A SUSTAINABLE TRANSIT NETWORK FREQUENCY SETTING APPROACH AND ITS APPLICATION IN ISTANBUL BUS NETWORK

(BİR SÜRDÜRÜLEBİLİR TOPLU TAŞIMA SEFER SIKLIĞI BELİRLEME YAKLAŞIMI VE İSTANBUL UYGULAMASI)

by

Büşra BURAN, B.S.

Thesis

Submitted in Partial Fulfillment
of the Requirements
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Büşra BURAN

İstanbul, 25/06/2012.

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List of Symbols

AFIT: “Air Force Institute of Technology”

BLP: “Bi-level Programming”

BLPP: “Linear Bi-level Programming”

BLPPs: “Bi-level Programming Problems”

BRT: “Bus Rapid Transit”

DMM: “Dekati Mass Monitor”

EMBARQ: “The WRI Center for Sustainable Transport”

EMO: “Evolutionary Multi-Objective Optimization”

GA: “Genetic Algorithm”

GENMOP: “General Multi-Objective Evolutionary Algorithm”

GHG: “Greenhouse Gases”

GIS: “Geographic Information Systems”

IBB: “Istanbul Metropolitan Municipality”

IEA: “International Energy Agency”

IETT: “Istanbul Electricity, Tramway and Tunnel General Management”

IMP: “Istanbul Metropolitan Plan”

ISSRC: “International Sustainable Systems Research Center”

MINLP: “Mix Integer Nonlinear Programming”

MLP: “Multi-level Linear Programming “

MOEA: “Multi-Objective Evolutionary Algorithms”

MOMGA: “Multi-Objective Messy Genetic Algorithm”

MOP: “Multi-Objective Programming”

MOSGA: “Multi-Objective Struggle Genetic Algorithm”

MOTS: “Multi-Objective Tabu Search Procedure”

MSA: “Method of Successive Averages”

NEC: “National Emission Ceilings”

NPGA: “Niched-Pareto Genetic Algorithm”

NSG: “Non-dominated Sorting Genetic Algorithm”

OD: “Origin-Destination”

OMOEA: “Orthogonal Multi-Objective Evolutionary Algorithm”

PAES: “Pareto Archived Evolution Strategy Algorithm”

PESA: “Pareto Envelope-Based Selection Algorithm”

PRC : “People's Republic of China”

SP: “Side Populations”

SPEA: “Strength Pareto Evolutionary Algorithm”

TAPAS: “Traffic Assignment by Paired Alternative Segments”

THC: “Total Hydrocarbons”

TLPPs: “Three-level Programming Problems”

TNDFSP: “Transit Network Design And Frequency Setting Problem”

TNDP: “Transit Network Design Problem”

TNDSP: “Transit Design and Scheduling Problem”

TNFSP: “Transit Network Frequencies Setting Problem”

TNFSP: “Transit Network Frequency Setting Problem”

TNP: “Transit Network Problems”

TNTP: “Transit Network Timetabling”

UITP: “International Association of Public Transport”

UKOME: “Center of Transportation Coordination”

UNFCC: “United Nations Framework Convention on Climate Change”

VMT: “Vehicle Miles Travelled”

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Abstract

Significant changes must occur in human interaction with the natural environment if the world is to move towards a state of sustainability. While the need for such change is widely recognized, planning in many sectors continues to lead to development that is unsustainable. Urban transportation is one such sector.

As a result of economic growth, the trend of urbanization has continued since the industrial revolution, when the increasing opportunities for jobs, education, housing, and reduced commuting and transportation cost attract new immigrants from rural areas. Although living in cities provides individuals and firms the advantage of proximity to market and activities, urbanization is also viewed as a negative trend because of its side effects, such as traffic congestion, environmental impacts, segregation, as well as other inequity issues. These urban problems are getting worse and will hold back the economic development, and even threaten the living environment of future generations.

Increasing environmental concerns as well as economic and social impacts of transportation in communities necessitate the incorporation of sustainability into the planning process. Along this line, we develop a sustainable transit assignment model in this study. The model is formulated as a bi-level optimization model with two objectives: minimizing the average passenger travel time and minimizing the total carbon dioxide emitted from the bus fleet. With these two objectives, we identify the optimum line frequencies at the upper level while considering the fleet size and the minimum service constraints. At the lower level, we model the transit route choice of the passengers with the objective to minimize the total in-vehicle and station waiting times given passengers demand and existing lines.

A genetic algorithm that is known to efficiently solve multi-objective programming problems is adapted to solve the problem. The efficiency of the model and the associated solution method is validated through a case study undertaken in Istanbul. The bus network of Istanbul is one of the largest networks across Europe with 593 lines serving 39 distinct zones and 3 million passengers daily in 2012. The sustainable solution is identified among the Pareto solutions obtained by the solution method, and it is shown that network emission could be reduced more than fifty percent while having average passenger travel time shorter than the actual situation by altering line frequencies.

Résumé

La structure préexistante de l'interaction de l'homme avec son environnement naturel doit changer si le monde va passer à un état durable. La nécessité de changement est largement acceptée, néanmoins la planification dans plusieurs secteurs amène un développement qui n'est pas durable. Les transports urbains sont l'un de ces secteurs.

Etant le résultat du développement économique, l'urbanisation a une tendance à la hausse depuis la révolution industrielle. Comme les occasions de travail, d'éducation et de logement s'améliorent et les coûts des transports s'abaissent, l'exode rurale s'accélère. Vivre en ville a pour avantage d'être en proximité des marchés et des évènements importants, mais l'urbanisation a aussi des aspects négatifs comme les embouteillages, les effets environnementaux, la ségrégation et les autres problèmes d'inégalité. Ces problèmes urbains s'aggravent jour par jour et défavorisent le développement économique, et même mettent en danger l'avenir des générations futures.

Comme les effets économiques et sociaux des transports pour la société, les soucis environnementaux aussi nécessitent l'intégration de la notion de durabilité dans le processus de planification. Par conséquence, nous avons développé un modèle pour l'affectation durable des transports en commun dans cette étude. Le modèle d'optimisation possède deux niveaux et aussi deux objectives ainsi que la minimisation du temps de parcours moyen des passagers et la minimisation du dioxyde de carbone total émis le parc d'autobus. Avec ces deux objectifs, nous avons identifié au premier niveau les fréquences optimales de service des lignes d'autobus en tenant compte les contraintes à propos de la taille du parc de véhicule et du service minimum.

