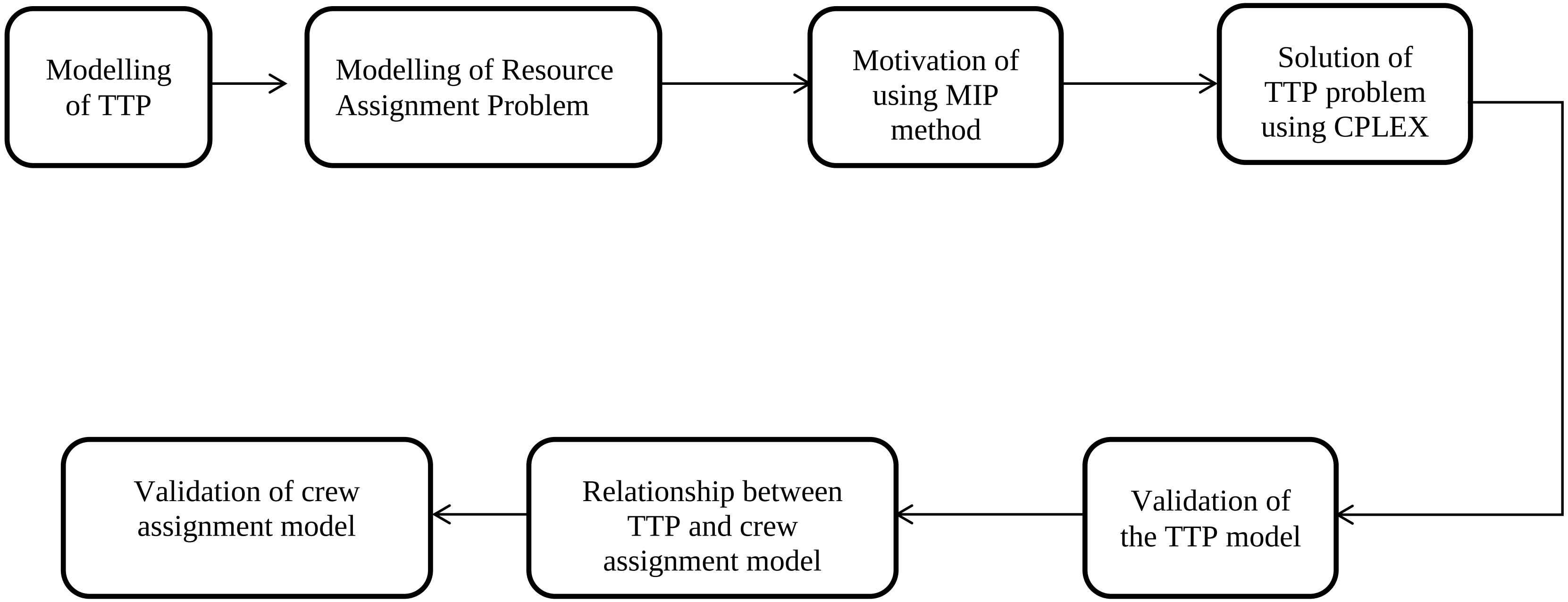

Figure 1-2: Flow of thesis.

2. TIMETABLING AND CREW ASSIGNMENT PROBLEMS

This chapter summarizes the literature about timetabling and crew assignment problems. There exists a rich literature about timetabling problems which mainly focuses on two problem areas as lecture/class timetabling and transportation timetabling. Our research problem is mainly about light rail transit timetabling which is closely related with train time-tabling. At Section 2.1, basic definitions of the timetabling problem and personnel scheduling problem are explained. In Section 2.2 the literature about timetabling, crew assignment and combination of these two are briefly summarized. Train timetabling model characteristics and comparison of models are summarized at Section 2.3. Crew assignment problems are explained in Section 2.4.

2.1 Definitions

Timetabling is the process of assigning events, and resources, to timeslots subject to constraints (Wren, 1995a, Burke and Petrovic, 2002).

The basic terminology used in timetabling can be described as follows (Yang, 2004):

- Event (object): An activity to be scheduled.
- Period (timeslot): An interval of time to which events can be allocated.
- Resource: The resource (e.g. rooms or pieces of equipment) is required by events.
- Constraint: A restriction on when or where events may be scheduled.

Most of the time-tabling problems belong to the class of NP-hard problems, as there exists no deterministic polynomial algorithm (Chu and Fang, 1999). A problem is NP, if there is a known polynomial-time algorithm for a non-deterministic machine to get the answer. And a problem is NP-Hard if all the problems in NP can be reduced to it in polynomial time or equivalently if there is a polynomial time reduction of any other NP-Hard problem to it. Large variety of solving techniques has been tried out in literature for solution of timetabling problems (Burke and Trick, 2005).

Personnel scheduling problems involve the allocation of staff to timeslots and possibly locations (Wren, 1995a). Personnel scheduling covers many areas, such as the nurse rostering problem (Burke et al, 2001 and Dowsland, 1998), transportation staff scheduling (Wren, 1995b), educational institute staff scheduling (Schaerf, 1999) and airline crew scheduling (Emden-Weinert and Proksch, 1999).

2.2 Literature Review

2.2.1 Timetabling literature review

Several approaches have been used to solve timetabling problems up to now. Simulation (Komaya, 1991, Vromans et al., 2006), linear programming (Vansteenwegen and Oudheusden, 2006; Felici and Mecolli, 2007; Yakoob and Sherali, 2007) and metaheuristics (Sheung et al., 1993; Isaai and Singh, 2001, Jamili et al., 2012) are used for railway timetabling. Evolutionary algorithms have been applied with very good results to various types of timetabling problems (Adamis and Arapakis, Chu and Fang, 1999; Feizhou et al., 2003; Carrasco and Pato, 2004; Beligiannis, 2008). Also, metaheuristics have become increasingly popular in the field of automated timetabling (Isaai and Singh, 2001, Lewis, 2007, Burke et al., 2010).

Evolutionary Algorithms (EAs) have been successfully applied to various types of timetabling problems, such as school timetabling (Abramson and Abela 1992, Colorni and Dorigo 1990), railway timetabling (Wezel and Kok 1994), course timetabling (Corne et al 1994, Beligiannis et al 2008) and examination timetabling (Burke et al. 1994a, Burke et a1. 1994b,). These algorithms are derived from biologically inspired concepts and are well-suited to solve timetabling problems since they are highly scalable and flexible in terms of handling constraints and multiple objectives (Dahal et al, 2007).

Meta-heuristics can be thought of as a class of search methods that represent high-level approaches for directing other heuristics to search through complex search spaces. They include but are not limited to evolutionary algorithms, artificial immune systems, variable neighbourhood search, tabu search, simulated annealing, and a wide range of hybrid approaches (Tan et al, 2007).

All of the solution methods in literature explained above are summarized at Table 2.1

In this study, mixed integer programming is used for solving the proposed novel model. During 1990s there were limits on number of variables, constraints and non-zero coefficients, but nowadays the only limitation is the memory of computers which were increased at incredible advances in the last decade.

Table 2.1 : Taxonomy of researches about timetabling.

Application areas	Solution Methods	Citations
Railway scheduling	Simulation	Komaya (1991)
Lecture timetabling	Genetic algorithm and Simulated annealing	Sheung et al. (1993)
Lecture timetabling	Evolutionary algorithm	Adamidis and Arapakis (1999)
Exam scheduling	Genetic algorithm and Tabu search	Chu and Fang (1999)
Railway timetabling	Metaheuristics	Isaai and Singh (2001)
Train timetabling	Lagrangian and heuristic	Caprara et al. (2001)
Public traffic vehicle scheduling	Hybrid genetic algorithm	Feizhou et al. (2003)
Train timetabling	Evolutionary algorithm	Kwan and Mistry (2003)
Class/Teacher timetabling	Neural network	Carrasco and Pato (2004)
Train Timetabling	Evolutionary algorithm	Semet and Schoenauer (2005)
Train Timetabling	Simulation	Vromans et al. (2006)
Train Timetabling	Linear programming and Simulation	Vansteenwegen and Oudheusden (2006, 2007)
Course/student Timetabling	Heuristics	Head and Shaban (2007)
Class Timetabling	Mixed-Integer programming	Yakoob and Sherali (2007)

Table 2.1 (continued): Taxonomy of researches about timetabling.

Application areas	Solution Methods	Citations
School Timetabling	Evolutionary algorithm and Simulation	Beligiannis et al. (2008)
Train Timetabling	Stochastic optimization model	Kroon et al. (2008)
Train Timetabling	Heuristics	Lee and Chen (2009)
Train Timetabling	Hybrid metaheuristics algorithm	Jamili et al. (2012)
Train Timetabling	Metaheuristics	Ho et al. (2012)

2.2.2 Crew assignment literature review

Crew assignment problem is widely analysed in literature in recent years. Different solution methods are proposed for solution of the crew assignment problem. Heuristic algorithm is used at study of Liao and Kao (1997) for solution of nurse scheduling problem and used at study of Chu and Chan (1998) for solution of light rail transit problem. Genetic algorithm is used as a solution method by several researchers such as Aickelin and Dowsland (2000) and Easton and Mansour (1999). Constraint programming is used as a solution method at study of Meisels and Schaerf (2003). Integer programming is used as a solution method at studies of Alfares (1999) and Felici and Mecoli (2007). Some researches combining two or more solution techniques also exist in literature, such as study of Deblaere (2007), which combines integer programming with heuristics. Tabu search is used as an alternative solution method for crew timetabling (Gomes et al., Zeghal and Mineoux, 2006). Memetic algorithm is used for nurse scheduling problem (Burke et al, 2001). Simulated annealing is used at research of Emden-Weinert and Proksch (1999). Also, decomposition algorithm is used at study of Jütte and Thonemann (2012). A summary of solution methods used for crew assignment problem are listed at Table 2.2.

Table 2.2 : Taxonomy of researches about crew assignments.

Solution Methods	Application area	Citations
Heuristic algorithm	Nurse scheduling	Liao and Kao (1997)
Network modelling approach and heuristics	Light rail transit	Chu and Chan (1998)
Genetic algorithm	Nurse scheduling	Aickelin and Dowsland (2000)
Genetic algorithm	Labour scheduling	Easton and Mansour (1999)
Constraint programming	Employee timetabling	Meisels and Schaerf (2003)
Integer programming	Aircraft maintenance	Alfares(1999)
Integer programming	Crew scheduling	Felici and Mecoli (2007)
Integer programming-based heuristics	Resource constrained projects	Deblaere et al. (2007)
Tabu search	Crew scheduling	Zeghal and Minoux (2006)
Tabu search	Crew timetabling	Gomes et al. (2006)
Memetic algorithm	Nurse scheduling	Burke et al. (2001)
Simulated annealing	Airline crew scheduling	Emden-Weinert and Proksch (1999)
Decomposition algorithm	Railway crew scheduling	Jütte and Thonemann (2012)
Column generation-based algorithm	Railway crew scheduling	Veelenturf et al. (2012)

2.2.3 Literature review combining timetabling and crew assignment

The studies combining timetabling problem together with crew assignment problem are listed in Table 2.3. This thesis study is also listed at the last row of the table. Up to researchers' knowledge, this thesis study is a volunteer study which combines timetabling and crew assignment problems in light rail transit transportation area.

Table 2.3 : Academic researches about timetabling and crew assignments.

Citations	Solution Methods	Application area
Cowling et al. (2002)	Hyper heuristic genetic algorithm	Trainer and course scheduling
Sigl et al. (2003)	Genetic algorithm	Class scheduling
Walker et al. (2005)	Integer programming	Train timetabling (Short-term level revision of existing timetable)
Veelenturf et al. (2012)	Column generation	Train timetabling (Short-term level revision of existing timetable)
PROPOSED STUDY	Mixed integer programming	Light rail transit scheduling and crew assignment (Operational level constituting a new timetable)

Considering the listed studies in Table 2.3, it is obvious that there is limited literature up to researcher's knowledge which solves timetable scheduling and crew assignment problem at the same time. The studies which propose timetabling considering crew constraints are:

1. Trainer and course scheduling by hyper heuristic genetic algorithm (Cowling et al, 2002)

In this study a hyper-GA developed for scheduling geographically distributed training staff and courses. There are a number of training events to be scheduled using a limited number of staff, locations and time slots. The delivery of these events is highly constrained by the working ability of staff and crew limits upon time and location. The model is solved for 25 staff, 10 training centres and 60 time slots. Each staff can only work up to 60% of his/her working time. There are six constraints in the model. The objective is to maximize the total priority of courses which are delivered in the period while minimizing the amount of travel for each trainer.

2. Class timetabling by genetic algorithms considering resources (Sigl et al., 2003).

In this study, the quality of timetable is determined by earliness of scheduled classes. The genetic algorithm tried to schedule classes as early in the morning as it can while minimizing the number of holes in a student's schedule. Minimizing the number of conflicts is achieved by number of conflict by a large number K and then selecting the best individuals in a population according to smallest fitness value. Instructors and rooms are considered as hard constraints.

3. Simultaneous disruption recovery of a train timetable and crew roster real time (Walker et al., 2005).

The aim of this study is developing recovery model which involves two related processes:

- Determination of a revised or amended train schedule
- Involving the adjustment or repair of the associated driver duties

The objective is to minimize deviation from the existing schedule while incurring as little cost increase as possible. The research is mainly about short-term level timetabling. An integer programming model is developed to resolve disruptions to an operating schedule in the rail industry. For the construction of the train timetable and crew roster, this model constraints two distinct blocks, with separate variables and constraints. These blocks are coupled by piece of work sequencing constraints and shift length constraints which involve variables from both blocks.

4. Railway crew rescheduling with retiming (Veelenturf et al., 2012).

In this study, the crew scheduling problem is modelled and solved by retiming. This problem extends the crew rescheduling problem by the possibility to slightly delay the departure of some trains, so that some more flexibility in the crew scheduling process is obtained. The algorithm focuses on rescheduling the duties of the train drivers. The model is based on column generation techniques combined with Lagrangian heuristics.

At the proposed study, a new mathematical model is developed for light-rail transit timetabling and crew assignment. The study of Cowling et al. (2002) is mainly about class scheduling which is completely different from timetabling and crew scheduling for light-rail transportation. Moreover at the study of Cowling et al. (2002), the scheduling and assignment processes are combined by building a unique model which includes variables, constraints and objective function for both trainer and course scheduling. But in the proposed study the timetabling and crew assignment steps are combined by eliminating rolling stock phase.

The main difference between the proposed model and the study of Walker et al. (2005) and Veelenturf et al. (2012) is, these studies concentrated on short-term level revision of an existing timetable. But the proposed study builds a new timetable and integrates the results with crew assignment model.

2.3 Train Timetabling Problems

The train time-tabling problems (TTP) mainly concentrated on determining a timetable for set-of trains which does not violate track capacities and satisfies some operational constraints (Caprara et al. 2001). From a marketing point of view, the level-of-service of train timetables is an important factor that affects travellers' and freight carriers' decisions in choosing desirable transportation modes (Zhou and Zhong, 2007).

The key hierarchical planning for public rail traffic system is illustrated in Figure 2.1. and composed of the steps below:

Analysis of Demand: Passenger demand has to be analysed. As a result, the amount of travellers wishing to go from certain origins to certain destinations is known.
Line Planning: Lines and the frequencies for the lines are determined.
Train Schedule Planning: All arrival and departure times of the lines are fixed subject to the periodicity of the system.
Planning of Rolling Stock: Engines and coaches have to be assembled to trains, which are assigned to lines.
Crew management: Distribution of personnel in order to guarantee that each train is equipped with the necessary staff.

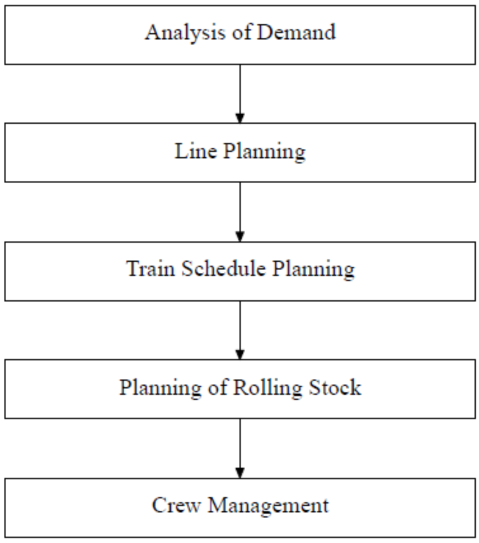

Figure 2-3: Hierarchical planning process, Adapted from Lindler (2000).

The TTP problems are mainly classified into two categories according to periodicity (Tormos et al., 2008):

1. Periodic train timetabling: Each trip is operated in a periodic way. Timetable is easy to remember for passengers but system is not cost effective for use of resources such as crew. PESP (Periodic Event Scheduling Problem) is most widely used in the literature (Nachtigall and Voget, 1996, Odijk, 1996, Kroon and Peeters, 2003, Liebchen, 2006, Ingolotti et al., 2006) for solution of periodic train timetabling problems.

2. Non-periodic train timetabling: Relevant on heavy traffic, long distance corridors where the capacity of the infrastructure is limited due to great traffic densities Generally references consider Mixed-Integer problem formulations in which arrival and departure times are represented by continuous variables and there are binary variables expressing the order of train departures from each station (Barber et al., 2009). This type of problem is considered by Javanovic and Harker, 1991, Cai and Goh, 1994, Carey and Lockwood, 1995, Higgins et al, 1997, Kwan and Mistry, 2003, Caprara et al., 2006.

2.3.1 Timetabling model characteristics

Key parameters that are used for TTP problem at literature are listed at Table 2.4. Positive dwell times are typically required for trains to load and unload passengers at stations (Zhou and Zhong, 2007). Dwell times generally depends on:

- Number of passengers boarding and alighting
- Method of fare collection
- Number of loading passengers
- Door arrangement and number
- Seating arrangement

The constraints of train time-tabling are classified as soft and hard constraints in the literature (Chang and Chung, 2005).

The physical constraints that are considered at time-tabling problems in literature are as follows:

1. Station capacities (Caprara et al. , 2001, Zhou and Zhong, 2007)
2. Minimum Headway: minimum time gap between two trains travelling in the same direction on the same track (Kwan and Mistry, 2003, Carey and Carville, 2003, Chang and Chung, 2005)
3. Connections: some trains might best be arrive within a time-window so that passengers could connect with another service at a selected station (Kwan and Mistry, 2003)
4. Minimum running time between two stations (Komaya and Fukuda, 1991b)
5. Minimum stopping time at each station (Komaya and Fukuda, 1991b)

The assumptions of a typical TTP problem are:

- Trains have to be run every day of a given time horizon (Caprara et al. 2001).
- A train is allowed to stop in any intermediate station (Caprara et al. 2001).
- On daily basis the number of a train’s departing and arriving passengers can be assumed equal (Vansteenwegen and Oudheusden, 2007).