Au second niveau, nous avons modelé le choix d'itinéraire des passagers en transport en commun avec le but de minimiser le temps d'attente dans les stations et de transportation entre les stations tout en satisfaisant la demande des passagers avec les lignes existants. Nous avons reconçu un algorithme génétique qui a une performance reconnue envers la résolution des problèmes d'optimisation multiobjectif pour résoudre ce problème. L'efficacité du modèle et de la méthode de résolution est validée par une étude de cas. Le réseau d'autobus d'Istanbul est l'un des plus grands de l'Europe avec 593 lignes qui servent 39 zones et plus de trois millions de passagers par jour en 2012. La solution durable est identifiée parmi les solutions Pareto obtenues par la méthode de résolution, et tout en changeant les fréquences de service, il est démontré que l'émission pourra être réduite plus de cinquante pourcent dans le cas actuel avec même une baisse du temps de parcours moyen des passagers.

Özet

Eğer dünyada sürdürülebilir bir ortam oluşturmak istiyorsak, insanın doğal çevre ile ilişkisinin ciddi biçimde değiştirilmesi gereklidir. Her ne kadar böyle bir değişimin gerekliliği genel kabul görmekteyse de, pek çok sektördeki yanlış planlama süreçleri sürdürülebilir olmayan bir kalkınmaya neden olmaktadır. Kent içi ulaşım bu sektörlerden biridir.

Ekonomik gelişimin bir neticesi olarak kentleşme, sanayi devriminden beri artan bir yönelime sahiptir. İş, eğitim ve barınma olanaklarının artması ve ulaşım giderlerinin azalması kırsal alandan göçü hızlandırmaktadır. Kentte yaşamak bireylere ve firmalara pazara ve önemli faaliyetlere yakın olma imkanı tanımaktadır. Ancak kentleşme aynı zamanda yarattığı trafik sıkışıklığı, çevresel etkiler, ayrımcılık ve diğer eşitsizlik unsurlar nedeniyle olumsuz bir yönelim olarak görülmektedir. Tüm bu kentsel problemler daha da kötü bir hal almakta ve ekonomik gelişimi baltalamakta, hatta gelecek nesillerin yaşam ortamını tehdit etmektedir.

Artan çevresel endişelerle beraber ulaşımın toplumdaki ekonomik ve sosyal etkileri de düşünüldüğünde sürdürülebilirliğin planlama sürecine dahil edilmesi gereği açıktır. Bu bağlamda bu çalışmada bir sürdürülebilir hat sefer sıklığı belirleme modeli geliştirilmiştir. Model iki seviyeli ve iki amaçlı bir eniyileme modeli olarak düzenlenmiştir. Amaçlar ortalama yolcu bekleme süresinin ve otobüs ağındaki tüm araçların toplam karbondioksit salınımlarının azaltılması olarak belirlenmiştir. Bu iki amaç ile birlikte üst seviye probleminde mevcut filo ve en az sefer sıklığı kısıtlarını da dikkate alarak en iyi hat sefer sıklıklarının bulunması hedeflenmiştir.

Alt seviye probleminde ise mevcut hatlardaki talebi karşılarken araç içi toplam yolculuk süresi ve istasyondaki bekleme süresini en aza indirecek bir güzergah belirleme modeli kurulmuştur. Problemin çözümü için çok amaçlı problemleri etkili bir şekilde çözdüğü bilinen bir genetik algoritma uyarlanmıştır. Kurulan modelin ve buna ilişkin çözüm yönteminin etkinliği İstanbul'u temel alan bir çalışmayla sınanmıştır. 39 ilçede ve 593 otobüs hattıyla üç milyona yakın yolcuya günlük hizmet veren İstanbul otobüs ağı 2012 yılında Avrupa'nın en büyüğüdür. Çözüm yöntemi ile elde edilen Pareto çözümler arasından sürdürülebilir olan çözüm belirlenmiş ve mevcut durumdaki sefer sıklıklarının değiştirilerek hem sınırlı miktarda olsa da ortalama seyahat süresinin hem de toplam salınımın yarıdan fazla azaltılabileceği ortaya konmuştur.

1 INTRODUCTION

Public transport is a shared passenger transportation service which is available for the use of large masses. Public transportation system is an important and essential part of big and crowded cities. Increasing car ownership in the societies causes many important economical, environmental and social problems. This problem can be solved by public transportation system so transportation system has become one of the most significant issues in the cities. Due to the traffic congestion, passengers total travel times increased. Time is a nonrenewable resource so travel and waiting times should be minimized by public transportation system by decreasing private car ownership. Another aspect related to the transportation is that it is a major source of pollution and greenhouse gases (GHS) especially carbon dioxide (CO_2). Greenhouse gas emissions of public transportation are increasing at a faster rate than any other energy using sector.

According to International association of public transport (UITP) survey, 23 percent of total CO_2 gases are due to transportation; including rail, bus, sea, air transportation systems and 98 percent of all land transport depends on fossil fuels (UITP, 2012). This result highlights the significant influence of road transportation. Any type of change for the road transportation directly affects the environment. For this reason governments or transit authorities build new policies to achieve sustainable transportation. The sustainable transportation does not include only minimizing air pollution, but also the reduction of noise pollution, health problems, etc.

Transportation impacts on sustainability can be investigated along three dimensions; economic, social and environmental. Economic criteria are composed of traffic congestion, mobility barriers, crash damages, transportation facility costs, consumer transportation costs and depletion of non-renewable resources.

Social criteria include inequity of accessibility, mobility of handicapped people, human health impacts, community cohesion, community livability and aesthetics. Environmental criteria are composed of air pollution, climate change, habitat loss, water pollution, hydrologic impacts and noise pollution. By considering all these dimensions concurrently, it is possible to create a sustainable transportation system which is indispensable to improve the quality of life in cities. Sustainable transportation depends on transportation decision making, automobile dependency, transportation equity, facility design and operations, land use, developing regions decisions.

The Kyoto Protocol is an international agreement based to the United Nations Framework Convention on Climate Change (UNFCC). The UNFCCC aims to achieve stabilization of greenhouse gas concentrations in the atmosphere. Countries pay attention to comply with its form. For instance, there is a study about providing sustainable transportation for Canada. According this idea, a document is introduced that helps ensure that meeting the requirements of Kyoto Protocol (Prades et al., 2002).

In the literature, there are many studies about frequency setting problem. Some researchers take into account network design with the frequency setting problem. They optimize both design and frequency in the network. Also, capacity constraint, stochastic assignment and dynamic assignment are integrated with the frequency setting problem. While the complexity of models increases, it is getting more difficult to solve. For this reason, special methods are developed to solve this type of problems. When the model is simpler, it can be solved by exact methods, such as branch and bound, cutting planes, strong valid inequalities, Lagrangian duality and column generation.

For complex models, heuristic approaches are developed. They can be greedy and local search, improved local search and MIP-based heuristics. Improved local search methods include tabu search, simulated annealing and genetic algorithm.

In this study, we aim to develop a sustainable transit assignment model. This model is formulated as a bi-level optimization model with two objectives: minimizing the average passenger travel time and minimizing the total carbon dioxide emitted from the network. With these two objectives, we aim to identify the optimum line frequencies at the upper level while taking into account the fleet size and the minimum service constraints. At the lower level, we model the transit route choice of the passengers with the objective of minimizing the total in-vehicle and station waiting times given passengers demand and existing lines. A genetic algorithm that is known to efficiently solve multi-objective programming problems is adopted. The efficiency of the model and the associated solution method is validated truth a case study. Istanbul bus line network which is one of the largest networks across Europe with 593 lines serving 39 distinct zones and 3 million passengers is the center of this case study. The sustainable solution is identified among the Pareto solutions obtained, and it is shown that network emission could be reduced more than halved while having average passenger travel time shorter than the actual situation by altering line frequencies.

This thesis is organized as follows: An extensive literature survey is given in Chapter 2 and finding this survey prompted to us to develop sustainable transit assignment model for filling an important gap in the literature. Chapter 3 consists of mathematical programming models from general to specific one. Solution methodologies for the described models are introduced, and also a genetic algorithm which is developed solves overall model in Chapter 4. In Chapter 5, the case study involving Istanbul bus network is introduced and computational results and analysis are provided. Finally, Chapter 6 includes some concluding remarks and perspectives.

2 LITERATURE SURVEY

In the literature, there are lots of different studies about public transportation systems. Over the last two decades, public transport system has become more important than before. It impacts all its elements from transit authorities to users and more globally the entire population. Especially for the last years sustainable transport system is the most important issue between transit system studies. Many planners, authorities and academics are interested in this issue. The aim of these studies is to find applicable solutions for sustainable transportation.

Generally, the transit planning is composed of five main steps. First step is the design of routes which is related to transit network. Second step is the setting of frequencies for transit lines. Third step is the timetabling, in the other words planning of bus departure times, forth one is the vehicle scheduling and the last one is the crew scheduling. The first three steps are main elements of transit planning system.

2.1 Sustainability

Sustainability is one of the most important issues in the last centuries. It is indispensable to prevent the excessive use of natural resources. Sustainability is related to sustainable development. Sustainability development is defined as “development which meets the needs of the present without compromising the ability of future generations to meet their own needs” by the Brundtland Commission in 1983. This definition focuses on futurity objectives.

The specific definition of Sustainability development can be made as “a process of dynamic change in which the exploitation of resources, the direction of investment, the orientation of technological development and institutional change are all in harmony and enhance both current and future potential meet human needs and aspirations (Gerçek & Tekin, 1996)"

Two main approaches exist: economic and ecological. While economic approach refers to maintaining the productivity of systems, ecological approach is related to protect natural resources.

With benchmarking between sustainability and development; sustainability provides long-term stability for society, while development is the perceptible improvement of the quality of human life for the present generation as opposed to a Figure 2.1.

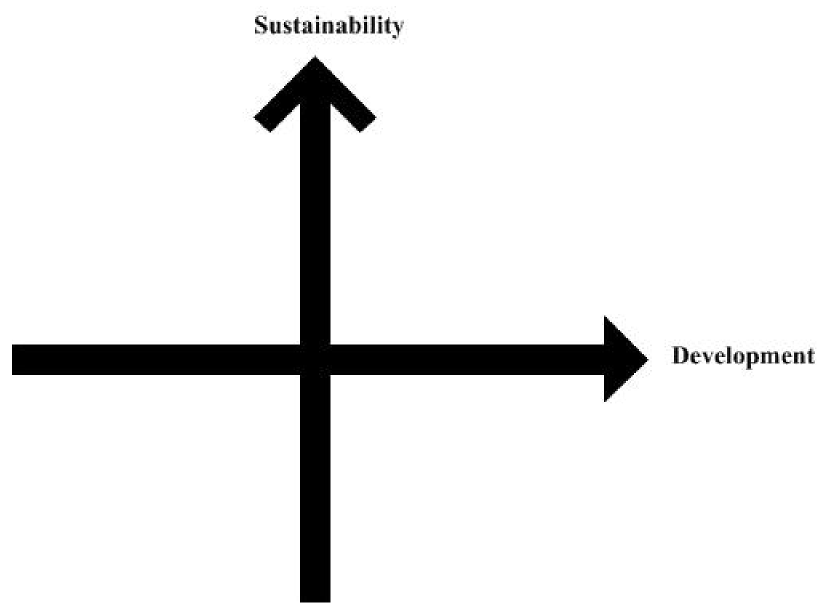

Figure 2. 1: Multi-directional concept of sustainable development
(van Maarseveen & Zuidgeest, 2003).

Sustainable development brings important questions such as; how to provide social equity, how to improve quality of life, how to protect natural resources etc. These questions can be more specifically stated as (Van Maarseveen & Zuidgeest, 2003):

1. How to use limited transportation related resources to guarantee intergenerational equity?

2. How to sustain or enhance basic mobility and accessibility options to people? (Sustainability for transportation has three dimensions: economic, social and environmental.

Economic criteria are composed of traffic congestion, mobility barriers, crash damages, transportation facility costs, consumer transportation costs and depletion of non-renewable resources. Social criteria include inequity of accessibility; mobility disadvantaged people, human health impacts, physical inactivity, community cohesion, community livability and aesthetics. Environmental criteria are composed of air pollution, climate change, habitat loss, water pollution, hydrologic impacts and noise pollution. To improve quality of life, three dimensions can be taken into account together or separately for sustainability studies in Figure 2.2. No sustainable city is possible without sustainable transportation, i.e., improving transport's benefits while reducing its environmental impact to sustainable levels (Soria Alves et al., 2002). Economic, environmental and social sustainability in transport are often mutually reinforcing. This urges the need to develop sets of policy instruments that serve the different dimensions of sustainability in a synergetic way (van Maarseveen & Zuidgeest, 2003).