There are several performance measurement parameters exists in the literature of time-tabling problems which are classified as follows:

- Delay-based
    - Sum of weighted waiting-times, average of unit waiting time, maximum ratio of waiting time to journey time (Isaai and Singh, 2001)
    - Minimizing total accumulated delay is also used as objective function at previous researches (Semet and Schoenauer, 2005).
- Waiting cost based
    - Minimizing waiting cost is used as an objective function at study of Vansteenwegen and Oudheusden (2006). Waiting cost includes deviating from the ideal buffer times, cost of waiting in the stations and cost of extended transfer times.
- Punctuality is a commonly used reliability measure
    - Percentage of trains that arrives less than x minutes late (Huisman, 2005).
- Number of passengers transported
    - Maximizing the number of passenger transported is also used as an objective function at study of Adenso-Diaz at al. (1999).
- Train idle times
    - Minimizing train idle times is another objective function at study of Walker et al (2005).
- Weighted sum of violations
    - Minimizing weighted sum of violations from the constraints (Kwan and Mistry, 2003).
- Total travel time
    - Minimizing total travel time is used as objective function at study of Zhou and Zhong (2007) and Ping et al., (2005)
    - Minimizing sum of relative travel times are selected as a solution at the study of Castillo et al. (2011) out of minimizing maximum relative travel time solutions.

Table 2.4: Key parameters at TTP literature.

Parameters	Parameter Explanation-formulation	References
Set of stations	S= {1, ...s}	Caprara et al. (2001)
Set of terminals	Shunting stations	Chang et al. (2000) Carey and Carville (2003)
Arrival times	Time that train t arrivals at station s	Komaya (1991); Carey and Carville (2003)
Departure times	Time that train t leaves station s	Carey and Carville (2003)
Headway times	The time between the arrival time of train t+1 and the departure time of train t	Chang and Chung (2005)
Running times	Time of train t travelling between stations	Chang and Chung (2005)
Dwell times	Time interval of train t staying at station	Chang and Chung (2005)
Minimum headways	Safety time interval required for train operation	Chang and Chung (2005); Vansteenwegen and Oudheusden (2006)
Passenger travel times	Train arrival time- passenger arrival time + running time	Chang and Chung (2005)
Number of platforms		Chang and Chung (2005)

The studies at literature are summarized at Table 2.5 according to the solution methods and content of the study. Some of the studies are just concentrated on single track railways (Zhou and Zhong, 2007), while some of them focused on n lines (Vansteenwegen and Oudheusden, 2006). Moreover the studies can be divided into two according to short-term or long-term timetabling solutions. Short-term timetabling problems mainly focused on reconstructing the schedule in a short-period of time (Semet and Schoenauer, 2005) while operational time-tabling problems focused on constructing timetables for long-term use.

Table 2.5: Taxonomy of researches about train timetabling.

Context	Solution Methods	Citations
Operational level and short-term level timetabling	Simulation	Komaya (1991)
	Heuristics	Adenso-Diaz et al. (1999)
Single-track railway with some double-track stretches	Metaheuristics (hybrid methods combination of tabu search and simulated annealing)	Isaai and Singh (2001)
	Lagrangian and heuristic	Caprara et al. (2001)
Single, one-way track linking two major stations	Integer linear programming model that is relaxed at Lagrangian way	Caprara et al. (2002)
	Co-Evolutionary algorithm	Kwan and Mistry (2003)
Focused on reconstruction of schedule	Evolutionary algorithm	Semet and Schoenauer (2005)
	Simulation	Vromans et al. (2006)
N station, n train lines	Linear programming& Simulation	Vansteenwegen and Oudheusden (2006, 2007)
Single track train timetabling	Branch and bound algorithms	Zhou and Zhong (2007)
Focused on minimizing delays, robust timetable for disturbances	Stochastic optimization model	Kroon et al. (2008)
Single track train timetabling	Hybrid metaheuristics algorithm	Jamili et al. (2012)

2.3.2 Comparison of train timetabling models

Table 2.6 summarizes the model parameters, constraints and objective functions used at literature for building mathematical model of train timetabling problems.

Arrival and departure times of trains are the most common used parameters of the studies. Constraints such as dwell times and headway times are common used constraints which prevents departure and arrival of two trains at the same station at the same time.

The objective functions of the studies about crew assignment problem can be categorised as follows:

- Minimization of total cost based
- Minimization of delay based
- Minimization of total travel times/departure times/dwell times

The studies in literature try to satisfy one or more objectives at the same time. The researches that aims to minimize costs may include operation costs, costs of deviating from original timetable, cost of waiting at stations.

At the study of Castillo et al. (2008), origin departure time constraints, segment running time constraints, dwell time constraints, safety headway constraints are taken into consideration. The objective function includes minimizing maximum relative travel time, sum of departure times of all trains, sum of station dwell times for all trains.

The study of Zhou and Zhoung includes departure time and free run time constraints. The objective function of this study is minimizing the total sum of arrival times of all trains. At the study of Higgins et al. (1996), the overtake constraint for inbound and outbound trains exists. The objective is to minimize delay of train and operating costs. At the study of Caprara et al. (2006), there are constraints about at arcs and also control constraints such as two trains cannot depart/arrive at the same station at the same time and the arrival and departure time constraints that prevent two consecutive arrivals and departures at the same station i to be too close in time. The objective of this study is the sum of the profits of the arcs associated with each patch in the solution. At the study of Vansteenwagen and Oudheusden (2006), there are constraints about scheduled run times, cyclic schedule, departure during first hour, connections, time spacing and single track control. The objective is to minimize overall generalised waiting cost. The study of Ghoseiri et al. (2004) includes, train movement continuity constraints, events continuity constraints, trip times on links and dwell times at platform constraints, one train at a time on link constraints, headway constraints at some nodes and lower and upper bound constraints. The objective function of the study is minimizing fuel consumption cost and minimizing trip time. The study of Semet and Schoeunauer (2005) includes constraints about initial times, stopping time, speed, safety spacing, connections and switching gates. The objective of the study is minimizing accumulated delay.

Table 2.6: Taxonomy of the model parameters for TTP problem.

#	Variables	Constraints	Objective Function	Citations
1	e_{ij}: Leaving time for train i from segment j . $p_{i,j}$: Actual running time for train i at segment j . r_i: Actual departure time of train i from its first station. s_{ij}: Entering time for train i at segment j $x_{i,i1,j}$: A binary variable, which takes value 1 if train i1 is scheduled before train i2 in segment j .	Origin departure time constraints Segment running time constraints Dwell time constraints Safety headway constraints at track segments.	Minimizing maximum relative travel time The sum of departure times of all trains is minimized The sum of station dwell times for all trains is minimized.	Castillo et. al, 2008
2	$s_{i,j}$ = entering time for train i at segment j, i.e., start time for job i on machine j $e_{i,j}$ = leaving time for train i at segment j, i.e., end time for job i on machine j $y_{ii'j}$ = 1 if train i is scheduled before train i' on segment j, 0 otherwise $d_{i,j,t}$ = 1 if train i occupies segment j at time t, 0 otherwise e_{iut} = 1 if train i occupies station u at time t, 0 otherwise	Departure time constraints Free running time constraints	Minimize delay of train and operating costs	Zhou and Zhong, 2007
3	x^i_{aq} : arrival time of train i at station q x^i_{dq} : departure time of train i at station q x^i_{Oi} : departure time of train i from its origin station x^i_{Di} : departure time of train i from its destination station e_{iut} = 1 if train i occupies station u at time t, 0 otherwise	Overtake constraint for inbound and outbound trains	Minimize delay of train and operating costs	Higgins et al., 1996

Table 2.6(continued): Taxonomy of the model parameters for TTP problem.

#	Variables	Constraints	Objective Function	Citations
4	For each node v€V , y_v be a binary variable equal to 1 if and only if there exists a train j whose associated path visits node v. Each train j €T and for each node v€V, z_{jv} be a binary variable equal to 1 if and only if the path of train j visits node v.	At most one arc associated with a train is selected among those leaving the starting node. Equality on the number of selected arcs associated with a train entering and leaving each arrival or departure node. Two trains cannot depart/arrive at the same station at the same time. The arrival and the departure time constraints prevent two consecutive arrivals and departures at the same station i to be too close in time	Sum of the profits of the arcs associated with each path in the solution	Caprara et al., 2006
5	scheduled arrival times scheduled departure times transfer times stopping times buffer times	Scheduled running times Cyclic schedule Departure during first hour Connections Time spacing Single track control	Minimize overall generalised waiting cost= cost of deviating from the ideal buffer times +cost of waiting in the stations + cost of extended transfer times	Vansteenwegen and Oudheusden, 2006

Table 2.6 (continued): Taxonomy of the model parameters for TTP problem.

#	Variables	Constraints	Objective Function	Citations
6	Continuous variables: $a_{k(m)}$ time at which train k starts its mth sub-journey $d_{k(m)}$ time at which train k ends its mth sub-journey a_{kl} time at which train k enters link l d_{kl} time at which train k departs link l V_{kl} average velocity of train k on link l X_{kl} binary train k traverses through link l A_{ijl} train i traverses through link l after train j B_{ikl} train i traverses through link l after train k C_{jkl} train j traverses through link l after train k	Train movement continuity constraints Events continuity constraints Trip times on links and dwell times at platform constraints One train at a time on links constraints Headway constraints at some nodes Lower and upper bound constraints	Minimize fuel consumption cost Minimize trip time	Ghoseiri et al, 2004
7	$a_{(c,i)}$ arrival train c node i $d_{(c,i)}$ departure train c node i $r_{(c,i)}$ track choice route	Initial times Stopping time Speed Safety spacing Connections Switching gates	Minimize total accumulated delay	Semet and Schoenauer, 2005

2.4. Crew Assignment Problems

Resource assignment problem is basically the problem of allocating tasks to a set of identical resources (Gomes and Hsu, 1996). Key variables that are used for resource assignment problems are mainly focused on assigning employees to tasks in a set of shifts during a fixed period of time (Meisels and Schaerf, 2003). Specifically for transportation problems the resources are defined as crew and the assignment of crew to duties are made after the preparation of timetables.

Machinist scheduling at train transportation literature is defined as detailed daily duties, assuming generic drivers. Each duty is a sequence of train runs to man with breaks, is one day's work for one driver (Sodhi and Norris, 2004). Crew rostering is defined as assigning specific drivers at each depot a sequence of duties for the next so many weeks (Sodhi and Norris, 2004). This thesis study is concentrating both on machinist scheduling and machinist rostering for light rail transit systems. The planning horizon of the study is a week based on shifts, so that the study can also be classified as shift scheduling problem.

Given a planning horizon divided into periods of equal length, a set of employees and a demand for different activities (work activities, lunch, break, rest) at each period, the shift scheduling problem consists of assigning an activity to each employee at each period in such a way that the demands are met, while optimizing an objective and satisfying several rules (Cote et al., 2009).

Variables, performance measures, objectives and assumptions and constraints that are used for crew assignment problems at literature are listed at Table 2.7. Generally shifts, duties, driving and non-driving periods, rest days and rest hours, decision variables for crew assignments are the widely used parameters and variables at crew assignment models. The performance measures can be average number of cover crews or average deviation from target profile. Assumptions can be about minimum off periods and meal breaks. Constraints can be about upper limit of weekly workload.

The objective function of crew assignment problems are generally about minimizing combination of several costs such as trip costs, over cover or undercover penalty costs and fixed cost of employing crews (Ernst et al., 2001).

In Table 2.7 the objectives are listed as: minimum cost, maximum availability, maximum reliability, maximum flexibility, maximum speed and optimality or minimum workload of most loaded employee.

Table 2.7: Taxonomy literature about crew assignment problems.

Model		Citations
Variables and Parameters	Shifts	Meisels and Schaerf, 2003
	Driving periods and non-driving periods	Gomes et al., 2006
	Duty number	Sodhi and Norris, 2004
	Rest days	Sodhi and Norris, 2004
	Rest hours	Sodhi and Norris, 2004
	Binary decision variable Z(u, v) take value 1 if crew number u is assigned to time session v	Chu and Chan, 1998
Performance measures	Average number of cover crews (cover crews intended to replace scheduled crews who fail to report for work)	Gomes et al., 2006
	Average deviation from the target profile	Gomes et al., 2006
Objectives	Minimum cost, maximum availability and maximum reliability	Alfares, 1999
	Maximum flexibility, maximum speed and optimality	Sodhi and Norris, 2004
	Minimum cost	Ernst et al. 2001
	Minimum workload of most loaded employee	Hertz et al. 2010
Assumptions	Minimum off period for personnel should be 2 days	Alfares, 1999
	Breaks should be made for the crew to have meal	Gomes et al., 2006
Constraints	Upper limit of weekly workload	Meisels and Schaerf, 2003; Sodhi and Norris, 2004

Table 2.8 summarizes studies about crew assignment literature. Some of the methods used for crew assignment problem are integer programming, heuristics and tabu search. The models at Table 2.8 are built for rail transportation, land transportation, underground transportation and air transportation.

Table 2.8 : Academic researches about crew assignments.

Solution Methods	Scope	Citations
Network modelling approach and heuristics	Light rail transit crew assignment	Chu and Chan (1998)
Local search heuristic based on tabu search	Underground Transportation	Gomes et al. (2006)
Integer Programming	Crew assignment to flights	Felici and Mecoli (2007)
Integer programming-based heuristics	Robust assignment	Deblaere et al. (2007)
Tabu Search	Crew assignment at air transportation	Zeghal and Minoux (2006)
Integer programming	Railroad crew scheduling	Vaidyanathan et al. (2007)

3. MATHEMATICAL MODEL DEVELOPMENT OF THE PROBLEM

This chapter presents the mathematical model of the light rail transit timetabling and crew assignment problem. The stages of developing model for our problem are explained. Section 3.1 gives a brief definition of the system and addresses assumptions which develop the foundations of the mathematical models. Mathematical formulations which describe the system in means of parameters, variables, objective function, and constraints are given at Section 3.2 and Section 3.3.

3.1 System Structure

A double track, two ways, light rail transit system with one depot and N stations of a LRTS is illustrated in Figure 3.1. Trips are starting from two opposite directions and trains are making loop to the starting stations.

Depots are places where trains are preserved in operation route, trains leave from depot to main line in peak period, the trains return to depot from main line in off-peak period (Su and Huang, 2006).

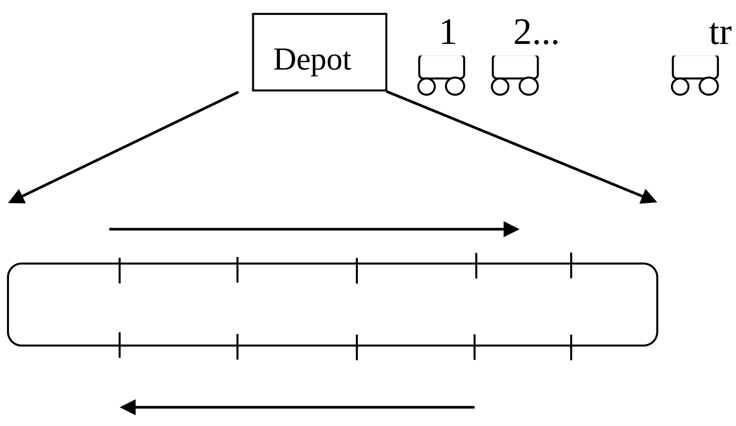

Figure 3-1: System structure of LRTS.

In this study, both machinist scheduling and machinist rostering is considered within the model. Machinist scheduling is construction of duties in such a way that the timetable is covered adequately. Machinist rostering is a second phase in crew management in which duties generated during the crew scheduling phase are sequenced together to form a roster for each crew (Ernst et al, 2001).

3.2 Modelling of Timetabling problem

A novel mathematical model is developed for LRT timetabling problem in this thesis study. The output of the model is integrated with crew assignment model. The strength of the LRT timetabling model is its relationship with crew assignment problem. Moreover, passenger demand data is considered within the model together with cyclic pattern constraints. The general assumptions of the model are explained at Section 3.2.1, problem formulation is explained at Section 3.2.2, the model constraints are explained at Section 3.2.3 and finally the objective function is explained at Section 3.2.4.

3.2.1 General assumptions

Before building the model, general assumptions related with light rail transit control systems should be defined in order to define the application context.

General assumptions that hold for the light rail traffic control system are given below:

1. The demand data is measured at certain time-intervals so the trip frequency is determined at this frequency.

2. The dwell time among every station might not be same.

3. Trains can follow each other on a track segment with a minimum headway (Higgins et al., 1996).

4. Passengers arriving to the stations will take the first train.

5. Trip durations are cyclic (Vansteenwegen and Oudheusden, 2006).

6. All trains are of the same type.

7. The passenger capacity of stations assumed to be infinite.

8. Passengers arrive to the stations according to uniform distribution between specific time intervals.

9. The route of train is bi-directional

10. The capacity of the train, which is directly related with the length of the train is fixed. Length of a train is determined by its number of cars (Claessens et al., 1998).

11. Run duration from depot to initial station is not considered in the model.

3.2.2. Problem formulation

The purpose of the train timetabling model is to provide near optimal timetable parameters for the light rail system for each period in order to minimize the number of passengers waiting at stations and the number of trains on trip as well.

The following notation is used for the model:

i: Trip index i= 1,2...I

k: Station index k= {1... K} represents the set of stations numbered according to the order in which they appear along the track.

t: Time index t=1,2...T

The trains have to be run every day of a given time horizon. We discrete the time into 1-min time slots and expressed as integers from 1 to T:= 1200 (the number of minutes in a day).

Parameters:

mdw: Minimum dwell time. Waiting duration at stations for boarding and alighting (Khan and Zhou, 2010).

maxdw: Maximum dwell time. Maximum allowed difference between arrival and departure time of a trip at specific station (Castillo et al., 2008).

β_{k} : Duration that a train need to cover distance between stations k, k +1 (Tormos et al., 2008)

NT: The total number of trains (Nielsen et al., 2006)

M: A big number

$In_{k,t}$: The number of passengers arriving at station k at time t

HW: Headway time- Minimum time difference between the departure of train from a station and arrival of next train to the same station (Zhou and Zhong, 2005).

C: Passenger capacity of train

S: Start hour of trips

F: Finish hour of trips

Ct: Cycle time of trips (Cacchiani and Toth, 2012)

w1: Weight factor of first objective

w2: Weight factor of second objective

Variables:

$d_{k,i}$: Departure time from station k, for trip i (Higgins, 1996).

$a_{k,i}$: Arrival time to station k, for trip i (Higgins, 1996).

$dw_{k,t}$: Dwell time at station k time t (Castillo et al., 2008).

$PS_{k,t}$: Current number of passengers at station k, at time t.