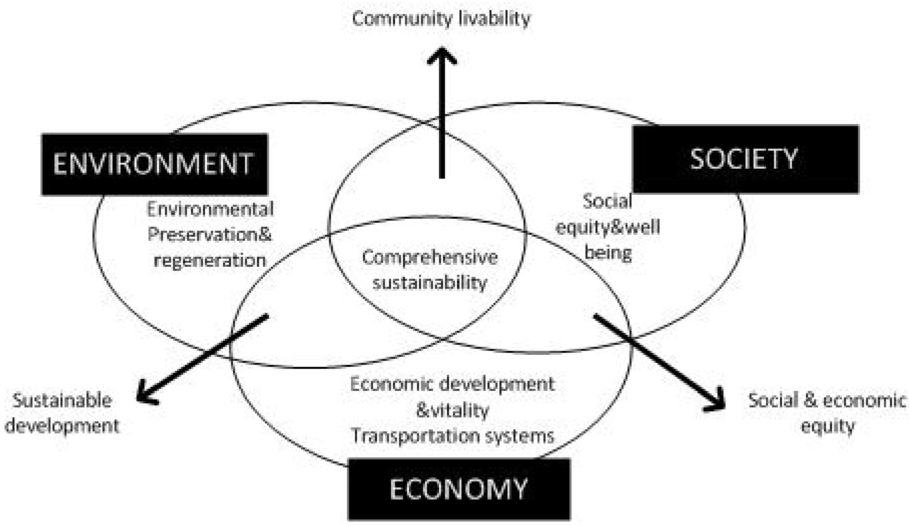

Figure 2.2: Components of sustainability (Hızır, 2006).

Prades et al. (2002) propose a post-kyoto sustainable transport strategy. They also present the documents which are authorized by Richard Gilbert, are related to provide continued discussions on how transportation in Canada can be moved towards sustainability and help to ensure meeting the requirements of Kyoto Protocol.

Vito, which is Flemish Institute for Technological Research in Belgium, worked on a project focused on the possibilities to reduce CO_2 with the national program 'Sustainable Mobility' (1996-2001). It is the most convenient way to have an international agreement for reducing negative impact on environment. For example, Belgium agreed to reduce the emission of greenhouse gases by 7.5 % averaged over the period 2008-2012 compared to 1990 with the Kyoto Protocol. Moreover, The European NEC (National Emission Ceilings) Directive sets national emission limits on NO_X, $S0_2$ (sulphur dioxide) and VOC for 2010 (De Vlieger et al., 2002).

Transit system has a special challenge for sustainable development. For this reason, it has a big impact on economic, social and environmental conditions. If one of these conditions is improved, lots of advantages can be obtained for quality of life. For that, governments or transit authorities produce new policies and make some decisions to provide sustainability.

2.2 Sustainability for Transportation System

Sustainable transportation is defined as "the transportation that meets mobility needs while also preserving and enhancing human and ecosystem health, economic progress and social justice now and in the future (Deakin, 2001)."

Table 2.1: Sustainable transportation issues (Hızır, 2006).

Economic	Social	Environmental
Productivity	Human healthy	Pollution emission
Business activity	Community livability	Climate change
Employment	Cultural values	Habitat preservation
Tax burden	Public involvement	Aesthetics

Table 2.1 categorizes sustainable transport issues with economic, social and environmental criteria.

Sustainable Transportation Center in Canada is states that sustainable transportation system elements allow "the basic needs of individuals and societies to be met safely and in a manner consistent with human and ecosystem health (...); are affordable, operate efficiently, offer choice of transport mode, and support a vibrant economy, and; limit emissions and waste within the planet's ability to absorb them (...) (Soria Alves et al., 2002)". With this explanation, aims of sustainable transportation are integrated with social, economic and environmental principles. Sustainable transport implies finding a proper balance between (current and future) environmental, social and economic qualities. Environmental, social and economic qualities have different effect on the passengers. Their content can vary with passenger perspective. Sustainable transportation should provide these qualities. For the environmental side different transport modes are responsible for approximately 30% of global warming. This ratio is much larger compared to those of energy production or industry.

In Europe, even despite increasingly cleaner engines, CO_2 emissions have not decreased, but keep growing (+ 25 % since 1990) (Rusko & Kotovicová, 2009).

Global warming has become one of the critical issues all over the world. Governments and organizations focus on this topic. Public transportation companies from different countries start to put new objectives for providing sustainability transport. Some of them determine deadline of sustainability transportation projects and they have an arrangement with environmental organizations such as UITP. For example Translink, British Columbia, Canada began to collect bus idling data over one year using a newly implemented Vehicle Data Capture System. The data showed that bus idling represented up to a peak of 21% of operating time of the buses, fuel consumption costs approximately CAN$ 1,500,000 burning 1.76 million liters of fuel and causing 440,000 hours of unnecessary engine wear. Policies to manage this better (taking into account seasonal needs) not only reduced fuel consumption but also brought environmental benefits and reduced CO_2 emissions (UITP, 2010).

Governments produce new policies to provide sustainability of transportation systems. There are different solutions for sustainability transport. Advantages in technology renewable sources are used for transportation with costly investments such as using solar, wind or biofuel. The other way of providing sustainability transport is to reorganize the transit system for optimizing transit line frequencies regard with minimizing greenhouse gas emissions.

23% of CO_2 emission is composed of transport sector for the latest estimates of the International Energy Agency (IEA). CO_2 emission, which is related to transport will be increase rapidly for developed countries. This case can be understood with Figure 2.3.

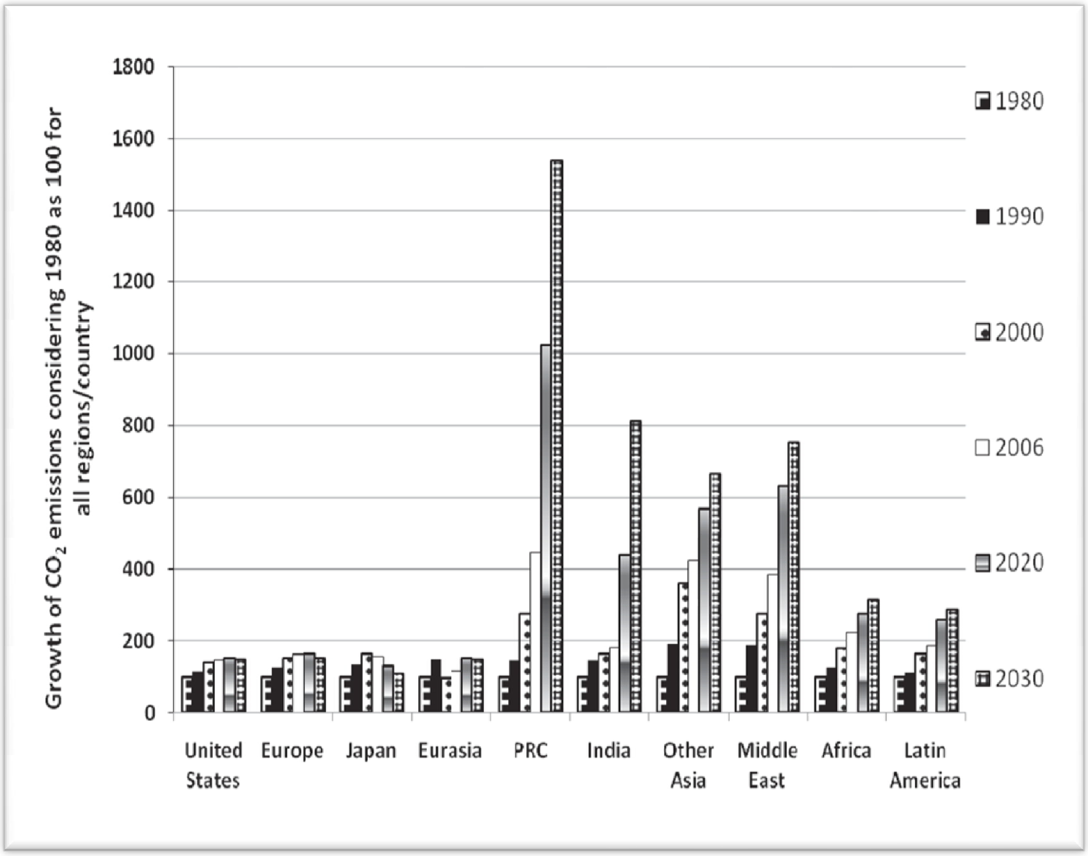

Figure 2.3: Transport sector energy-related CO_2 emissions (Schipper et al., 2009).

(PRC= People's Republic of China, Source: Modified from IEA, 2008. World Energy Outlook, assuming a datum of 100 for all regions and/or countries in 1980 under reference scenario.)

Sustainable transportation is a popular topic in the literature. Rising economical power of citizens causes that increasing use of private owned cars. At this point, public transport system has critical importance for decreasing negative impacts of greenhouse emission. In the literature, there are lots of studies for providing sustainable transportation. While some of them are related to analyzing recent negative results for our world, the others propose a model to improve transportation system.

Although it is difficult and costly process for calculating pollution such as; air, water, soil, noise, with some instruments any pollution and their impacts on the environment can be measured. Most researchers are interested in not only air pollution, but also the other pollution for finding sustainable transport model.

Regard with Kyoto protocol, Prades et al. (2002) present towards a post-kyoto sustainable transport strategy. Their aim of this study is to collect together the necessary elements and practical understanding of sustainable transportation. They show the Documents*,* which is authorized by Richard Gilbert who is an independent consultant in urban issues. The Documents provides wide information about improving Canada transportation system's sustainability. The Documents follow this order:

1. Setting out and justifying three scenarios for 2010 and a target for 2025.
2. Concerned relevant data.
3. Actions required to meet the three scenarios for 2010.
4. Actions required for the period 2010-2025.
5. Concluding remarks (Prades et al., 2002).

Taking into account economic growth, Gerçek & Tekin (1996) propose the relationships between the transport sector, economic growth and environment. Current transportation systems' shares in Istanbul is analyzed and scenarios are generated for developing transit system. At the last, methodologies are discussed for decreasing negative impact of transport system in Istanbul.

Soria Alves et al. (2002) propose a strategic planning model to analyze vehicular air pollution. A neural gee-spatial approach is applied to forecast vehicular air pollution for providing sustainable transportation. A case study in Nagoya City Area is applied to assess the efficiency of the model and to evaluate the best NN structure. Like Soria Alves et al.'s study, Simões et al. (2002) represent analysis of the environmental impact of urban buses. CARRIS, which is a company responsible for transport system of Lisbon, Portugal, is conducted with CORINAIR methodology (that is supported by European Environment Agency's Topic Centre on Air Emissions).

Latini et al. (2003) presents air pollution problems and deal with reducing transport-related air pollution. They focus on "how to control transport" and "how to improve air quality". Road-traffic emission is modeled with Gaussian Dispersion Model AERMOD-PRIME.

To analyze relation of private-public transportation system, van Duin et al. (2003) make a first attempt for developing a library of simulation building blocks is discussed in order to be able to evaluate SAT-project. The SAT-project, which is private-public transportation system, will provide sustainable transport system.

Wadhwa (2000) represents several approaches to achieving transportation sustainability in the study. Though, the approaches are categorized as technological, economic, behavioral, planning and management to need strong political decisions for their implementation. Wadhwa recommends that charging full costs of road travel to road users is the most effective way providing sustainable transport system.

There are lots of approaches to achieve sustainable transportation. In Table 2.2 presents a classification of approaches for sustainable transport system.

Table 2.2: Approaches to sustainable transportation systems (Wadhwa, 2000).

Technological	**Behavioral & Economics**	**Planning & Management**
Vehicle performance	Driver behavior	Land-use planning
Traffic flow	Pricing, taxation, charges	Transportation planning
Infrastructure	Social acceptance	Systems management

For sustainable city, providing sustainable transport is indispensable condition. Result of many studies which is related to analyzing current transport system, is not sustainable. Providing sustainability for transport system will drastically improve the sustainability of cities. So, sustainable transport system is first step for sustainable city.

2.3 Transit Network Design and Scheduling

The transit network design and scheduling problem is the first step of transit planning process. Network design and scheduling affect directly quality of transport system. It involves finding a set of line routes and, generating timetables.

Two components of transit network design and scheduling model are basic line configuration problem and passenger line assignment. With using different constraints from user and operator perspective, the model can be complex.

Increasing private owned vehicle causes traffic congestion, energy consumption, air pollution problems. By providing quality transport system achieve to shift towards public transportation. At this point, transit network design and scheduling model has a critical role in the city life. While transit users want to take a better level of service, operators need to provide the service at the minimum possible cost. Transit network design and scheduling model should take into account a balance between users and operators.