$x_{k,i,t}$: Binary variable for train stops. Takes value 1 if at time t and trip i, train stops at station k otherwise 0. $x_{k,i,t} \in \{0,1\}$

tr: Number of trains on trip

$st_{i,t}$: Binary variable for start of trips. If trip i starts at time t, $st_{i,t}$= 1, otherwise $st_{i,t}$=0.

$fn_{i,t}$: Binary variable for finish of trips. If trip i ends at time t, $fn_{i,t}$= 1,

otherwise $fn_{i,t}$=0.

$z_{i,t}$: Binary variable if trip i is being made at time t takes value 1, otherwise. 0

y_i: Binary variable if trip i is being made takes value 1, otherwise. 0

TD_i: Trip duration for trip i

3.2.3. Model constraints

Model constraints are listed in this section, of which are related with LRT line conditions such as signalization constraints.

1. Headway constraint: Arrival time of a trip is greater or equal to the departure time of the previous trip plus headway time.

$$a_{k,i} \geq d_{k,i-1} + hw - M*(1-y_i) \quad \forall i,k,d \tag{3.1}$$

2. Arrival time of train for trip i is greater than departure time of train at trip i from the previous station plus run time.

$$a_{k,i} \geq d_{k-1,i} + \beta_{k-1} - M*(1-y_i) \tag{3.2}$$

3. Dwell time is greater or equal to minimum dwell time.

$$\mathrm{dw(k,t) \geq mdw} \tag{3.3}$$

4. Difference of a trains departure and arrival time at a specific station must be lower than maximum dwell time parameter.

$$d_{k,i} - a_{k,i} \leq \mathrm{maxdw} \tag{3.4}$$

5. Departure time of a trip is greater or equal to arrival time plus dwell time.

$$d_{k,i} \geq a_{k,i} + dw_{k,t} - M * (1 - y_i\ ) \tag{3.5}$$

6. Departure time of trains for all trips and stations must be less than finish time of trip hours.

$$d_{k,i} \leq F \qquad \forall i,k \tag{3.6}$$

7. Departure time of trains for all trips and stations must be greater than start time of trip hours.

$$d_{k,i} \geq S \qquad \forall i,k \tag{3.7}$$

8. The sum of all departure times for all stations and trips must be greater than zero.

$$\sum_k \sum_i d_{k,i} \geq 0 \qquad \forall i,k \tag{3.8}$$

9. If there will be no trip the sum of arrival and departure times is less than or equal to 0, otherwise less than M.

$$M * y_i \geq \sum_k a_{k,i} + d_{k,i} \qquad \forall i \tag{3.9}$$

10. If trip i will not be done, than the next trip will also not be done.

$$y_i \geq y_{i+1} \qquad \forall i \tag{3.10}$$

11. If train stops at time t at station k at trip i, departure time station k and trip i must be equal to t, otherwise departure time value can be greater or less than time t.

$$M*(1-x_{k,i,t})\geq d_{k,i}-t \qquad \forall k,i,t \tag{3.11}$$

$$M*(1-x_{k,i,t})\geq t-d_{k,i} \qquad \forall k,i,t \tag{3.12}$$

12. Big M times binary variable st_{it} is greater or equal to t minus arrival time of initial station of trip i plus 1 minus big M times 1 minus y_i.

$$M*st_{i,t}\geq t-a_{1,i}+1-M*(1-y_i) \qquad \forall k,i,t \tag{3.13}$$

13. If trip i started at time t-1, than at time t trip is also started.

$$st_{i,t}\geq st_{i,t-1} \qquad \forall i,t \tag{3.14}$$

14. Big M times 1 minus binary variable fn_{it} is greater or equal to minus t plus departure time of final station of trip i minus big M times 1 minus y_i.

$$M*(1-fn_{i,t})\geq -t+d_{K,i}-M*(1-y_i) \qquad \forall k,i,t \tag{3.15}$$

15. If trip i finished at time t-1, than at time t trip is also finished.

$$fn_{i,t}\geq fn_{i,t-1} \qquad \forall i,t \tag{3.16}$$

16. If trip i is being made at time t than trip is started but not finished.

$$z_{i,t}\geq st_{i,t}-fn_{i,t} \qquad \forall i,t \tag{3.17}$$

17. Number of trains on trip is equal to sum of binary variable z_{it} for all trips for time t.

$$tr=\sum_{i} z_{i,t} \qquad \forall t \tag{3.18}$$

18. Number of trains on trip is always less than or equal to total number of trains

$$tr\leq NT \tag{3.19}$$

19. Trip duration of trip i equals, arrival time to the final station minus arrival time to the initial station.

$$TD_i = a_{K,i} - d_{1,i} \quad \forall i \tag{3.20}$$

20. Number of passengers waiting at station k at time t is greater or equal to the previous passenger quantity at station k at time t-1, plus number of passengers arriving at station k at time t, minus passengers boarding on train if train arrives.

$$PS_{k,t} \geq PS_{k,t-1} + In_{k,t} - C * \sum_i x_{k,i,t} \tag{3.21}$$

21. Trip duration is greater or equal to cycle time if trip i is made.

$$a_{K,i} - d_{1,i} \geq ct - M*(1 - y_i) \quad \forall i \tag{3.22}$$

3.2.4. Objective function

The time a passenger spends waiting is a very critical issue for evaluating passenger service level. Typically, a railway passenger faces different types of waiting due to different causes. For instance, when connections are not properly scheduled, a passenger will have to wait a long time between trains. Trains running behind schedule will also create waiting times. During rush hours most of the trains meet with some considerable delay. Thus, for the actual travel time take during rush hour is typically longer than the ideal running time (Vansteenwegen and Oudheusden, 2006). Minimizing the cost of waiting in the stations is used as an objective at the study of Vansteenwegen and Oudheusden (2006). Minimizing operating cost of trains is used as an objective at the study of Claessens et al. (1998) and Lindler and Zimmermann (2005). Minimizing the sum of relative travel times is used as an objective function at the study of Castillo et al. (2011).

The objective of the proposed model is, to minimize number of passengers waiting at stations (1) and also to minimize number of trains on trip (2) according to the determined weight factors.

The decision makers can change the weights according to company's conditions.

Objective function:

$$\text{Min} \quad Z = w_1 * \sum_k \sum_t PS_{k,t} / \sum_k \sum_t In_{k,t} + w_2 * tr \tag{3.22}$$

3.2.5. Contribution to the timetabling problem

There are very few researches about timetabling which are specifically concentrated on light rail transit systems. So, this model is one of the very rare studies developed for timetabling of light rail transit systems. But on the other hand light rail transit is very similar to rail transportation. That's why, in this research we focus and inspired from train timetabling studies.

The parameters in this model such as transfer times (Vansteenwegen and Oudheusden, 2006), set of stations(Caprara et al., 2001, 2011), trip index (Chang and Chung, 2005), time index and minimum dwell time (Khan and Zhou, 2010), maximum dwell time (Castillo et al., 2008), headway time (Zhou and Zhoung, 2005), duration time between stations (Tormos et al., 2008), total number of trains (Nielsen et al.i 2006), capacity of train (Chang and Chung, 2005) and cycle time (Cacchiani and Toth, 2012) are all already used at other studies in literature. The new parameters introduced by the model are the number of passengers arriving at station k at time t and start and finish hour of trips.

The common variables used in this model are actual run time for train i (Castillo et al., 2008), arrival and departure time of train i at station q (Higgins et al., 1996). The new variable included in the model is, the number of passengers waiting at station k at time t.

The common constraints used in this model are headway and dwell time constraints (Castillo et al., 2008), arrival and departure time constraints (Caprara, 2006), cyclic schedule constraints (Vansteenwegen and Oudheusden, 2006), number of trains (Kroon and Peters, 2005) and trip time constraints (Cacchiani and Toth, 2012). The new constraints in the model are about the active number of trains on trip. Finally, the new objective function in the model is about minimizing number of trains on trip plus ratio of number of passengers waiting at station k and t over total number of passengers.

3.3 Modelling of Crew Assignment Problem

Crew assignment problem mainly considers assignment of machinists to days and shifts during a fixed period of time generally week period. It is extremely difficult to find good solutions to these highly constrained and complex problem and even more difficult to determine optimal solution that minimise costs, meet employee preferences, distribute shifts equitably among employees and satisfy all workplace constraints (Ernst, 2004). Generally machinist assignment problem is solved separately from timetabling problem. But in this model, the results of the timetabling problem give input to the machinist assignment problem.

There will be two input tables:

1. Start and finish hour of each trip
2. Whether there will be trip for the related day and shift or not.

At Section 3.3.1 general assumptions of machinist assignment problem are listed. Section 3.3.2 includes problem formulation and next section includes constraints of the model. Finally the objective function is explained at Section 3.3.4.

3.3.1 General assumptions

The assumptions of machinist assignment problem are made as generic as possible so that the model can be applied to several LRT companies.

1. Planning period for machinist assignment is one week. Each week starts at Monday and finish on Sunday.

2. All machinists must work at most six days.

3. There are j shifts at one day.

4. Each machinist can be assigned at most 1 shift in the same day.

5. The workload among all machinists must be balanced. If a machinist works more hours than others at previous week than this extra work is considered while making following weeks assignments.

6. All machinists are working with same shift hours.

7. Machinists must rest between two consecutive trips according to rest period (Ernst et. al, 2001).

8. There is minimum and maximum working hours for machinists (Gomes et al., 2006).

9. Machinist quantity working at the company is assumed to be constant as we focus on short-midterm planning.

10. It is assumed that all required machinists for a shift must be ready at the beginning time of a shift.

3.3.2 Problem formulation

The purpose of the crew assignment model is to balance machinists work load and make required assignments to shifts and trips.

The solution of model should provide answers to the questions listed below:

1. At which days of the week machinists should work or rest?
2. At which shift does the machinist assigned if it is the working day of machinist?
3. What should be the total working and resting duration will be for each machinist?

The following notation for explaining the model:

δ: Machinist index $\delta = 1, 2,...\delta$

d: Day index d=1, 2...7 (Zaffalon et al., 2008).

j: Shift index j= {1... J} represents the set of shifts in a day.(Zaffalon et al., 2008).

v: Trip start time and finish time index v= st, fn

Parameters:

$H_{\delta d}$: Order of off-day preference of machinist δ at day d (Hojati, 2010).

$SP_{\delta j}$: Preference of shift for machinist δ and shift j.

tr_{djiv}: Start and finish hour of each day, shift and trip.

y_{dji}: Binary parameter whether the trip i will be done at day d and shift j.

λ: Weight of machinists off-day preferences.

TC_{δ}: Total cumulative working hour of machinist δ.

Φ: Balance coefficient for working hours.

M: Big M number.

WH_{max}: Weekly maximum working hour of machinists.

WH_{min}: Weekly minimum working hour of machinists.

WHD_{max}: Daily maximum working hour of machinists.

WD_{max}: Maximum number of days in a week that a machinist must work.

Variables:

$w_{\delta dji}$: Binary variable for assignment of machinists. Whether machinist δ is assigned to trip i at day d and shift j. $w_{\delta dji} \in \{0,1\}$

$q_{\delta d}$: Binary variable for working day of machinist. Whether machinist δ is working at day d or not. $q_{\delta d} \in \{0,1\}$

$p_{\delta dj}$: Binary variable for working shift of machinist. Whether machinist δ is working at day d and shift j or not. $q_{\delta dj} \in \{0,1\}$

$tw_{\delta d}$: Total daily working hours of machinist δ.

U: Balance variable for working hours

3.3.3 Model constraints

1. Each machinist must work at most 1 shift in a day.

$$\sum_j p_{\delta dj} \leq 1 \quad \forall \delta \in \{A, B, ..., \delta\}, \quad \forall j \in \{1,2,...,J\} \tag{3.23}$$

2. If a machinist is assigned to late shift in a day, he must not assign to an early shift in the next day.

$$p_{\delta dJ} + p_{\delta d+11} \leq 1 \quad \forall \delta \in \{A, B, ..., \delta\}, \quad \forall d \in \{1,2,...,D\} \tag{3.24}$$

3. If a machinist is assigned to a trip he could not assigned to another trip at the same time.

$$\sum_{\delta} w_{\delta dji} \leq 1 \quad \forall d \in \{1,2,...,D\} \quad \forall j \in \{1,2,...,J\} \quad \forall i \in \{1,2,...,I\} \tag{3.25}$$

4. If a machinist is not assigned to any trip at a day, this means he is not working at that day.

$$\sum_i w_{\delta dji} \leq p_{\delta dj} * \mathrm{M} \quad \forall d \in \{1,2,...,D\} \quad \forall j \in \{1,2,...,J\} \tag{3.26}$$

5. A workload balance must be satisfied among machinists.

$$\sum_d \sum_j \sum_i (tr_{dji"fn"} - tr_{dji"st"}) * w_{\delta dji} + TC_{\delta} - U \leq 0 \quad \forall \delta \in \{A, B, ..., \delta\} \tag{3.27}$$

6. Balance variable is greater than 0 and less than maximum weekly working hour.

$$WH_{\max} \leq U \leq 0 \tag{3.28}$$

7. Total weekly working hour of each machinist must be less than or equal to maximum weekly working hour.

$$\sum_d \sum_j \sum_i (tr_{dji''fn''} - tr_{dji''st''}) * w_{\delta dji} \leq WH_{\max} \quad \forall \delta \in \{A, B, ..., \delta\} \tag{3.29}$$

8. Total daily working hour of each machinist must be less than or equal to maximum daily working hour.

$$\sum_d \sum_j \sum_i (tr_{dji''fn''} - tr_{dji''st''}) * w_{\delta dji} - tw_{md} \leq 0 \quad \forall \delta \in \{1,2,...,\delta\} \quad \forall d \in \{1,2,...,D\} \tag{3.30}$$

$$tw_{\delta d} \leq WHD_{\max} \quad \forall \delta \in \{1,2,...,\delta\} \quad \forall d \in \{1,2,...,D\} \tag{3.31}$$

9. Total working hour of each machinist for each day must be greater than or equal to minimum weekly working hour.

$$\sum_d \sum_j \sum_i (tr_{dji''fn''} \quad tr_{dji''st''}) * w_{\delta dji} \geq WH_{\min} \quad \forall \delta \in \{A, B, ..., \delta\} \tag{3.32}$$

10. Each machinist must work at most 6 (WDmax) days in a week.

$$\sum_d q_{\delta,d} \leq WD_{\max} \quad \forall \delta \tag{3.33}$$

11. If a machinist is not working at a specific day then this means also he does not work at any shift of that day.

$$q_{\delta,d} * M \leq \sum_j p_{\delta dj} \quad \forall \delta \in \{A, B, ..., \delta) \quad \forall d \in \{1,2,..., D\} \tag{3.34}$$

12. If a machinist is working at least 1 shift in a specific day then this means he is working at that day.

$$q_{\delta,d} * M \leq \sum_j \sum_i w_{\delta dji} \quad \forall \delta \in \{A, B, ..., \delta) \quad \forall d \in \{1,2,..., D\} \tag{3.35}$$

13. Machinists should not take two consecutive trips.

$$w_{\delta dji} + w_{\delta dji+1} \leq 1 \quad \textbf{(3.36)}$$

14. If there is a trip at day d shift j a machinist must be assigned to that trip.

$$\sum_{\delta} w_{\delta dji} = \mathrm{y}_{dji} \quad \forall d \in \{1....D\} \quad \forall j \in \{1....J\} \quad \forall i \in \{1,2,...,I\} \quad \textbf{(3.37)}$$

3.3.4 Objective function

The objective of the model is to minimize a linear combination of several costs (Ernst et al., 2001):

- Penalty cost of assigning machinists unparalleled to their off-day preferences
- Penalty cost of assigning machinists to the shifts that they do not prefer
- Penalty cost of unbalancing total working hours among machinists
- Fixed cost of total number of machinists working at a specific day

Objective function according to the objectives listed below is defined as:

$$\begin{aligned} &\mathrm{Min} \quad \mathrm{Z} = C1 * \sum_{\delta}\sum_{d}\sum_{j} h_{\delta,d} * p_{\delta,d,j} + C2 * \sum_{\delta}\sum_{j} SP_{\delta,j} * p_{\delta,d,j} + \\ &C3 * (1 - U / \phi) + C4 * \sum_{\delta}\sum_{d} q_{\delta d} \end{aligned} \quad \textbf{(3.38)}$$

3.3.5 Contribution to the machinist assignment problem

There are several studies in literature which are focusing on crew assignment for rail or air transportation. The models proposed in these studies are not integrated with timetabling models except the ones we already listed at Table 2.4. On the other hand, there are some constraints in machinist assignment models which can change according to the company or the country that the model is applied. Especially the rules about rest hours of machinists and weekly or monthly maximum workloads are determined by labour law or companies' policies. This model is a leading model which includes constraints compatible with labour law of Turkey. Also, the model is flexible enough for adapting to any kind of rail transportation company.

The common parameter of the model are day and shift (Zaffalon et al., 1998), off-day preferences (Hojati, 2010), maximum and minimum daily and weekly working hours

(Ernst et al., 2001). The new parameters are shift preferences, total cumulative work hour, trip start and finish hours and balance coefficient.

The common variable used in the model is the binary variable used for assignment of machinists. The new variables used in the developed model are: balance variable for working hours, binary variable for working day and working shift of the machinist. total daily working hour of machinists.

The common constraints in the model are workload constraints (Dorrian et al., 2011) and minimum, maximum working hour constraints (Ernst et al., 2001).

The common objectives in the model are penalty cost of unbalancing total working hour among machinists and fixed cost of total number of machinists working at a specific day (Ernst et al., 2001). The new introduced costs in the objective function is the penalty cost of assigning machinists unparalleled to their off-day preferences and penalty cost of assigning machinists to the shifts that they do not prefer.

3.4 Solution of Model with Using Mixed-Integer Programming

Mixed-integer programming is used in order to solve timetabling and crew assignment problem. In Section 3.4.1 the motivation for using MIP (mixed-integer programming) is explained. In Section 3.4.2 the results of the proposed model are explained.

3.4.1 Motivation for using mixed-integer programming

A mixed-integer programming problem results when some of the variables in the model are real valued and some of the variables are integer valued. The model is therefore “mixed”. Mixed integer programming is up today one of the most widely used techniques for dealing with hard optimization problems (Tramontani, 2009). They can be used to formulate just about any discrete optimization problem and are heavily used in practice for solving problems in transportation and manufacturing: airline crew scheduling (Klabjan et al., 2001), vehicle routing (Wen et al., 2009), production planning (Wolsey, 1997), etc.

Train scheduling is an optimization problem that has been argued to be NP-hard problem in the literature. It was formulated by many researchers using integer-programming techniques (Caprara et. al, 2001, Caprara et al, 2006, Vansteenwegen and Oudheusden, 2006- 2007, Zhou and Zhoung, 2007, Higgins et al., 1996).

It is necessary to combine continuous and binary or integer variables in order to solve timetabling problems which is leading to mixed integer (MIP) linear and nonlinear programming problems (Castillo et al, 2008).