Guihaire & Hao (2008) present a global review of transit network design and scheduling. The study provides the goals of strategic and tactical transit planning. They establish a terminology proposal in order to name sub-problems and thereby structure the review. Shih et al. (1998) propose the design of transit network model with coordinated operations. The model provides that a route generation procedure (RGP), network analysis procedure, a frequency-setting and vehicle-sizing procedure, a transit center selection procedure and a network improvement procedure. Guan et al. (2003) presents a model for simultaneous optimization of transit line configuration and passenger line assignment in a general network. The model is formulated as a linear binary integer program.

A mix integer nonlinear programming (MINLP) is used by Constantin & Florian (1995) for the transit network frequencies setting problem (TNFSP), and by Fan & Machemehl (2004) for the design and frequencies setting problem (TNDFSP). The transit network scheduling problem is modeled as a mixed integer linear program by Ceder et al. (2001). Borndörfer et al. (2005) present a multicommodity flow model based for the design and frequencies setting problem (TNDFSP). Yan & Chen (2002) is also used a multicommodity flow model for design and scheduling problem (TNDSP).

Exact methods can be used for linear programming and some forms of integer and mixed integer programming. More complex models are usually solved with heuristics methods. Heuristics solution methods can be classified as below:

- Greedy (construction) heuristics,
- Neighborhood search; Simulated annealing and Tabu search methods.
- Genetic algorithms.
- Hybrid search methods.

Any constraint and objective types are solved these solution methods with adapting forms. Due to the discrete nature of several variables of transit design network problem as well as the nonlinearity and the non-convexity of its objective function, genetic algorithm seems to be appropriate. Chakroborty (2003) highlights that in GA-based optimization technique it is possible to include problem-specific information and obtain optimal or near-optimal solutions with low computational effort.

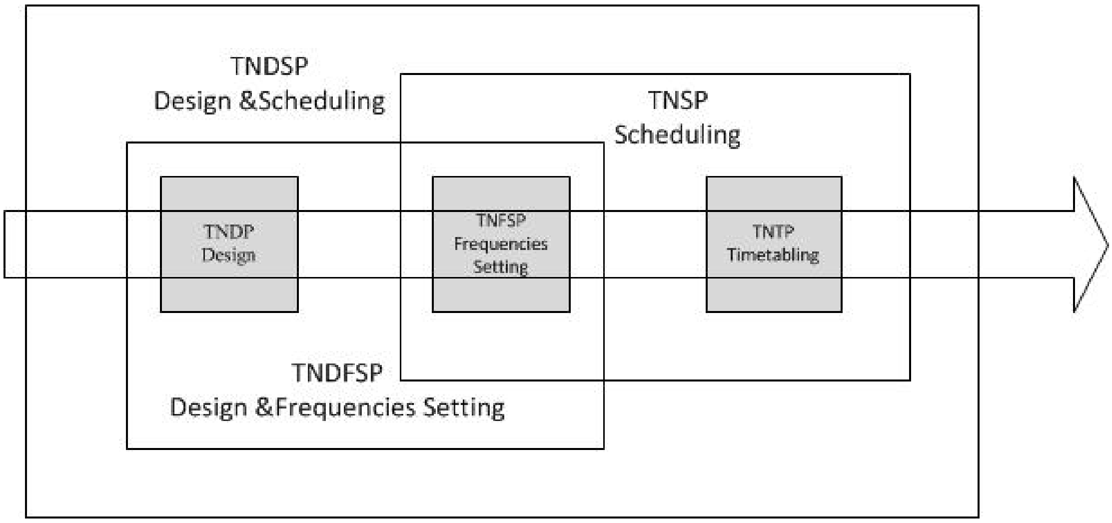

Figure 2.4: Transit network problems (TNP) structure (Guihaire & Hao, 2008).

Three main transit network problems are transit network design problem (TNDP), transit network frequencies setting problem (TNFSP) and transit network timetabling (TNTP) which are shown in Figure 2.4.

Any two of them create a new problem. Transit network design problem (TNDP) and transit network frequencies setting problem (TNFSP) generate design and frequencies setting problem (TNDFSP). Transit network frequencies setting problem (TNFSP) and transit network timetabling (TNTP) generate scheduling problem (TNSP). The whole design and scheduling problem (TNDSP) is defined as integration of the three main problems.

2.4 Transit Frequency Setting Problem

Transit network frequencies setting models aim to identify frequencies for each transit line in the network. Some of them is modeled for specific time period such as rush hours. Headway is inverse of the frequency over a determined period.

While frequency represents vehicle number for a specific line, headway corresponds to the time elapsing between consecutive line run departures. When transit network frequencies setting model is designed, transit route network, passenger demand and bus fleet inputs are taken into account in the model. The basic input is transit route network. For passenger demand, origin-destination (OD) matrices are needed. OD matrices can vary peak, peak off, day of the week etc. Bus fleet input is the available fleet size to service each transit line. Main constraints and objectives are demand satisfaction, number of lines, headway bounds for the transit network frequencies setting model. Demand satisfaction provides that the line frequency match passenger demand. Numbers of line are aimed to minimize for operator perspective due to operation cost. Headway bounds are related to minimum and maximum headway regard with passenger demand and strategy of transit operators. Objective function can be associated with total passenger travel time or number of operated vehicles. For providing more effective models, the frequency setting problem simultaneously solved with the route design problem because passenger travel time and number of operated vehicles depend on frequency.