MILP is in the NP-hard computation class. Many references consider mixed integer linear programming (MILP) formulations in which the arrival and departure times are represented by continuous variables and there are logical (binary) variables expressing the order of the train departures from each station.

The previous studies that used mixed-integer programming at timetabling and crew assignment problems are summarized at Table 3.1.

Table 3.1 : Use of MIP in timetabling and crew assignment problems.

Study	Objective	Citation
A mixed-integer programming approach to a class timetabling problem	Minimize class conflicts, providing good offering patterns, and enhancing traffic flow	Yakoob and Sherali, 2007
A flexible MILP model for multiple-shift workforce planning	Balancing the workload of the employees or minimizing the workforce size	Hertz et al., 2010
Finding Short Integral Cycle Bases for Cyclic Timetabling	Minimize the number of vehicles required to operate given pairs of hourly served railway lines, and the waiting times faced by passengers along the most important connections	Liebchen, 2003

3.4.2 Output variables of timetabling and crew assignment models

In order to solve the timetabling and crew assignment problem, commercial mixed integer solver CPLEX 9.0 is used.

The timetabling model coded at GAMS listed the results of the following variables as run results:

- Arrival times of trips
- Departure times of trips
- Dwell times for each station at time t
- Actual trip durations of each trip
- Number of passengers waiting at stations at station k at time t
- Start time of each trip
- Finish time of each trip

It is assumed that the timetabling model has to be run on shift basis for mid-term planning. This means the planner has the information of start and finish hour of each trip for each shift and day of the week, on hand before running machinist assignment model (TR (d,j,i,v)).

Moreover the information of whether a trip will be made at day d shift j is on hand as binary input parameter for machinist assignment model (y(d,j,i)).

The machinist assignment model coded at GAMS listed the results of the following variables as run results:

- Binary variable whether machinist is working at day d, shift j and trip i or not
- Total working hour of a machinist at a specific day and shift

4. A REAL-LIFE APPLICATION FOR INTEGRATED TIMETABLING AND CREW ASSIGNMENT PROBLEM

This chapter presents the real-life application of the model for LRT lines in İstanbul. Section 4.1 gives a brief definition of the data taken from a transportation company for solving the problem. The analysis of demand data and the first model run results are presented at Section 4.2. The relationship between timetabling and crew assignment models is explained at Section 4.3. In Section 4.4 the machinist model run results are presented.

4.1 Real-life Data Taken from a transportation company in Istanbul.

Istanbul is a metropolis which has serious traffic problem and population of 12 million people. However, in İstanbul and also in Turkey, LRT is at very early stage of its development. There is only one active line between Aksaray-Central Bus Station-Airport which operated by a transportation company in Istanbul. This line is 20 km long, carries 240 thousand passengers daily through the 18 stations within 31 minutes. The layout of the line is given at Appendix A.

Currently there are three different vehicle timetables prepared, one for weekdays and one for Saturday and one for Sunday. These timetables are prepared according to experiences of planners in the company. This means, heuristics is used for timetabling and crew assignment of LRT in real-life. These sets of three timetables are revised at least twice a year because of seasonal changes of passenger demand patterns.

List of data taken from the transportation company in Istanbul is listed below:

- Inflow of passengers for each station
- Distances between stations in terms of time
- Headway time of the line
- Minimum dwell time of train at stations

- Number of trains
- Capacity of trains

4.2. Analysis of Passenger Demand and Run Results

The passenger demand data is taken from LRT Aksaray-Airport line both for weekdays and weekends for two different month of the year. The graphics for demand data are listed at Appendix B. The demand data are analysed for 17 stations. For Aksaray station, the peak demand hours are between 18.00 and 20:00. The reason is that it is end of work hours for most of the people. The behaviour of demand graphic is also same for other stations. Also for some stations like Emniyet, Ulubatlı, Bayrampaşa and Kartaltepe the morning hours between 07:15 and 09:15 are also rush hours. The demand behaviour is only change for bus station and airport stations which are transportation hub points for land or air transportations. That's why; passenger volume graphic is smooth for whole day for Otogar and Havalimanı stations.

The transformation of passenger data from 15 minute intervals to 1 minute intervals considering uniform distribution is made. The reason of choosing uniform distribution is, assuming that, in this short time interval, the demand behaviour of passengers does not change. In order to solve the model, the passenger demand data realized for a specific day in 2008 for 17 stations, 450 minutes (time period 06:00-13:30) in Istanbul LRT system are taken into consideration. The run parameters are listed at Appendix C, Table C-1. Model is run six times by CPLEX-MIP -9.0. Passenger data is given as input to the model in minute's interval.

The parameters of train capacity and weights of objectives are changed and the results are listed at Table 4.1. The results are calculated considering first 100 minutes. Only the numbers of passengers waiting minutes are calculated for 450 minutes with the trip finish time of 300 minutes. The model run duration is, 9,992 seconds on average for 30 variables and 29 constraints for the six run listed at Table 4.1. The execution times are given at Appendix D for each run. The model is run on a notebook with CPU 2 Ghz, memory 8 GB and i7 processor. The execution time will be dramatically decreased when the model will be run on servers of transportation companies.

At the first run, capacity is taken as 1,000, the weight of the first objective is taken as 0.4 and the second objective is taken as 0.6, the maximum number of trains on trip is calculated as 7. At the second run, weight of first objective is increased to 0.6 and it is seen that the number of trips and active number of trains on trip are increased to 10, meanwhile number of passengers waiting minutes decreased. At the third run, weight of the first objective is increased to 0.8, the number of trips is again 10, active number of trains is decreased to 7 and number of passengers waiting minutes decreased as expected. At the fourth run, the capacity of train is decreased to 800so the number of trips is increased to 24 and active number of trains increased to 16 also number of passengers waiting decreased. At the fifth run, train capacity is increased to 1200, weight 1 is 0.6 and weight 2 is 0.4, number of trips is decreased to 5, active number of trains decreased to 3. And finally at the sixth run when the first weight increased to 0.8, number of trips is decreased to 8 and active number of trains decreased to 7.

Table 4.1 : Run results of timetabling model.

Parameters	Run #1	Run #2	Run #3	Run #4	Run #5	Run #6
Weight 1	0.4	0.6	0.8	0.8	0.6	0.8
Weight 2	0.6	0.4	0.2	0.2	0.4	0.2
Capacity	1,000	1,000	1,000	800	1,200	1,200
RESULTS						
Number of trips	7	10	10	24	5	8
Active number of trains	6	10	7	16	3	7
Number of passengers waiting minutes	6,556,903	6,547,361	6,482,294	6,366,015	6,558,087	6,525,488
Execution time	10,265	10,358	13,744	13,136	6,350	6,099

The timetable of a LRT line in İstanbul is compared with model results. The total number of passengers waiting at stations for each minute is compared according to actual timetable and proposed timetable. Two sets of results are compared for 100 minutes duration, in morning hours (06:00-09:20) for validation. The reason of selecting this interval is that, morning hours are rush hours. When we compare the passengers' total waiting minutes, fourth run seems to be the best alternative. The reason that fourth run is not selected is the capacity of the train is not the actual capacity in real life which is 1,000 passengers. That's why; third run is selected for comparison. Planning experts working at a transportation company declared that both the customer service level and cost of operating trains are important for them. But, it is more important to minimize waiting times for passengers than cost issues. This means, the weights of 0.8 and 0.2 reflects this preference. The number of trains on trip is 10 according to third run results, but it is 14 according to actual timetable. The cost of having an additional trip is so high that, planning 4 extra trips differs in terms of cost efficiency. As a performance indicator, the average number of customers waiting per minute is also calculated. Considering the total number of passenger minutes waiting, the model results and real-life results are listed at Table E.1. The average number of passengers waiting per minute is calculated by, dividing the total number of passengers' minute waiting to the total number of passengers who come to all the stations for the 100 minutes. According to model results this value is 7.51, while it is 4.13 according to real-life data. These results show us that, cost issue is not taken into consideration in the real-life timetable planning. The cost of using an extra train for trips is significantly more expensive than waiting passenger 3.38 minutes more, compared to real life waiting durations. But in our model, as we want to minimize number of trains on trip while minimizing the passengers waiting minutes, the optimum timetable may result for a worse duration than the actual situation in terms of passengers' waiting minutes.

Hypothesis testing is made for number of passengers waiting at stations between actual timetable and model results (Run 3). Anova test is applied to the figures at Appendix E and results are listed at Table 4-2. The hypothesis testing is made according to the following claims:

H_0: The actual timetable and model timetable are equal.

H_1: The actual timetable and model timetable are not equal.

The F-critical value 3.88 at Table 4.2is greater than 3.84, $F_{.05,1,198}$ value at significance level 0.05. This means H_0 is rejected and there is significant difference between model results and actual timetable results in terms of total number of passengers at time t at station k.

Table 4.2: Single factor ANOVA Test Results.

ANOVA

Source of Variation	SS	df	MS	P-value	F crit
Between Groups	7262623	1	7262623	53,63338	5,95E-12
Within Groups	26811648	198	135412,4		
Total	34074271	199			

4.3. Relation between Timetabling and Crew Assignment Models

The planning process of transportation systems consists of three main steps after the line planning phase finalized (Lindler, 2000):

1. Train schedule planning
2. Planning of rolling stock
3. Crew management

Train schedule planning frequency is generally based on seasonal demand changes which means timetables are updated four times a year. The duties of crew are created according to the timetables and finally crews are assigned to the duties not to the trips at the timetable. This process prevents the flexibility of the planning and is not sensitive to short-term demand changes. The only way of managing short term changes is to revise existing timetables manually or by simple algorithms which aims not to deviate from the original timetable as much as possible. But this method does not guarantee that the final schedule is the optimum solution under changing constraints.

The model proposed in this thesis study aims to get final timetable solution as direct input parameter for crew assignment. As the timetables are created dynamically on shift basis, and the crew is directly assigned to trips after solution of the second model not only the solution guaranteed the optimality based on constraints but also planning steps reduced from 3 to 2 by skipping the duty generation step.

The timetabling model solution results are taken into consideration as input parameters to the crew assignment problem are:

- Start and finish time of trip i, shift j and day d
- Binary variable whether trip i, shift j and day d is made or not.

The study of Walker et al. (2005) includes two blocks of constraints for train timetable generation and for the driver shifts. The two non-interacting blocks are linked by a piece of work sequencing constraints and shift length constraints. By the solution of this model day to day rescheduling of disrupted trains is satisfied. But the model developed in this thesis study is used for shift based timetabling and can be used for weekly assignment of machinists. The study of Veelenturf et al. (2012) is completely based on retiming of an existing timetable and assignments. But the model built in this thesis study in building a new timetable considering passenger demands.

4.4. Real-life Applications of Machinist Assignment Problem and Model Run Results

Machinist assignment model can be run on weekly, daily or shift basis. Generally it is preferred to prepare duties on weekly basis. Currently there are three duty plans prepared manually at the transportation company in Istanbul. One of the duty plans is for weekdays, one of them is for Saturday and last one is for Sunday. Duties are prepared according to two shifts for one day.

The daily working hour of a machinist is 570 minutes, but the available driving hour of machinists is taken as 430 minutes because machinists must rest between trips.

First shift trips starts at 06.00 and second shift starts at 14:00. These duties are than assigned to machinists according to the rules listed below:

- The machinists are assigned to trips according to first come first assigned rule.
- The machinists that assigned to earliest hours of trips are finalized their work day earlier than other machinists.

The main model parameters are listed at Table 4-3. The off-day and shift preferences, start and finish hours of trips, total extra work hours from previous week are also considered as input parameters. The off-day preferences are listed at Appendix F, Table F-1. The preferences are sorted from three to one. Three represents the most preferred; one represents the least preferred off-day for the related machinists.

Table 4.3 : Machinist model run parameters.

Parameters	Value
Number of machinists	40
Number of days	7
Number of shifts	2
Number of trips	90
Weight of day preferences of machinists	0.7
Workload balance coefficient	11,000
Minimum weekly work minute	200
Maximum working day in a week	6
Maximum daily work hours	430
Big number	1,000

In order to compare model results with the existing assignments more accurately the actual timetable data for March 2008 is taken into consideration for model run.

The total daily working hours of machinists for two shifts for weekdays, Saturday and Sunday according to the data taken from a transportation company in İstanbul for March 2008 are listed at Appendix G, Table G-1. The number of machinists working at specific days and shifts and efficiency rates are also listed at Appendix G, Table G-2 and compared both for real-life assignments and model run results. While calculating efficiency rates total working hours divided by daily working time limit of 570 minutes. Normally the target efficiency rate is 70%. This rate is the maximum value that can be achieved if the demand and trip frequency is too high.

When the results are analysed, it can be seen that the assigned number of machinists per day is significantly lower at model results, compared to real-life assignments.

Moreover, the average efficiency rate of machinists is 60.5% at real-life data while it is 61.4% according to model run results. Despite this improvement seems to be very slight, considering that this efficiency rate is reached by using a timetable that minimizes the number of trips, it is an important improvement. The target efficiency rate of 70% can be reached only when all the trains are completely scheduled to trips. But this is not the case, when cost of using trains on trip is considered. Moreover, the 60.5% efficiency rate is reached by heuristic method of transportation company planners according to years of experience. So, any small improvement on weekly plan base, have more impact on long-term.

5. CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

This chapter summarizes the main findings of the research. Section 5.1 gives a summary the results and discusses the opportunities and boundaries related to the application of the research, also explains the contribution of the research. In 5.2 the limitations of the study and directions for further research is discussed.

5.1 Conclusion

Due to the fact that, transportation is one of the most important problems for metropolis, there is rising need for solution of effective transportation planning problem. Quality of service is directly related with efficient planning which effects people's selections. Among several transportation alternatives, light rail transportation is a good alternative in terms of low initial building cost, low energy need per passenger and environmental advantages where passenger flows are high.

The scheduling of transportation systems is made by timetables. Timetable generation is the initial step. Then, considering the timetables, the duty generation step is made and finally crew assignment is made in order to guarantee that each train is equipped with necessary staff. The main operational problem here is, the timetabling problems are solved for long-periods and revised for shorter time periods if needed in real-life. That results to an inefficient timetable planning process.

In this study, the two new mathematical models are proposed for solution of the timetabling and crew assignment problem sequentially. Up to researchers' knowledge, there are very rare studies which concentrate on two problem areas sequentially. The passenger demand data is used as an input parameter in order to determine frequency of timetables. Parameters such as dwell time, cycle time, train capacity, headway time are considered in the model under certain assumptions. The objective of the developed model includes not only minimization of passengers waiting at stations but also minimizing number of trains on trips. This shows us that both the customer satisfaction and cost issues are considered in the model. Moreover, the model not only includes common parameters, variables and constraints which are also already used in literature but also includes new parameters, variable, constraint and objective function as a contribution to the literature.

The problems are built as the mixed-integer programming models and solved using GAMS. Then the effects of changes at parameters are interpreted. When the weight of the first part of objective function (ratio of the number of passengers waiting at time t at station k over inflow of passengers) is increased, and the weight of second part of objective function (number of trains on trip) is decreased, the number of trips planned is increased and the number of trains on trip is increased. This result is parallel with what is expected from the model according to weight input parameters. Because the model tries to minimize the number of trains on trip while at the same time tries to maximize the number of trips in order not to wait passengers at stations too long.

On the other hand, when the weight of the number of passengers waiting is decreased and the weight of number of trains on trip increased, the number of trips planned and the number of trains on trip is decreased. Normally the train capacity is fixed and 1,000 in real life. But, in order to test the behaviour of the model for changing parameters the capacity of train is increased. The capacity increase causes a decrease in the number of planned trips, while the train capacity decrease causes an increase at the number of planned trips as expected.

The validation of the model is made by comparing model results with real-life application. When the third run results compared with actual situation, it is concluded that, the number of planned trips is lower at the model run result compared to actual timetable. The number of trips planned is 14 in real life while it is 10 according to model results. On the other hand, the average number of passengers waiting per minute is 3.38 minutes higher than actual value. But considering the high cost of planning 4 additional train trips, we can conclude that model result is more efficient. Finally, hypothesis testing is made for the number of passengers waiting at stations. According to table 4.2., F value of 3.88 is higher than $F_{.05,1,198,}$ so we can conclude that model results and real life results are significantly different at significance level of 0.05.

Machinist assignment model is solved according to the actual timetable values. The start and finish hour of each trip for each shift and day of the week is given as an input parameter to the machinist assignment model. In addition, whether a trip will be made at a specific day and shift is also given as an input parameter to the machinist assignment model. The machinist assignment model is validated by comparing assigned machinist quantities per day and per shift and by comparing working hour efficiency rates according to the same timetable inputs. It is concluded that both the number of assigned machinists is lower at model run results and efficiency rate is higher at model run results.

To sum up, the main contributions of the study can be categorised in two main groups:

1. Theoretical contributions:

- Integrating the timetabling model with the crew assignment model. By combining two problems, trips are directly integrated with machinists, and a chance to bypass duty generation step is given. This provides more flexibility to regenerate machinist assignment tables for short and midterm planning periods. There are few studies in literature that combines two problems. Moreover, for LRT there is no study which handles these two problems together according to researchers' knowledge. These previous studies are listed at Table 2.3. Among four studies in literature that combines timetabling and crew assignment, two of them are about class and trainer scheduling, the rest is about train timetabling. LRT timetabling is similar to train timetabling. The two previous literature studies (Walker et al., 2005 and Veelenturf et al., 2012) which are focused on train timetabling and crew assignment simultaneously are especially concentrated on retiming of an existing timetable. So, there is limited integration between timetabling and crew assignment processes. At the study of Veelenturf (2012), the arrival and departure times are compared with planned arrival and departure times of train and it is aimed to minimize penalty cost of delay according to the original timetable. But in this study, a new timetable is generated at each run and arrival and departure times of train are calculated considering passenger demand and train trip cost. The constraints in the study of Walker (2005) are defined as two non-interacting blocks about train timetable generation and driver shifts.

These blocks are linked by piece of work sequencing and shift length constraints. The model developed in this study is integrating timetabling process with crew assignment process for short-middle period of time i.e. shift, daily, weekly basis. The outputs of the timetabling model are used as an input parameter at machinist assignment model. These parameters are: start and finish hour of each trip for each shift and day of the week and binary input parameter whether a trip is made or not at a specific day and shift.

- Usage of specific and new assumptions, parameters, constraints, variables and objective functions for problem area. As parameters, number of passengers arriving at stations at a specific time, and start and finish hour of trips are new introduced ones to the literature. The capacity of train is already used as a parameter by Chang and Chung (2005). But this parameter is used for calculating load factor of train, not used for calculating number of remaining passengers left at station at time the train arrives. As variable, number of passengers at stations is contribution of the research. Among the constraints of the model, the constraints for determining active number of trains are unique to this study. The studies focusing on customer satisfaction, generally tries to minimize cost of waiting time in stations or transfers (Vansteenwegen and Oudheusden, 2006) or tries to minimize the maximum relative travel time (Castillo et al., 2011). In this study, as a contribution passenger demand data is used at the objective function. The ratio of number of passengers waiting at stations over total passenger demand is used. Moreover, the active number of trains tried to be minimized at the same time considering cost effects.