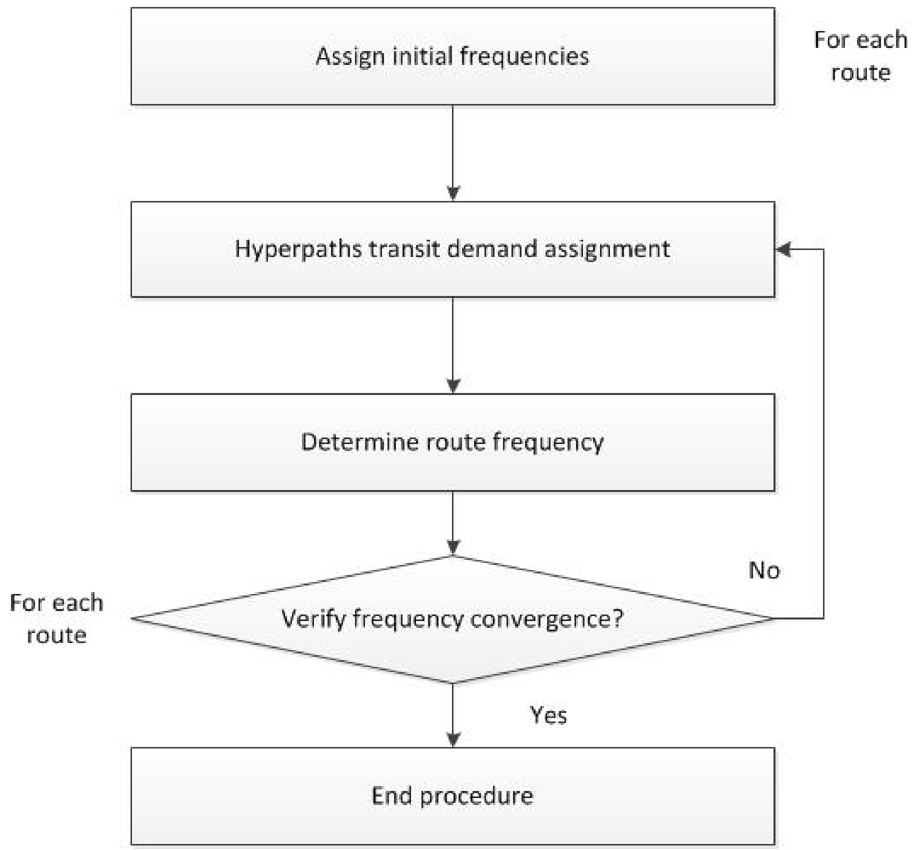

Figure 2.5: Assignment and frequency setting procedure (Ciprini et al., 2012).

First of all, initial frequencies are assigned. Then, transit demand is forecasted and assigned. After that frequency is identified for each route and evaluated frequency convergence which is the maximum difference among route frequencies in two consecutive iterations is lower than a given threshold. If there is a convergence, end the procedure. If there is not any convergence, go back transit demand assignment part of the procedure and repeat required steps. Assignment and frequency setting procedure is indicated in Figure 2.5.

Two sub-problems which are route designing and frequency setting, are composed of network design problem. Ceder & Wilson (1986) state transit planning process including route design and frequency setting. Many researchers, such as Carrese & Gori (2002) propose only the route design problem due to the combined problem (route design and frequency setting) is more difficult than single problem.

Kepaptsoglou & Karlaftis (2009) present route design, frequency setting and timetabling of transit lines problems with their combination as a global review. Guihaire & Hao (2008) propose comprehensive study about transit network design and frequency setting problems.

Scheele (1980) handles with transit network frequency setting problem (TNFSP) using a non-linear model. The model's objective is to minimize the total generalized passenger travel time. Passenger trip assignment is solved simultaneously with the frequencies setting problem. Furth & Wilson (1981) propose different mathematical approach for the transit network frequency setting problem (TNFSP). Objective function of the model is to maximize the net social benefit including ridership benefit and waiting time saving. Model constraints are fleet size, maximum headway and total budget. The problem is solved through an algorithm using the Kuhn–Tucker conditions on a relaxation of a non-linear program. Han & Wilson (1982) deal with transit network frequency setting problem (TNFSP) using a heuristic method. They represent a two stage heuristic to reach their objective, minimizing the maximum ‘‘occupancy level” at the maximum load point for each route. In the first phase, all passenger demand is satisfied with minimal frequencies. In the second phase, frequencies are increased uniformly among lines so as to utilize all the available vehicles.

Transit system performance depends on the service frequencies which should be satisfy passenger demand by the optimal way. Baaj & Mahmassani (1990) propose iterative assignment and frequency setting procedure for the first time. Constantin & Florian (1995) present a non-linear non-convex mixed integer programming model for transit network frequency setting problem (TNFSP). The model's objective function is to minimize the passengers total expected travel and waiting time under fleet size constraints. For solving the proposed model, a projected sub-gradient algorithm is used to find optimal line frequencies considering the passengers route choices. Stockholm, Winnipeg and Portland case is performed with the model.

Chowdhury et al. (2001) proposes transit network frequency setting problem (TNFSP) with fleet size and capacity constraints. Objective of the model consists of transfer coordination. Regard with stochastic condition, Park (2005) represents transit network frequency setting problem (TNFSP) with lines and stochastic buses arrival times. The model objective is related to waiting, walking, in vehicle time, the number of buses, unsatisfied demand costs.

For transit network design and frequency setting problem (TNDFSP), Van Nes et al. (1988) proposes a model with direct trips and satisfying the demand objectives under fleet size constraint. Shih (1988) presents transit network design and frequency setting problem (TNDFSP) with objective function which includes travel time, satisfied demand and fleet size. Its specificity is trip assignment model for timed transfer terminals.

Transit network design and frequency setting problem (TNDFSP) with headway, fleet size and capacity constraints is represented by Baaj & Mahmassani (1995). Objective function of the model is related to number of direct trips, waiting time and transfer time. Tests are performed in urban context in Austin.

Taking into account travel time as an objective function with transit network design and frequency setting problem (TNDFSP), Pattnaik et al. (1998) puts headway and load factor constraints, and operator cost objective. Bielli et al. (2002) models with pre-defined possible lines only constraint and fleet size, network performance objectives, too. Tests of Bielli model are performed in urban context in Parma.

Regard with cost as an objective function with transit network design and frequency setting problem (TNDFSP), Fusco et al. (2002) represents a model under level of service, satisfied demand, lines configuration, frequency constraints. The model can be applied for medium size towns. Ceder (2003) puts route length, deviation from shortest path constraints and fleet size objective, too. The model can be applied for medium size towns. Tom & Mohan (2003) represents transit network design and frequency setting problem (TNDFSP) with adding passenger total travel time objective.

Wan et al. (2003) takes into account frequency bounds and capacity constraints. Fan, et al. (2006) proposes a model with route length constraint and waiting, walking, in vehicle time, the number of buses objectives, too.

2.5 Transit Assignment Models

Transit assignment models take into account passenger demand for every transit line and adjust optimal frequency to satisfy the demand. These models are categorized into two types: frequency-based and schedule-based (Lam & Bell, 2003). Frequency-based models have static character such as based on assumption that constant headways, passengers arrive randomly at stops and board the first bus that arrives their origin stop (Marguier & Ceder, 1984; Spiess & Florian, 1989). In contrast, schedule-based models regard with service time-tables, transfer coordination and passenger arrival process that follows the schedule (Hickman & Wilson, 1995; Nuzzolo et al., 2001). Figure 2.6 indicates that general procedure of transit assignment.