The new introduced parameters, variables, constraints and objective function of machinist assignment problem are; shift preferences of crew, total cumulative work hour, trip start and finish hours and balance coefficient as parameters. Moreover as variables, balance variable for working hours, binary variable of machinists for assignment of a specific day, specific day and shift and total daily working hour of machinists are new variables specific to this study. The constraints about assignment to consecutive trips, working day and working shift constraints, machinist and trip assignment constraints are new constraints specific to this research. The objective function of machinist assignment problems generally includes cost terms such as penalty cost of unbalanced workload among crew (Ernst et al., 2001) or fixed cost of total number of crew working at a specific day (Ernst et al., 2001). But in this study in addition to these known costs, the penalty cost of assigning machinists unparalleled to their off-day preferences or shift preferences are also considered as a contribution to objective function of assignment models.

2. Managerial contributions:

- Instead of preparing manual timetables which are feasible but not optimal, automated GAMs model code can directly be used by planners for solution of the problem. By this way, not only the optimal solution is guaranteed, but also flexibility of regeneration of timetables and crew assignments when needed can be satisfied.
- The model covers extended parameters and constraints for LRT planning environment. So, by changing parameters, the model can fit many companies that needs to use an automated tool for timetabling and crew assignment. Especially, the rules about rest hours of machinists and weekly or monthly maximum workloads are determined by labour law or companies' policies. This model is a leading model which includes constraints compatible with labour law of Turkey. Also, the model is flexible enough for adapting to any kind of rail transportation company

5.2 Limitations and Future Research Directions

In this study several assumptions are made in order to solve the problem. This also brings some limitations to the study. The time unit is decided as minute which prevents sensitivity in seconds. The passenger capacity of stations are assumed to be infinite, because according to experts knowledge, in real-world the bottleneck point is the availability of trains to trips not the available space at stations. There can be extreme situations where station capacity is so small that, it also must be considered in the model. As the long-term planning is out of scope in the study, changes in machinist quantities because of hires and quits are ignored. The model is validated for a certain period. The period can be extended but, the model solution duration can be extremely high or even not possible because of memory limitations in order to solve at a standalone computer.

The possible future research directions are listed below:

- The extension of timetabling mathematical model for multi-line structures.
- Including connections of LRT lines to other modes of transportations such as bus or sea transportations in an extended model.
- Some of the parameters that are assumed constant within our model, such as train capacity, can be modelled dynamically by giving flexibility to change number of wagons connected at a train.

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APPENDICES

APPENDIX A: LRT Map of Istanbul

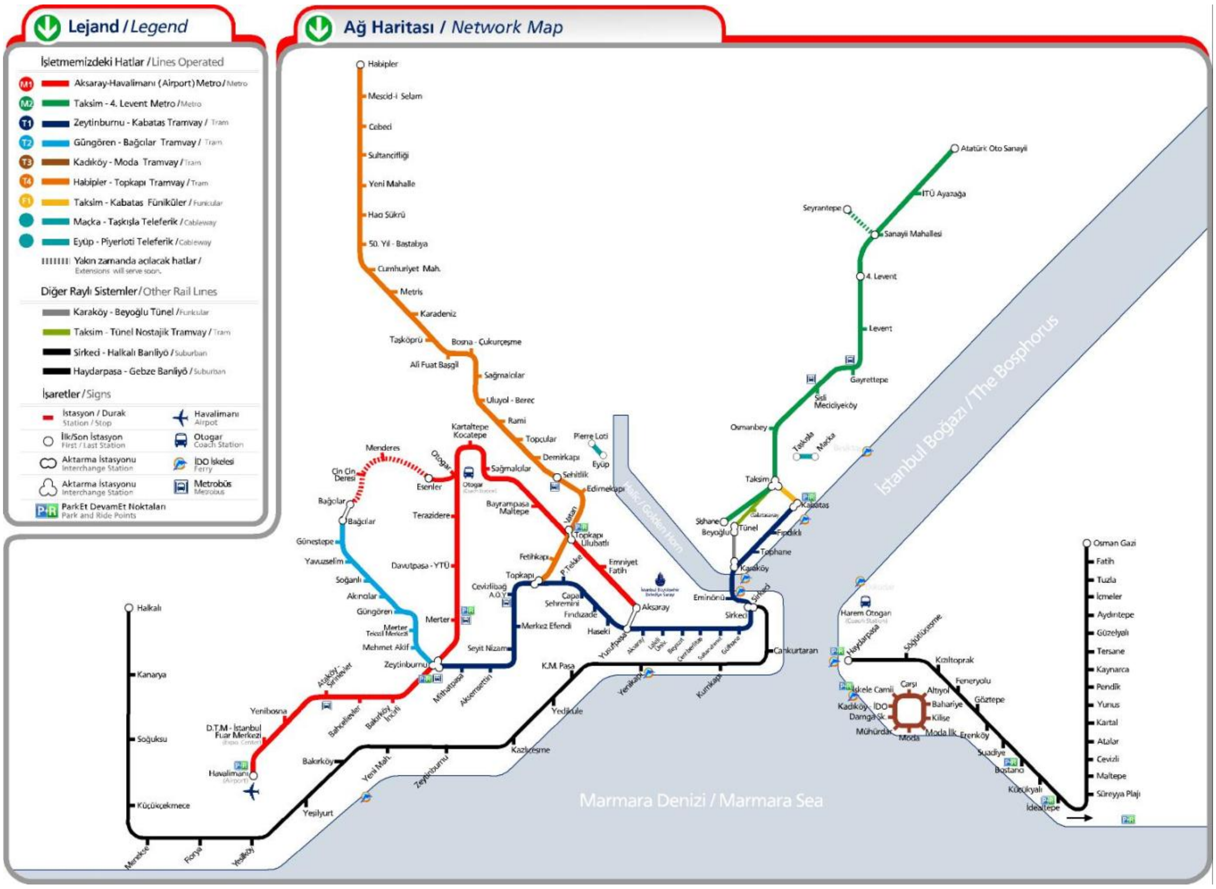

Figure A-1 : LRT layout of Istanbul.

APPENDIX B: Passenger Flow Graphics of Stations

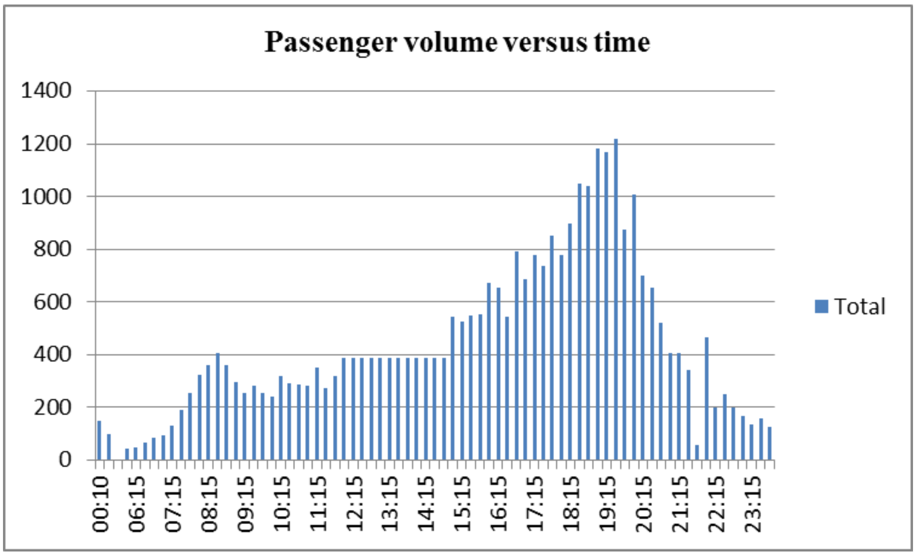

Figure B-1: Passenger volume versus time for Aksaray station.

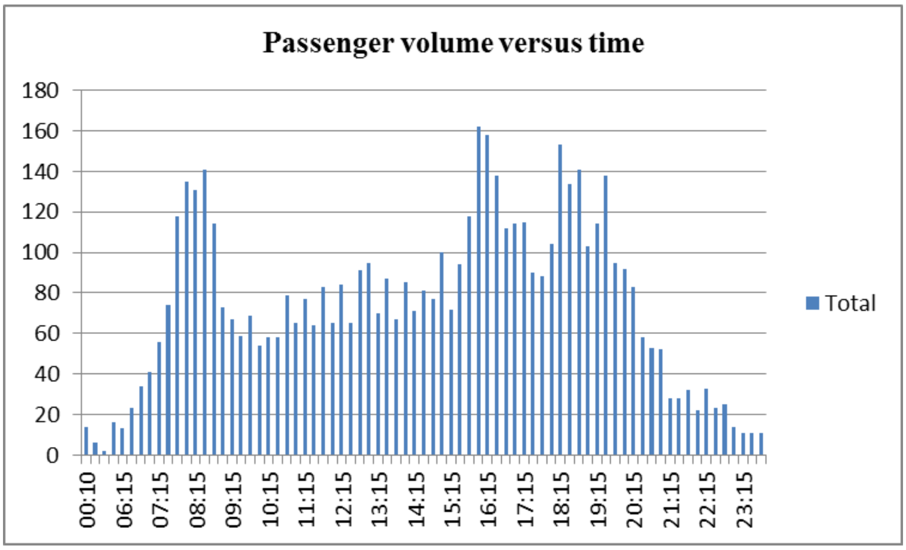

Figure B-2: Passenger volume versus time for Emniyet station.

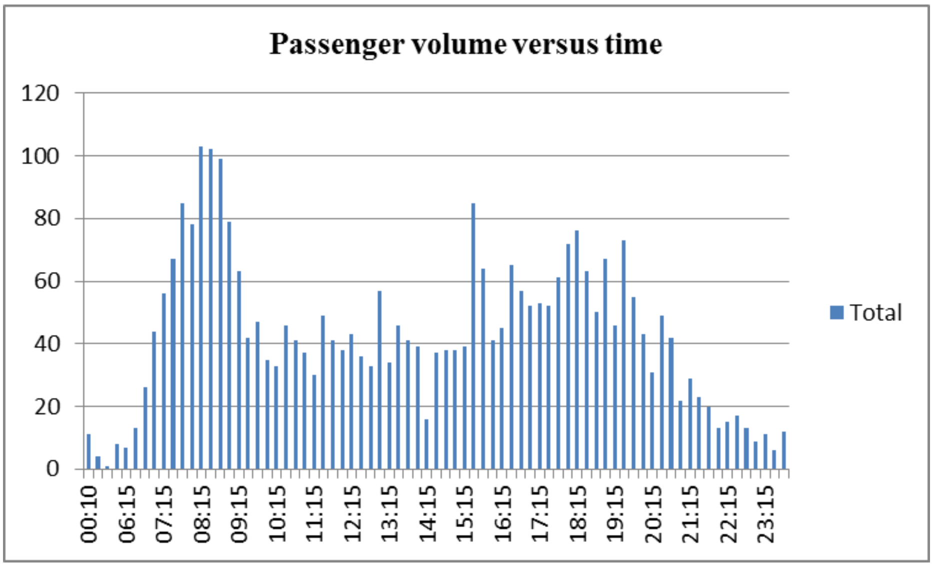

Figure B-3: Passenger volume versus time for Ulubatlı station.

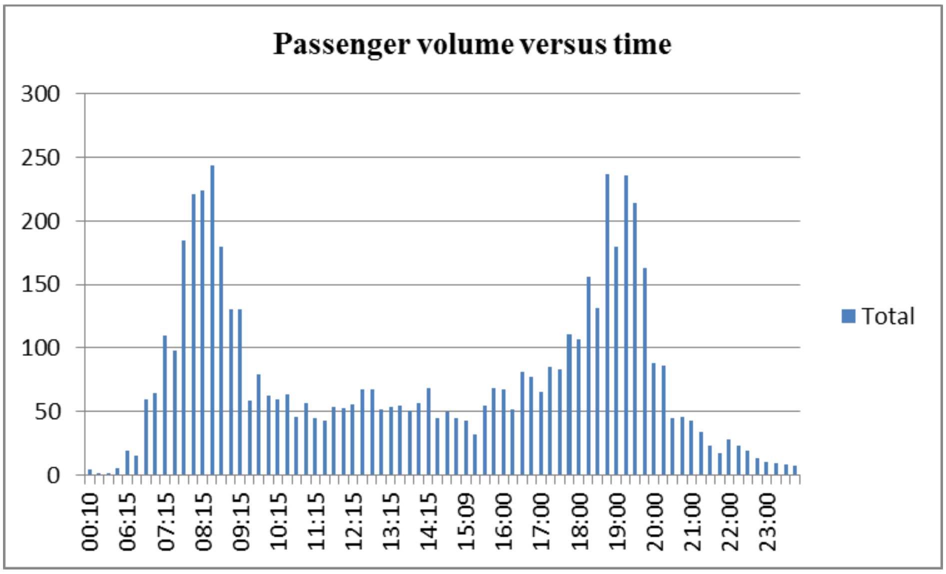

Figure B-4: Passenger volume versus time for Bayrampaşa station.

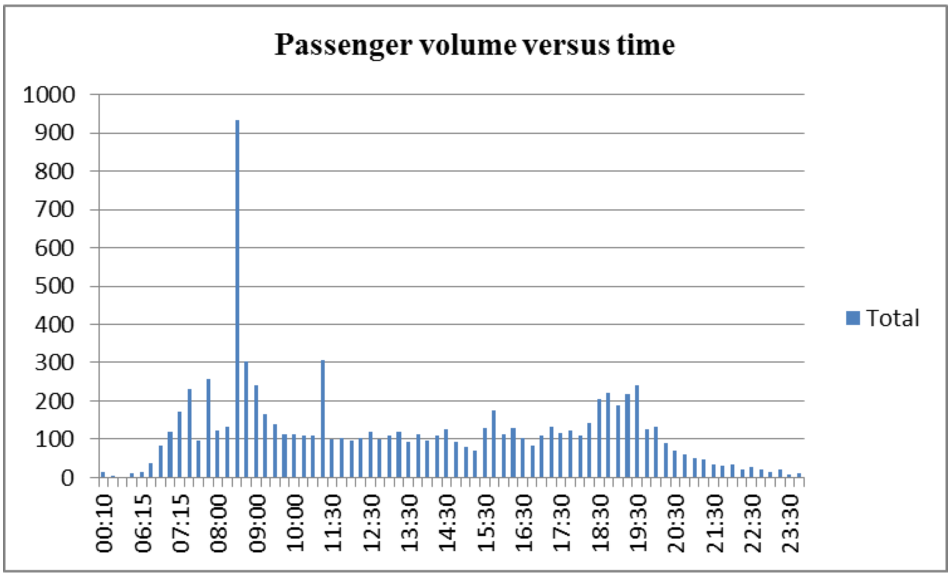

Figure B-5: Passenger volume versus time for Sağmalcılar station.

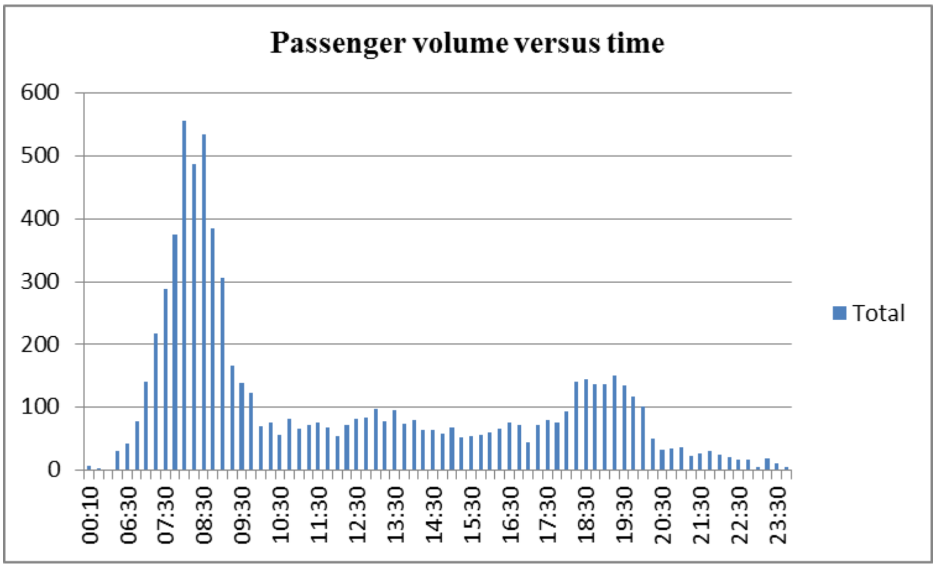

Figure B-6: Passenger volume versus time for Kartaltepe station.

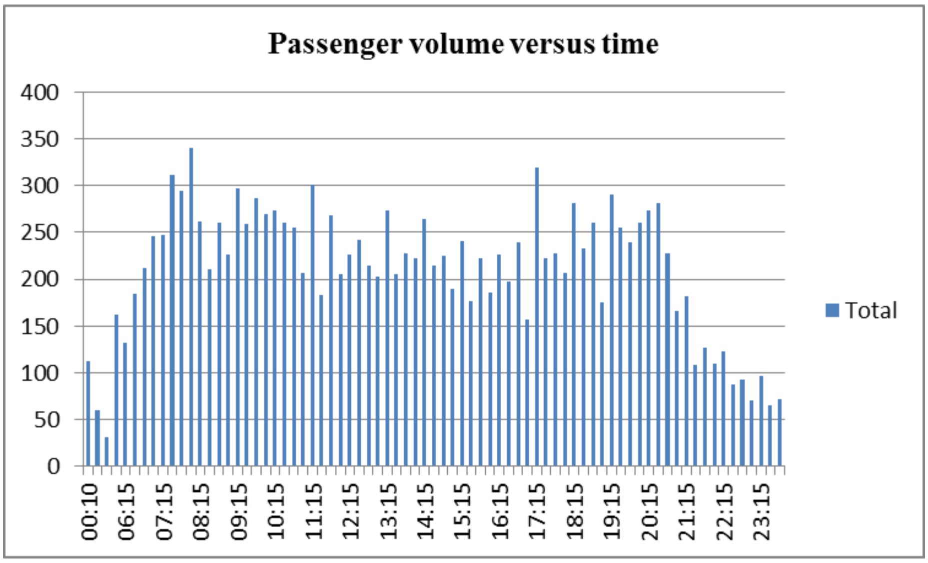

Figure B-7: Passenger volume versus time for Otogar station.

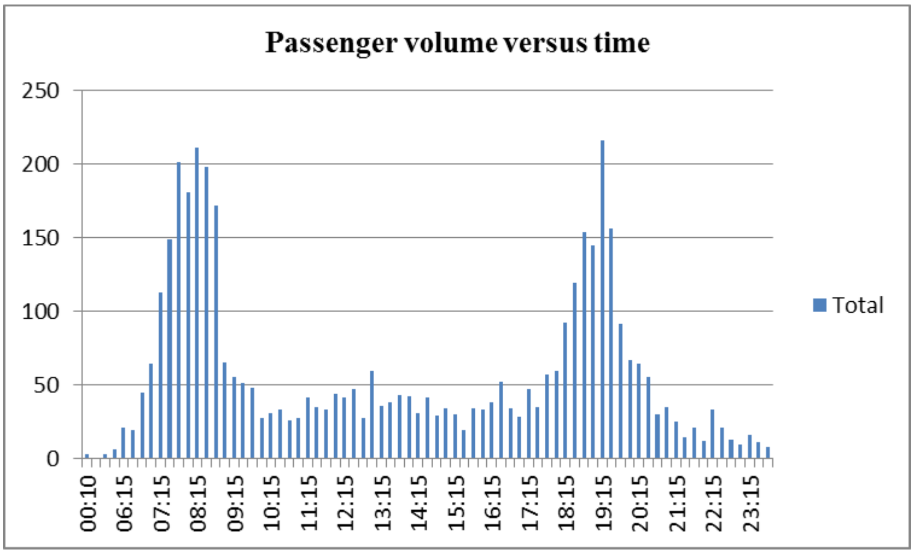

Figure B-8: Passenger volume versus time for Terazidere station.

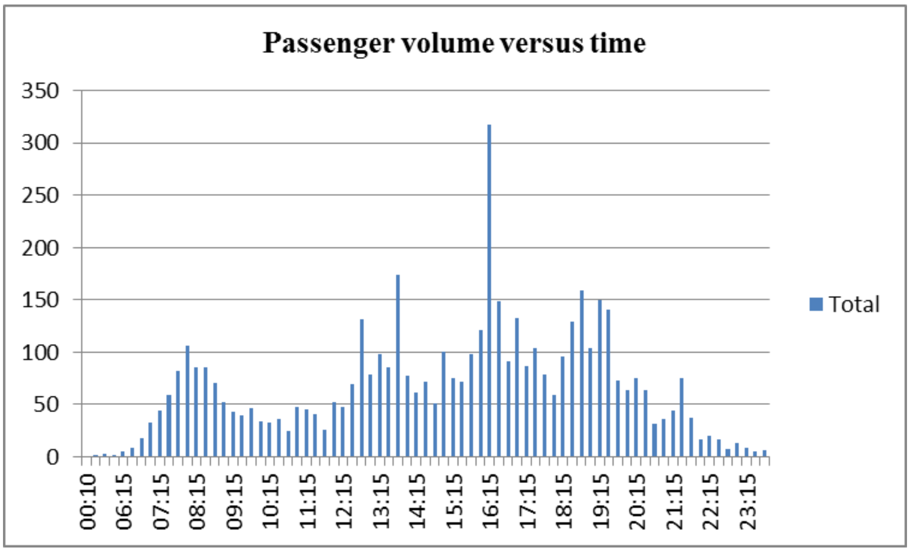

Figure B-9: Passenger volume versus time for Davutpaşa station.

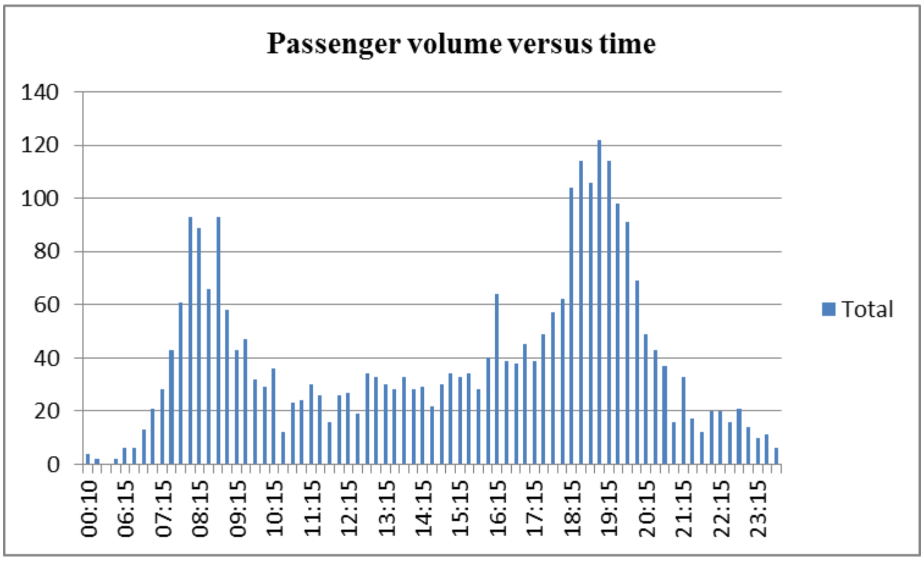

Figure B-10: Passenger volume versus time for Merter station.

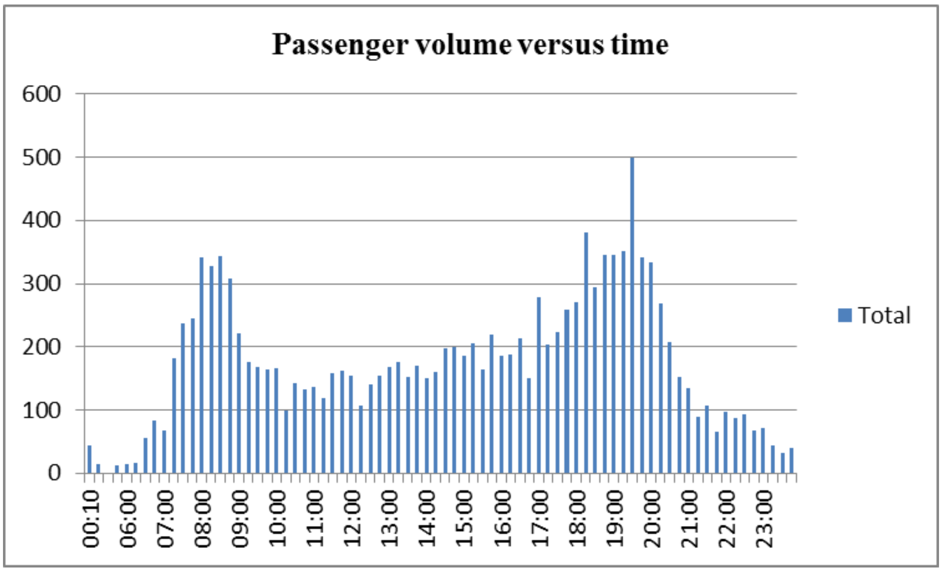

Figure B-11: Passenger volume versus time for Zeytinburnu station.

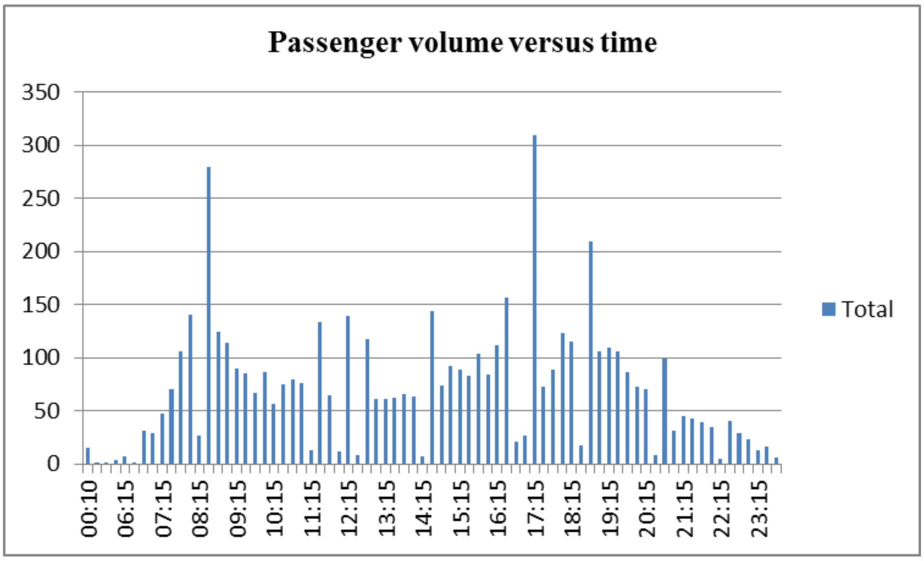

Figure B-12: Passenger volume versus time for Bakırköy station.

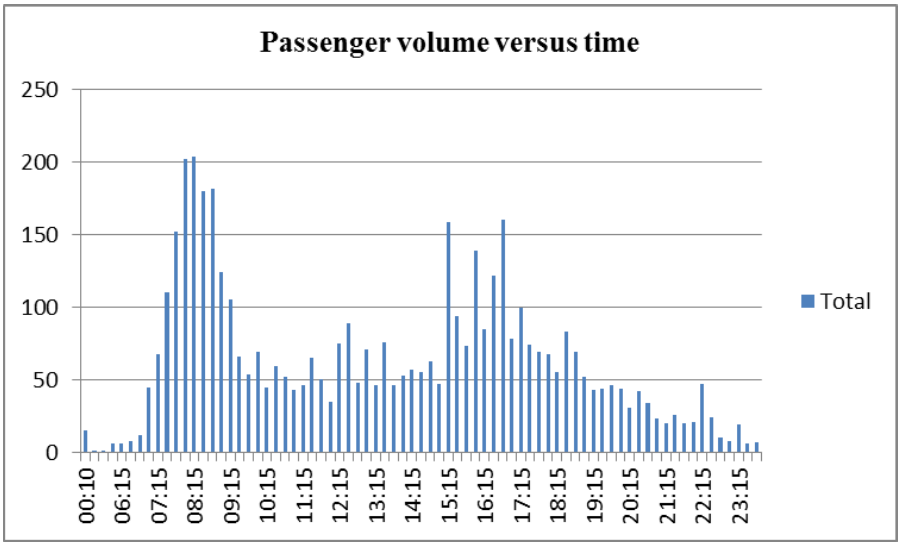

Figure B-13: Passenger volume versus time for Bahçelievler station.

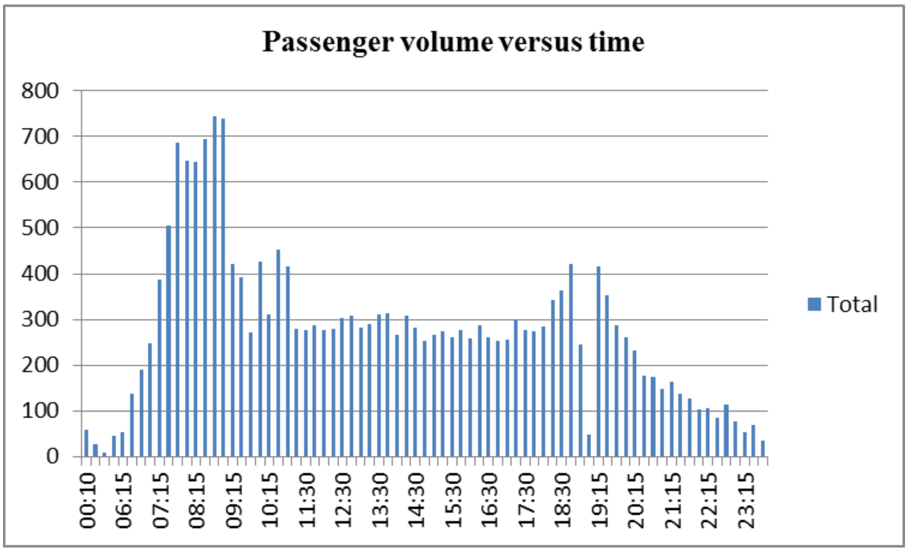

Figure B-14: Passenger volume versus time for Ataköy station.

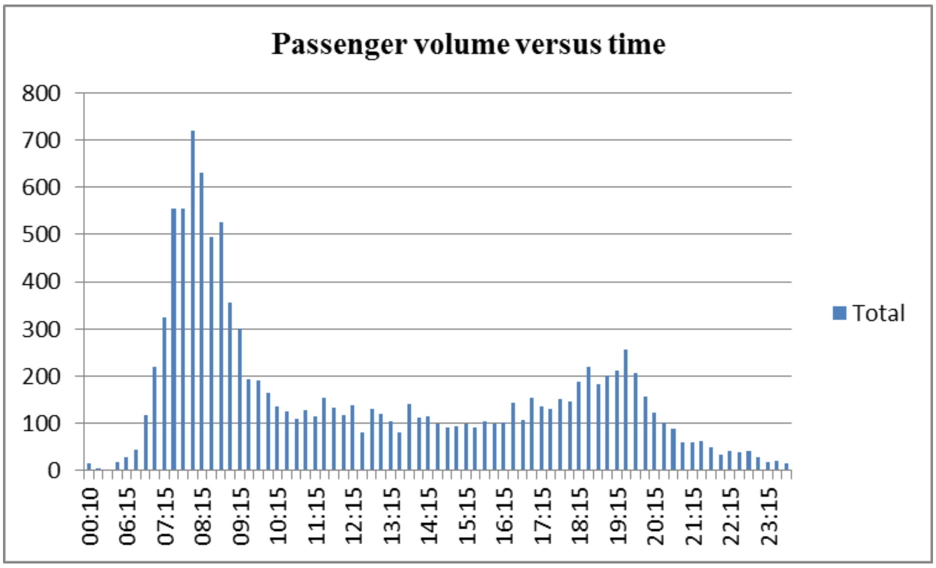

Figure B-15: Passenger volume versus time for Yenibosna station.

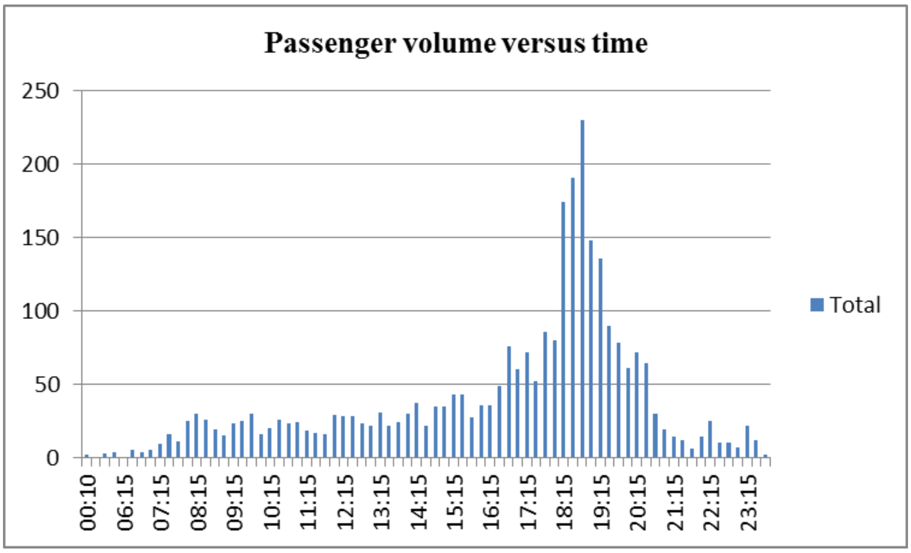

Figure B-16: Passenger volume versus time for DTM station.

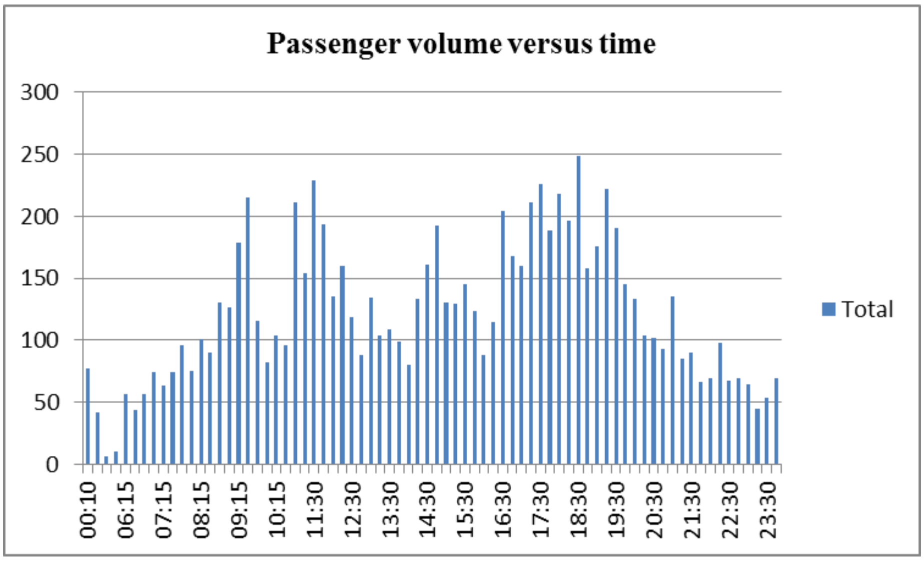

Figure B-17: Passenger volume versus time for HVL station.

APPENDIX C: Run Parameters of Timetabling Model

Table C.1 : Model run parameters

Parameters	Value
Number of stations	17
Number of trips	80
Time duration	450
Demand data duration	360
Minimum dwell time	0.5
Number of trains	20
Headway time	2.5
Start hour of trips	1
Finish hour of trips	300
Cycle time	62

APPENDIX D: Run Results of Timetabling Model

Table D.1: Model results for train capacity 1000, w1: 0.4, w2: 0.6.

---- 502 VARIABLE a.Larrival time of trip i to station k

	1	2	3	4	5	6
1	10,000	29,000	68,000	72,000	79,000	94,000
2	12,000	33,000	70,000	74,000	81,000	96,000
3	30,000	40,000	72,000	76,000	83,000	98,000
4	33,000	47,000	75,000	79,000	86,000	123,000
5	36,000	50,000	78,000	82,000	89,000	126,000
6	39,000	53,000	81,000	85,000	92,000	129,000
7	42,000	56,000	84,000	88,000	95,000	132,000
8	45,000	59,000	87,000	91,000	98,000	135,000
9	48,000	62,000	90,000	94,000	101,000	138,000
10	51,000	65,000	93,000	97,000	104,000	141,000
11	54,000	68,000	96,000	100,000	107,000	144,000
12	57,000	71,000	99,000	103,000	128,000	147,000
13	60,000	74,000	102,000	108,000	131,000	150,000
14	61,000	75,000	103,000	121,000	136,000	151,000
15	63,000	77,000	123,000	127,000	138,000	153,000
16	65,000	81,000	125,000	133,000	140,000	155,000
17	73,000	92,000	131,000	135,000	142,000	157,000

+	7	8
1	99,000	106,000
2	122,000	126,000
3	124,000	132,000
4	127,000	135,000
5	130,000	138,000
6	133,000	141,000
7	136,000	144,000
8	139,000	147,000
9	142,000	150,000
10	145,000	153,000
11	149,000	156,000
12	152,000	159,000
13	155,000	162,000
14	156,000	163,000
15	158,000	165,000
16	160,000	167,000
17	162,000	169,000

---- 502 VARIABLE d,Ldeparture time of trip i to station k

	1	2	3	4	5	6
1	11,000	30,000	69,000	73,000	80,000	95,000
2	13,000	38,000	71,000	75,000	82,000	97,000
3	31,000	45,000	73,000	77,000	84,000	99,000
4	34,000	48,000	76,000	80,000	87,000	124,000
5	37,000	51,000	79,000	83,000	90,000	127,000
6	40,000	54,000	82,000	86,000	93,000	130,000
7	43,000	57,000	85,000	89,000	96,000	133,000
8	46,000	60,000	88,000	92,000	99,000	136,000
9	49,000	63,000	91,000	95,000	102,000	139,000
10	52,000	66,000	94,000	98,000	105,000	142,000

Table D.1 (continued): Model results for train capacity 1000, w1: 0.4, w2: 0.6.

	1	2	3	4	5	6
11	55,000	69,000	97,000	101,000	108,000	145,000
12	58,000	72,000	100,000	106,000	129,000	148,000
13	61,000	75,000	103,000	109,000	136,000	151,000
14	62,000	76,000	104,000	126,000	137,000	152,000
15	64,000	80,000	124,000	132,000	139,000	154,000
16	66,000	82,000	130,000	134,000	141,000	156,000
17	74,000	97,000	132,000	136,000	143,000	158,000

+	7	8
1	100,000	107,000
2	123,000	131,000
3	125,000	133,000
4	128,000	136,000
5	131,000	139,000
6	134,000	142,000
7	137,000	145,000
8	140,000	148,000
9	143,000	151,000
10	146,000	154,000
11	150,000	157,000
12	153,000	160,000
13	156,000	163,000
14	157,000	164,000
15	159,000	166,000
16	161,000	168,000
17	163,000	170,000

---- 502 VARIABLE tr.L = 6,000 number of trains on trip at time t
---- 502 VARIABLE avg1.L = 121,508 average passenger waiting time
VARIABLE a1.L = 122,055
VARIABLE a2.L = 6,000
VARIABLE yt1.L = 5,3721,000total number of passengers
VARIABLE byt1.L = 6,556,903total number of passengers waiting at stations
VARIABLE obj.L = 52,422 objective
EXECUTION TIME = 10,265 SECONDS 185 Mb WIN235-235 Jul 2, 2010

Table D.2: Model results for train capacity 1000, w1: 0.6, w2: 0.4.

---- 502 VARIABLE a.Larrival time of trip i to station k

	1	2	3	4	5	6
1	29,000	38,000	67,000	71,000	75,000	79,000
2	31,000	55,000	69,000	73,000	77,000	81,000
3	33,000	61,000	71,000	75,000	79,000	83,000
4	36,000	66,000	74,000	78,000	82,000	86,000
5	39,000	69,000	77,000	81,000	85,000	89,000
6	42,000	72,000	80,000	84,000	88,000	96,000
7	45,000	75,000	83,000	87,000	91,000	99,000
8	48,000	78,000	86,000	90,000	94,000	102,000
9	51,000	81,000	89,000	93,000	97,000	105,000
10	54,000	84,000	92,000	96,000	100,000	108,000
11	57,000	87,000	95,000	99,000	103,000	111,000
12	60,000	90,000	98,000	102,000	106,000	118,000
13	63,000	93,000	101,000	105,000	109,000	121,000
14	64,000	94,000	102,000	106,000	114,000	130,000
15	84,000	96,000	104,000	112,000	116,000	132,000
16	90,000	103,000	107,000	114,000	136,000	140,000
17	92,000	105,000	130,000	134,000	138,000	142,000

+	7	8	9	10	11
1	83,000	87,000	95,000	99,000	104,000
2	85,000	89,000	97,000	111,000	125,000
3	87,000	91,000	99,000	117,000	131,000
4	90,000	94,000	106,000	120,000	134,000
5	97,000	101,000	116,000	123,000	137,000
6	100,000	108,000	119,000	126,000	140,000
7	103,000	111,000	122,000	129,000	143,000
8	106,000	114,000	125,000	132,000	146,000
9	113,000	117,000	128,000	135,000	149,000
10	116,000	120,000	131,000	138,000	152,000
11	119,000	123,000	135,000	141,000	155,000
12	122,000	126,000	138,000	144,000	158,000
13	125,000	129,000	141,000	147,000	161,000
14	134,000	138,000	142,000	148,000	162,000
15	142,000	146,000	150,000	158,000	164,000
16	144,000	148,000	156,000	160,000	166,000
17	146,000	150,000	158,000	162,000	169,000

---- 502 VARIABLE d.Ldeparture time of trip i to station k

	1	2	3	4	5	6
1	30,000	43,000	68,000	72,000	76,000	80,000
2	32,000	60,000	70,000	74,000	78,000	82,000
3	34,000	62,000	72,000	76,000	80,000	84,000
4	37,000	67,000	75,000	79,000	83,000	87,000
5	40,000	70,000	78,000	82,000	86,000	94,000
6	43,000	73,000	81,000	85,000	89,000	97,000
7	46,000	76,000	84,000	88,000	92,000	100,000
8	49,000	79,000	87,000	91,000	95,000	103,000
9	52,000	82,000	90,000	94,000	98,000	106,000
10	55,000	85,000	93,000	97,000	101,000	109,000
11	58,000	88,000	96,000	100,000	104,000	116,000
12	61,000	91,000	99,000	103,000	107,000	119,000
13	64,000	94,000	102,000	106,000	114,000	122,000
14	65,000	95,000	103,000	107,000	115,000	131,000
15	89,000	97,000	105,000	113,000	117,000	137,000
16	91,000	104,000	111,000	115,000	137,000	141,000
17	93,000	106,000	131,000	135,000	139,000	143,000

Table D.3 (continued): Model results for train capacity 1000, w1: 0.6, w2: 0.4.

+	7	8	9	10	11
1	84,000	88,000	96,000	100,000	107,000
2	86,000	90,000	98,000	116,000	130,000
3	88,000	92,000	104,000	118,000	132,000
4	91,000	99,000	111,000	121,000	135,000
5	98,000	106,000	117,000	124,000	138,000
6	101,000	109,000	120,000	127,000	141,000
7	104,000	112,000	123,000	130,000	144,000
8	111,000	115,000	126,000	133,000	147,000
9	114,000	118,000	129,000	136,000	150,000
10	117,000	121,000	132,000	139,000	153,000
11	120,000	124,000	136,000	142,000	156,000
12	123,000	127,000	139,000	145,000	159,000
13	126,000	130,000	142,000	148,000	162,000
14	135,000	139,000	143,000	150,000	163,000
15	143,000	147,000	155,000	159,000	165,000
16	145,000	149,000	157,000	161,000	167,000
17	147,000	151,000	159,000	163,000	170,000

---- 502 VARIABLE tr.L = 10,000 number of trains on trip at time t
---- 502 VARIABLE avg1.L = 121,325 average passenger waiting time
VARIABLE a1.L = 121,877
VARIABLE a2.L = 10,000
VARIABLE yt1.L = 53,721total number of passengers
VARIABLE byt1.L = 6,547,361total number of passengers waiting at stations
VARIABLE obj.L = 77,126 objective
EXECUTION TIME = 10,358 SECONDS 185 Mb WIN235-235 Jul 2, 2010

Table D.4: Model results for train capacity 1000, w1: 0.8, w2: 0.2.

---- 501 VARIABLE a.Larrival time of trip i to station k

	1	2	3	4	5	6
1	3,000	10,000	17,000	29,000	42,000	50,000
2	5,000	14,000	24,000	31,000	45,000	52,000
3	7,000	16,000	26,000	39,000	47,000	60,000
4	10,000	22,000	29,000	42,000	50,000	66,000
5	13,000	25,000	32,000	45,000	53,000	69,000
6	16,000	28,000	35,000	48,000	56,000	73,000
7	19,000	31,000	38,000	51,000	61,000	76,000
8	22,000	34,000	41,000	54,000	64,000	80,000
9	25,000	37,000	45,000	57,000	67,000	83,000
10	28,000	40,000	48,000	60,000	70,000	86,000
11	31,000	43,000	51,000	63,000	73,000	89,000
12	34,000	46,000	60,000	68,000	76,000	92,000
13	37,000	53,000	68,000	74,000	85,000	99,000
14	38,000	54,000	74,000	78,000	86,000	103,000
15	40,000	56,000	76,000	87,000	101,000	106,000
16	42,000	59,000	78,000	89,000	103,000	109,000
17	66,000	73,000	80,000	92,000	105,000	113,000

+	7	8	9	10	11
1	69,000	84,000	91,000	100,000	106,000
2	77,000	92,000	103,000	114,000	130,000
3	83,000	94,000	105,000	116,000	132,000
4	92,000	100,000	109,000	119,000	135,000
5	96,000	103,000	112,000	124,000	138,000
6	99,000	108,000	118,000	128,000	141,000
7	102,000	111,000	121,000	131,000	144,000
8	105,000	114,000	124,000	134,000	147,000
9	108,000	117,000	127,000	137,000	150,000
10	111,000	120,000	130,000	140,000	153,000
11	114,000	123,000	133,000	144,000	156,000
12	117,000	126,000	136,000	147,000	159,000
13	120,000	129,000	139,000	150,000	162,000
14	121,000	130,000	140,000	151,000	163,000
15	123,000	132,000	142,000	153,000	165,000
16	125,000	134,000	144,000	155,000	167,000
17	132,000	147,000	154,000	163,000	169,000

---- 501 VARIABLE d.Ldeparture time of trip i to station k

	1	2	3	4	5	6
1	4,000	11,000	18,000	30,000	43,000	51,000
2	6,000	15,000	25,000	32,000	46,000	53,000
3	8,000	17,000	27,000	40,000	48,000	61,000
4	11,000	23,000	30,000	43,000	51,000	67,000
5	14,000	26,000	33,000	46,000	54,000	70,000
6	17,000	29,000	36,000	49,000	57,000	74,000
7	20,000	32,000	39,000	52,000	62,000	77,000
8	23,000	35,000	42,000	55,000	65,000	81,000
9	26,000	38,000	46,000	58,000	68,000	84,000
10	29,000	41,000	49,000	61,000	71,000	87,000
11	32,000	44,000	52,000	64,000	74,000	90,000
12	35,000	47,000	61,000	69,000	75,000	93,000
13	38,000	54,000	69,000	75,000	86,000	100,000
14	39,000	55,000	75,000	79,000	87,000	104,000
15	41,000	57,000	77,000	87,000	102,000	107,000
16	45,000	60,000	79,000	90,000	104,000	110,000
17	67,000	75,000	81,000	94,000	106,000	116,000

Table D.5 (continued): Model results for train capacity 1000, w1: 0.8, w2: 0.2.

+	7	8	9	10	11
1	70,000	85,000	92,000	101,000	107,000
2	78,000	93,000	104,000	115,000	131,000
3	84,000	95,000	106,000	117,000	133,000
4	93,000	101,000	110,000	120,000	136,000
5	97,000	104,000	113,000	125,000	139,000
6	100,000	109,000	119,000	129,000	142,000
7	103,000	112,000	122,000	132,000	145,000
8	106,000	115,000	125,000	135,000	148,000
9	109,000	118,000	128,000	138,000	151,000
10	112,000	121,000	131,000	141,000	154,000
11	115,000	124,000	134,000	145,000	157,000
12	118,000	127,000	137,000	148,000	160,000
13	121,000	130,000	140,000	151,000	163,000
14	122,000	131,000	141,000	152,000	164,000
15	124,000	133,000	143,000	154,000	166,000
16	126,000	135,000	145,000	156,000	168,000
17	136,000	148,000	157,000	164,000	170,000

---- 501 VARIABLE tr.L = 7,000 number of trains on trip at time t
---- 501 VARIABLE avg1.L = 120,131average passenger waiting time

VARIABLE a1.L = 120,678

VARIABLE a2.L = 7,000
VARIABLE yt1.L = 53,721total number of passengers
VARIABLE byt1.L = 6,482,924total number of passengers waiting at stations
EXECUTION TIME = 13,744 SECONDS 185 Mb WIN235-235 Jul 2, 2010

Table D.6: Model results for train capacity 800, w1: 0.8, w2: 0.2.

---- 502 VARIABLE a.L arrival time of trip i to station k

	1	2	3	4	5	6
1	3,000	7,000	11,000	15,000	19,000	23,000
2	5,000	9,000	13,000	17,000	21,000	25,000
3	7,000	11,000	15,000	19,000	23,000	27,000
4	10,000	14,000	18,000	22,000	26,000	30,000
5	13,000	17,000	21,000	25,000	29,000	33,000
6	16,000	20,000	24,000	28,000	32,000	36,000
7	19,000	23,000	27,000	31,000	35,000	39,000
8	22,000	26,000	30,000	34,000	38,000	42,000
9	25,000	29,000	33,000	37,000	41,000	45,000
10	28,000	32,000	36,000	40,000	44,000	48,000
11	31,000	35,000	39,000	43,000	47,000	51,000
12	34,000	38,000	42,000	46,000	50,000	54,000
13	37,000	41,000	45,000	49,000	53,000	57,000
14	38,000	42,000	46,000	50,000	54,000	58,000
15	40,000	44,000	48,000	52,000	56,000	60,000
16	44,000	48,000	52,000	56,000	60,000	64,000
17	66,000	70,000	74,000	78,000	82,000	86,000

+	7	8	9	10	11	12
1	27,000	31,000	35,000	39,000	43,000	47,000
2	29,000	33,000	37,000	41,000	45,000	49,000
3	31,000	35,000	39,000	43,000	47,000	51,000
4	34,000	38,000	42,000	46,000	50,000	54,000
5	37,000	41,000	45,000	49,000	53,000	57,000
6	40,000	44,000	48,000	52,000	56,000	60,000
7	43,000	47,000	51,000	55,000	59,000	63,000
8	46,000	50,000	54,000	58,000	62,000	66,000
9	49,000	53,000	57,000	61,000	65,000	69,000
10	52,000	56,000	60,000	64,000	68,000	72,000
11	55,000	59,000	63,000	67,000	71,000	75,000
12	58,000	62,000	66,000	70,000	74,000	78,000
13	61,000	65,000	69,000	73,000	77,000	81,000
14	62,000	66,000	70,000	74,000	78,000	82,000
15	64,000	68,000	72,000	76,000	80,000	84,000
16	68,000	72,000	76,000	80,000	84,000	88,000
17	90,000	94,000	98,000	102,000	106,000	110,000

+	13	14	15	16	17	18
1	51,000	55,000	59,000	63,000	67,000	71,000
2	53,000	57,000	61,000	65,000	70,000	74,000
3	55,000	59,000	63,000	68,000	73,000	77,000
4	58,000	62,000	66,000	71,000	76,000	80,000
5	61,000	65,000	69,000	74,000	79,000	83,000
6	64,000	68,000	72,000	77,000	82,000	86,000
7	67,000	71,000	75,000	80,000	85,000	89,000
8	70,000	74,000	78,000	83,000	88,000	92,000
9	73,000	77,000	81,000	86,000	91,000	95,000
10	76,000	80,000	84,000	89,000	94,000	98,000
11	79,000	83,000	87,000	92,000	97,000	101,000
12	82,000	86,000	90,000	95,000	100,000	104,000
13	85,000	89,000	93,000	98,000	103,000	107,000
14	86,000	90,000	94,000	99,000	104,000	108,000
15	88,000	92,000	96,000	101,000	106,000	111,000
16	92,000	96,000	100,000	104,000	108,000	113,000
17	114,000	118,000	122,000	126,000	130,000	134,000

Table D.7 (continued) : Model results for train capacity 800, w1: 0.8, w2: 0.2.

+	19	20	21	22	23	24
1	75,000	79,000	83,000	87,000	91,000	97,000
2	78,000	83,000	87,000	91,000	97,000	101,000
3	81,000	85,000	89,000	93,000	99,000	103,000
4	84,000	88,000	92,000	96,000	102,000	106,000
5	87,000	91,000	95,000	99,000	105,000	109,000
6	90,000	94,000	98,000	102,000	108,000	112,000
7	93,000	97,000	101,000	105,000	111,000	115,000
8	96,000	100,000	104,000	110,000	117,000	121,000
9	99,000	103,000	107,000	113,000	120,000	124,000
10	102,000	106,000	110,000	116,000	123,000	127,000
11	105,000	109,000	113,000	119,000	126,000	130,000
12	108,000	112,000	116,000	122,000	129,000	133,000
13	111,000	115,000	119,000	125,000	145,000	152,000
14	112,000	116,000	120,000	126,000	147,000	153,000
15	116,000	120,000	125,000	130,000	149,000	155,000
16	118,000	123,000	143,000	147,000	151,000	157,000
17	138,000	142,000	146,000	150,000	154,000	160,000

+	25	26
1	101,000	106,000
2	116,000	126,000
3	119,000	132,000
4	122,000	135,000
5	129,000	138,000
6	132,000	141,000
7	135,000	144,000
8	138,000	147,000
9	141,000	150,000
10	144,000	153,000
11	147,000	156,000
12	150,000	159,000
13	156,000	162,000
14	157,000	163,000
15	159,000	165,000
16	161,000	167,000
17	164,000	169,000

---- 502 VARIABLE d.Ldeparture time of trip i to station k

	1	2	3	4	5	6
1	4,000	8,000	12,000	16,000	20,000	24,000
2	6,000	10,000	14,000	18,000	22,000	26,000
3	8,000	12,000	16,000	20,000	24,000	28,000
4	11,000	15,000	19,000	23,000	27,000	31,000
5	14,000	18,000	22,000	26,000	30,000	34,000
6	17,000	21,000	25,000	29,000	33,000	37,000
7	20,000	24,000	28,000	32,000	36,000	40,000
8	23,000	27,000	31,000	35,000	39,000	43,000
9	26,000	30,000	34,000	38,000	42,000	46,000
10	29,000	33,000	37,000	41,000	45,000	49,000
11	32,000	36,000	40,000	44,000	48,000	52,000
12	35,000	39,000	43,000	47,000	51,000	55,000
13	38,000	42,000	46,000	50,000	54,000	58,000
14	39,000	43,000	47,000	51,000	55,000	59,000
15	41,000	45,000	49,000	53,000	57,000	61,000
16	45,000	49,000	53,000	57,000	61,000	65,000
17	67,000	71,000	75,000	79,000	83,000	87,000

Table D.8 (continued) : Model results for train capacity 800, w1: 0.8, w2: 0.2.

+	7	8	9	10	11	12
1	28,000	32,000	36,000	40,000	44,000	48,000
2	30,000	34,000	38,000	42,000	46,000	50,000
3	32,000	36,000	40,000	44,000	48,000	52,000
4	35,000	39,000	43,000	47,000	51,000	55,000
5	38,000	42,000	46,000	50,000	54,000	58,000
6	41,000	45,000	49,000	53,000	57,000	61,000
7	44,000	48,000	52,000	56,000	60,000	64,000
8	47,000	51,000	55,000	59,000	63,000	67,000
9	50,000	54,000	58,000	62,000	66,000	70,000
10	53,000	57,000	61,000	65,000	69,000	73,000
11	56,000	60,000	64,000	68,000	72,000	76,000
12	59,000	63,000	67,000	71,000	75,000	79,000
13	62,000	66,000	70,000	74,000	78,000	82,000
14	63,000	67,000	71,000	75,000	79,000	83,000
15	65,000	69,000	73,000	77,000	81,000	85,000
16	69,000	73,000	77,000	81,000	85,000	89,000
17	91,000	95,000	99,000	103,000	107,000	111,000

+	13	14	15	16	17	18
1	52,000	56,000	60,000	64,000	68,000	72,000
2	54,000	58,000	62,000	66,000	71,000	75,000
3	56,000	60,000	64,000	69,000	74,000	78,000
4	59,000	63,000	67,000	72,000	77,000	81,000
5	62,000	66,000	70,000	75,000	80,000	84,000
6	65,000	69,000	73,000	78,000	83,000	87,000
7	68,000	72,000	76,000	81,000	86,000	90,000
8	71,000	75,000	79,000	84,000	89,000	93,000
9	74,000	78,000	82,000	87,000	92,000	96,000
10	77,000	81,000	85,000	90,000	95,000	99,000
11	80,000	84,000	88,000	93,000	98,000	102,000
12	83,000	87,000	91,000	96,000	101,000	105,000
13	86,000	90,000	94,000	99,000	104,000	108,000
14	87,000	91,000	95,000	100,000	105,000	109,000
15	89,000	93,000	97,000	102,000	107,000	112,000
16	93,000	97,000	101,000	105,000	109,000	114,000
17	115,000	119,000	123,000	127,000	131,000	135,000

+	19	20	21	22	23	24
1	76,000	80,000	84,000	88,000	92,000	98,000
2	79,000	84,000	88,000	92,000	98,000	102,000
3	82,000	86,000	90,000	94,000	100,000	104,000
4	85,000	89,000	93,000	97,000	103,000	107,000
5	88,000	92,000	96,000	100,000	106,000	110,000
6	91,000	95,000	99,000	103,000	109,000	113,000
7	94,000	98,000	102,000	106,000	112,000	116,000
8	97,000	101,000	105,000	111,000	118,000	122,000
9	100,000	104,000	108,000	114,000	121,000	125,000
10	103,000	107,000	111,000	117,000	124,000	128,000
11	106,000	110,000	114,000	120,000	127,000	131,000
12	109,000	113,000	117,000	123,000	130,000	134,000
13	112,000	116,000	120,000	126,000	146,000	153,000
14	113,000	117,000	121,000	127,000	148,000	154,000
15	117,000	122,000	126,000	131,000	150,000	156,000
16	119,000	124,000	144,000	148,000	152,000	158,000
17	139,000	143,000	147,000	151,000	155,000	161,000

Table D.9 (continued) : Model results for train capacity 800, w1: 0.8, w2: 0.2.

+	25	26
1	102,000	107,000
2	118,000	131,000
3	120,000	133,000
4	123,000	136,000
5	130,000	139,000
6	133,000	142,000
7	136,000	145,000
8	139,000	148,000
9	142,000	151,000
10	145,000	154,000
11	148,000	157,000
12	151,000	160,000
13	157,000	163,000
14	158,000	164,000
15	160,000	166,000
16	162,000	168,000
17	165,000	170,000

---- 502 VARIABLE tr.L = 16,000 number of trains on trip at time t
---- 502 VARIABLE avg1.L = 117,955 average passenger waiting time

VARIABLE a1.L = 118,501

VARIABLE a2.L = 16,000
VARIABLE yt1.L = 53,721total number of passengers
VARIABLE byt1.L = 6,366,015total number of passengers waiting at stations
VARIABLE obj.L = 98,001 objective
EXECUTION TIME = 13,136 SECONDS 185 Mb WIN235-235 Jul 2, 2010

Table D.10: Model results for train capacity 1200, w1: 0.6, w2: 0.4.

---- 502 VARIABLE a.L arrival time of trip i to station k

	1	2	3	4	5	6
1	3,000	13,000	42,000	84,000	97,000	106,000
2	5,000	15,000	44,000	88,000	105,000	130,000
3	7,000	33,000	68,000	90,000	107,000	132,000
4	10,000	38,000	71,000	93,000	112,000	135,000
5	14,000	41,000	74,000	98,000	122,000	138,000
6	17,000	44,000	77,000	105,000	125,000	141,000
7	20,000	47,000	80,000	108,000	129,000	144,000
8	23,000	50,000	83,000	115,000	132,000	147,000
9	26,000	53,000	86,000	118,000	135,000	150,000
10	29,000	56,000	89,000	121,000	138,000	153,000
11	32,000	59,000	92,000	124,000	141,000	156,000
12	43,000	62,000	95,000	127,000	144,000	159,000
13	46,000	65,000	98,000	130,000	149,000	162,000
14	47,000	69,000	99,000	131,000	150,000	163,000
15	49,000	72,000	101,000	133,000	152,000	165,000
16	59,000	74,000	103,000	138,000	158,000	167,000
17	66,000	76,000	105,000	147,000	160,000	169,000

---- 502 VARIABLE d,L departure time of trip i to station k

	1	2	3	4	5	6
1	4,000	14,000	43,000	85,000	98,000	107,000
2	6,000	16,000	45,000	89,000	106,000	131,000
3	8,000	34,000	69,000	91,000	108,000	133,000
4	11,000	39,000	72,000	94,000	113,000	136,000
5	15,000	42,000	75,000	99,000	123,000	139,000
6	18,000	45,000	78,000	106,000	127,000	142,000
7	21,000	48,000	81,000	109,000	130,000	145,000
8	24,000	51,000	84,000	116,000	133,000	148,000
9	27,000	54,000	87,000	119,000	136,000	151,000
10	30,000	57,000	90,000	122,000	139,000	154,000
11	33,000	60,000	93,000	125,000	142,000	157,000
12	44,000	63,000	96,000	128,000	145,000	160,000
13	47,000	66,000	99,000	131,000	150,000	163,000
14	48,000	70,000	100,000	132,000	151,000	164,000
15	50,000	73,000	102,000	134,000	153,000	166,000
16	60,000	75,000	104,000	139,000	159,000	168,000
17	67,000	78,000	106,000	148,000	163,000	170,000

---- 502 VARIABLE tr.L = 3,000 number of trains on trip at time t
---- 502 VARIABLE avg1.L = 121,530 average passenger waiting time
VARIABLE a1.L = 122,077
VARIABLE a2.L = 3,000
VARIABLE yt1.L = 53,721 total number of passengers
VARIABLE byt1.L = 6,558,087total number of passengers waiting at stations
VARIABLE obj.L = 74,446 objective
EXECUTION TIME = 6,350 SECONDS 185 Mb WIN235-235 Jul 2, 2010

Table D.11: Model results for train capacity 1200, w1: 0.8, w2: 0.2.

---- 502 VARIABLE a.L arrival time of trip i to station k

	1	2	3	4	5	6
1	3,000	27,000	42,000	67,000	75,000	80,000
2	8,000	29,000	50,000	69,000	77,000	82,000
3	10,000	37,000	52,000	71,000	79,000	84,000
4	13,000	40,000	55,000	74,000	83,000	92,000
5	16,000	43,000	58,000	77,000	86,000	95,000
6	19,000	46,000	61,000	80,000	110,000	114,000
7	22,000	49,000	64,000	83,000	113,000	117,000
8	25,000	52,000	71,000	86,000	116,000	120,000
9	28,000	55,000	78,000	111,000	119,000	123,000
10	31,000	58,000	81,000	114,000	122,000	126,000
11	34,000	61,000	84,000	117,000	125,000	129,000
12	37,000	64,000	87,000	120,000	128,000	132,000
13	40,000	67,000	94,000	123,000	131,000	135,000
14	41,000	70,000	95,000	124,000	132,000	136,000
15	43,000	72,000	98,000	126,000	134,000	138,000
16	45,000	88,000	103,000	128,000	136,000	141,000
17	66,000	90,000	105,000	130,000	138,000	143,000

+	7	8	9	10
1	88,000	92,000	100,000	106,000
2	90,000	94,000	114,000	126,000
3	92,000	96,000	116,000	132,000
4	97,000	111,000	119,000	135,000
5	100,000	118,000	122,000	138,000
6	118,000	122,000	127,000	141,000
7	121,000	125,000	130,000	144,000
8	124,000	128,000	133,000	147,000
9	127,000	131,000	136,000	150,000
10	130,000	134,000	139,000	153,000
11	133,000	137,000	142,000	156,000
12	136,000	140,000	145,000	159,000
13	139,000	143,000	148,000	162,000
14	140,000	144,000	149,000	163,000
15	142,000	147,000	155,000	165,000
16	149,000	153,000	157,000	167,000
17	151,000	155,000	163,000	169,000

---- 502 VARIABLE d.L departure time of trip i to station k

	1	2	3	4	5	6
1	4,000	28,000	43,000	68,000	76,000	81,000
2	9,000	30,000	51,000	70,000	78,000	83,000
3	11,000	38,000	53,000	72,000	80,000	85,000
4	14,000	41,000	56,000	75,000	84,000	93,000
5	17,000	44,000	59,000	78,000	87,000	96,000
6	20,000	47,000	62,000	81,000	111,000	115,000
7	23,000	50,000	65,000	84,000	114,000	118,000
8	26,000	53,000	72,000	87,000	117,000	121,000
9	29,000	56,000	79,000	112,000	120,000	124,000
10	32,000	59,000	82,000	115,000	123,000	127,000
11	35,000	62,000	85,000	118,000	126,000	130,000
12	38,000	65,000	88,000	121,000	129,000	133,000
13	41,000	68,000	95,000	124,000	132,000	136,000
14	42,000	71,000	96,000	125,000	133,000	137,000
15	44,000	73,000	99,000	127,000	135,000	139,000

Table D.12 (continued): Model results for train capacity 1200, w1: 0.8, w2: 0.2.

16	46,000	89,000	104,000	129,000	137,000	142,000
17	69,000	91,000	106,000	131,000	139,000	144,000

+	7	8	9	10
1	89,000	93,000	101,000	107,000
2	91,000	95,000	115,000	131,000
3	93,000	97,000	117,000	133,000
4	98,000	112,000	120,000	136,000
5	101,000	119,000	123,000	139,000
6	119,000	123,000	128,000	142,000
7	122,000	126,000	131,000	145,000
8	125,000	129,000	134,000	148,000
9	128,000	132,000	137,000	151,000
10	131,000	135,000	140,000	154,000
11	134,000	138,000	143,000	157,000
12	137,000	141,000	146,000	160,000
13	140,000	144,000	149,000	163,000
14	141,000	145,000	150,000	164,000
15	143,000	152,000	156,000	166,000
16	150,000	154,000	158,000	168,000
17	152,000	156,000	164,000	170,000

```
----   502  VARIABLE tr.L        =   7,000  number of trains on trip at time
----   502  VARIABLE avg1.L      =   120,923  average waiting time per passenger
            VARIABLE a1.L        =   121,470
            VARIABLE a2.L        =   7,000
            VARIABLE yt1.L       =   53,721 total number of passengers
            VARIABLE byt1.L      =   6,525,488total number of passengers waiting at stations
            VARIABLE obj.L       =   98,576  objective
            EXECUTION TIME       =   6,099 SECONDS    185 Mb  WIN235-235 Jul  2, 2010
```

APPENDIX E: Total Number of Passengers Waiting at Stations

Table E.1 : Total number of passengers waiting at stations according to model results vs. actual figures

Time	Model result	Actual figures
1	257	184
2	274	192
3	291	203
4	308	217
5	325	218
6	342	232
7	359	232
8	376	246
9	393	243
10	410	256
11	427	210
12	444	213
13	461	206
14	478	213
15	611	214
16	640	245
17	669	271
18	698	297
19	727	304
20	756	323
21	785	316

Table E.1 (continued) : Total number of passengers waiting at stations according to model results vs. actual figures

Time	Model result	Actual figures
22	480	385
23	509	386
24	538	406
25	543	246
26	572	191
27	601	125
28	622	134
29	639	106
30	812	225
31	756	256
32	815	298
33	851	334
34	890	380
35	949	290
36	966	281
37	1013	290
38	678	281
39	633	283
40	692	184
41	588	180
42	528	212
43	575	244
44	625	276
45	652	326

Table E.1 (continued) : Total number of passengers waiting at stations according to model results vs. actual figures

Time	Model result	Actual figures
46	738	275
47	824	285
48	797	297
49	883	367
50	969	378
51	980	434
52	1066	432
53	1119	369
54	1153	248
55	1211	280
56	1230	228
57	1169	296
58	1255	341
59	1229	391
60	1363	544
61	1443	598
62	1432	545
63	1473	419
64	1095	426
65	1137	494
66	891	590
67	428	659
68	450	666
69	401	732

Table E.1 (continued) : Total number of passengers waiting at stations according to model results vs. actual figures

Time	Model result	Actual figures
70	531	612
71	563	565
72	409	603
73	485	593
74	398	538
75	577	765
76	683	723
77	590	855
78	712	900
79	808	804
80	790	428
81	890	571
82	977	529
83	931	711
84	247	774
85	258	896
86	272	723
87	299	885
88	414	879
89	492	1027
90	643	1135
91	766	1277
92	663	874
93	848	512

Table E.1 (continued) : Total number of passengers waiting at stations according to model results vs. actual figures

Time	Model result	Actual figures
94	489	652
95	588	654
96	438	866
97	560	733
98	740	693
99	767	840
100	904	1006

APPENDIX F: Model Input Parameters for Machinist Assignment Problem

Table F.1: Off-day preference of machinists.

Machinist/Day	1	2	3	4	5	6	7
1	1	0	0	0	0	3	2
2	0	1	0	0	0	3	2
3	0	0	0	0	3	2	1
4	0	0	3	2	1	0	0
5	1	0	0	0	0	3	2
6	0	1	0	0	0	3	2
7	0	0	0	0	3	2	1
8	0	0	3	2	1	0	0
9	1	0	0	0	0	3	2
10	0	1	0	0	0	3	2
11	0	0	0	0	3	2	1
12	1	0	3	2	1	0	0
13	1	0	0	0	0	3	2
14	0	1	0	0	0	3	2
15	0	0	0	0	3	2	1
16	0	0	3	2	1	0	0
17	1	0	0	0	0	3	2
18	0	1	0	0	0	3	2
19	0	0	0	0	3	2	1
20	0	0	3	2	1	0	0
21	1	0	0	0	0	3	2
22	0	1	0	0	0	3	2
23	0	0	0	0	3	2	1

Table F.1 (continued): Off-day preference of machinists.

Machinist/Day	1	2	3	4	5	6	7
24	0	0	3	2	1	0	0
25	1	0	0	0	0	3	2
26	0	1	0	0	0	3	2
27	0	0	0	0	3	2	1
28	0	0	3	2	1	0	0
29	1	0	0	0	0	3	2
30	0	1	0	0	0	3	2
31	0	0	0	0	3	2	1
32	0	0	3	2	1	0	0
33	1	0	0	0	0	3	2
34	0	1	0	0	0	3	2
35	0	0	0	0	3	2	1
36	0	0	3	2	1	0	0
37	1	0	0	0	0	3	2
38	0	1	0	0	0	3	2
39	0	0	0	0	3	2	1
40	0	0	3	2	1	0	0

APPENDIX G: Comparison of Crew Assignment Results

Table G.1: Real-life crew assignment results.

Real-life assignments	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
Shift	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Number of machinists	20	19	20	19	20	19	20	19	20	19	18	14	14	15
Averages working minutes	345.3	345.5	345.3	345.5	345.3	345.5	345.3	345.5	345.3	346	371	354.4	302.5	333
Efficiency	61	61	61	61	61	61	61	61	61	61	65	62	53	58

Table G.2: Model run crew assignment results.

Model run results	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
Shift	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Number of machinists	15	17	18	15	15	18	15	20	15	15	15	13	10	12
Averages working minutes	375,9	317,3	313,2	359,6	375,9	299,7	375,9	269,7	375,9	359,6	370,1	375,5	371,8	361,8
Efficiency	66	56	55	63	66	53	66	47	66	63	65	66	65	63

APPENDIX H: GAMS Code of Timetabling and Machinist Assignment Models

Given in CD

CURRICULUM VITAE

Name Surname:	Selmin Danış Öncül
Place and Date of Birth:	İstanbul, 11.07.1978
E-Mail:	selmindanis@gmail.com
B.Sc.:	Marmara University, Industrial Engineering, 2000
M.Sc.:	Boğaziçi University, Industrial Engineering, 2003

Professional Experience and Rewards:

15.11.2011-..	BIMSA SAP Project Manager
01.01.2005-25.10.2011	Anadolu Bilişim Hizmetleri Project Manager
01.02.2002-30.03.2005	Globalsoft JD Edwards Consultant
01.01.2000-01.01.2002	Temmuz Endüstriyel Danışmanlık, MFG PRO Consultant

List of Publications and Patents:

Turan, S., **Danış, S.** and Gözlü, S., 2006: Performance Criteria for Radio Frequency Identification Technology: Cases of Vehicle Identification Systems in Gas Stations and Automobile Manufacturing, PICMET 2006 Conference Paper, Vol. 4, pp. 1647-1656.

PUBLICATIONS/PRESENTATIONS ON THE THESIS

- **Danış Öncül, S.** and Bayraktar D., 2012: An Integrated Optimization Model for Timetabling and Machinist Assignment in Light Rail Transit Systems. *25th European Conference on Operational Research*, July 8-11, Vilnius, Lithuania.

- **Danış Öncül, S.** and Bayraktar D., 2010: A Proposed Mathematical Model for Light Rail Transit Timetabling. *16th International Working Seminar on Production Economics*, March 1-5, Innsbruck, Austria.

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- **Danış, S.,** Aykaç, D.S.O., Bayraktar, D. and Çelebi, D., 2009: A review of timetabling and resource allocation models for light rail transportation systems, *Proceedings of the International Conference on Prospects for Research in Transport and Logistics on a Regional-Global Perspective*, Doğuş University Publications, İstanbul, Turkey, s. 219-224.