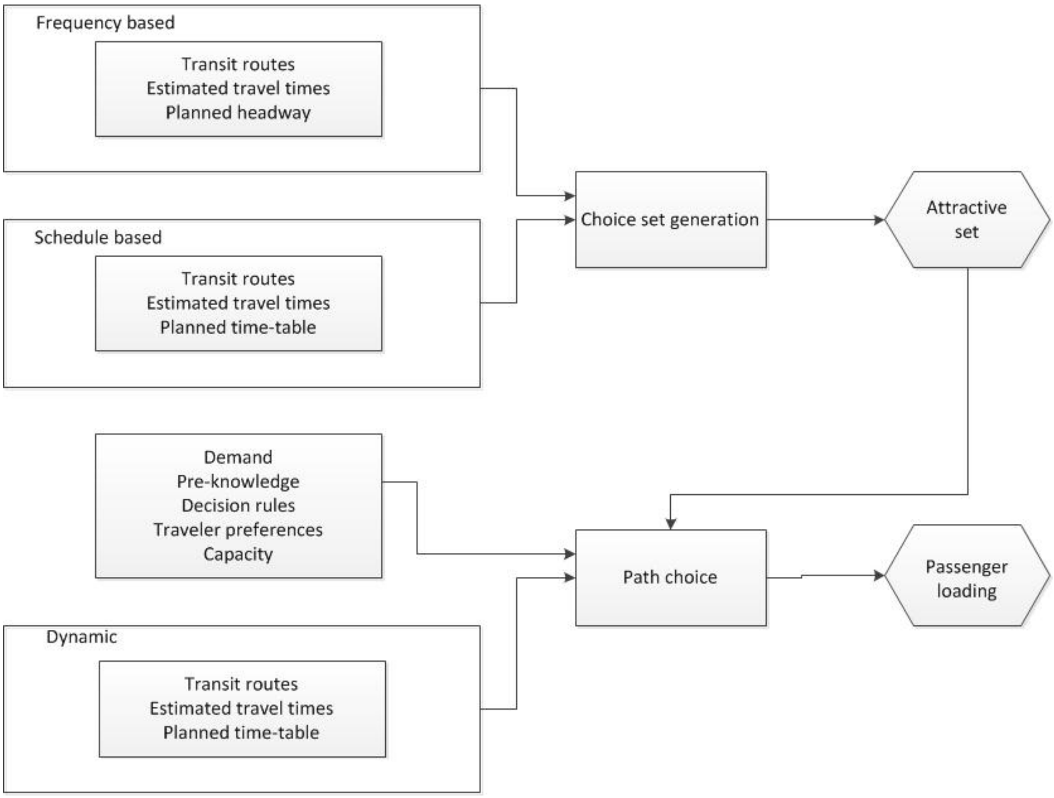

Figure 2.6: Framework of transit assignment[1]

1. Capacity Restraint Model

Capacity restraint assignment problems have certainly become important for urban transportation with intense demands. Especially, modeling with peak hour of transit systems, capacity restraint models can be used.

Considering the congestion, Kurauchi et al. (2003) present a model regard with congested transit network and common lines. The model deals with unable to travel passenger for insufficient capacity of vehicles. Passengers prefer transit lines which are to minimize expected travel cost. Travel cost includes the cost of a risk of failing to board a train.

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[1] http://www.ctr.kth.se/publications/2010/ctr2010_wp01.pdf

The proposed model is solved with method of successive averages (MSA). Regard with both congestion and dynamic model, Poon et al. (2004) represent the equilibrium assignment problem in a congested, dynamic and schedule-based transit network. The route choice problem is also considered. For a given varying origin-destination (OD) demand, the model aims to minimize generalized cost, which includes; in-vehicle time, waiting time, walking time and a line change penalty. By using time-increment simulation, the passenger demand is loaded onto the network and the available capacity of each vehicle is updated dynamically. MSA is used to find the dynamic user-optimal solution. With an example of hypothetical network, the solution algorithm converges. Schmöcker et al. (2008) propose a quasi-dynamic capacity constrained frequency-based transit assignment model. This study aims to enclose the gap between schedule-based and frequency-based models. The common line and passenger route choices are taken into account for the model. London case is applied with during the peak period regard with capacity constraint. Nuzzolo et al. (2001) propose a schedule-based dynamic assignment model for congested transit network under explicit vehicle capacity constraint. A joint choice model is used for departure times. The assignment model has a dynamic approach with network loading process. Application of the model is Naples transit network in southern Italy.

With route choice approach, Cepeda et al. (2006) present frequency-based route choice model for congested transit networks regard with congestion on the flows effects that expected passenger waiting and travel time. Their study is an extension of results of Cominetti & Correa (2001)'s studies. The proposed model is solved using the method of successive averages (MSA).

Cortés (2011) proposes an optimization of transit services model for a single line regard with integrating short turning and deadheading. The model integrates short turning and deadheading in a strategy where variables are both continuous and discrete. The study look likes the classical ''square root rule'' for obtaining closed solutions in some cases.

2. Stochastic Transit Assignment Model

Stochastic transit assignment models present more accurate results than deterministic ones. When conditions are not stable (perceived travel time, perceived waiting time, etc.), the stochastic transit assignment models are used to ensure more realistic models.

With capacity constraints, Lam et al. (1999) propose a stochastic user equilibrium assignment model for congested transit networks. When the transit link capacity constraints are reached, it is proven that the Lagrange multipliers of the mathematical programming problem are equivalent to the equilibrium passenger overload delays in the congested transit network. Selected optimal routes and total passenger travel cost can be predicted by the proposed model in a congested network. Improving previous study with elastic line frequency, W. H. K. Lam et al. (2002) represent capacity restraint transit assignment with elastic line frequency. For elastic line frequency approach, the line frequency changes with passenger flows on transit lines. A stochastic user equilibrium transit assignment model takes into account congestion and elastic line frequency is proposed. A numerical example is used to illustrate the application of the proposed model and solution algorithm. Teklu (2007) presents a stochastic transit assignment model with capacity constraints, which is based on realistic route cost estimates and provides forecasts of mean route flows, costs together with their associated day-to-day variations. For capacity constraints and their effects on passenger, a Monte Carlo simulation approach is applied. With this study, a stochastic user equilibrium equivalent of the capacity constrained transit assignment model which is proposed in De Cea & Fernandez (1993) is also highlighted.

Nielsen (2000) presents stochastic transit assignment model regard with differences in passenger's utility functions. The proposed model takes into account choices through chains of sub-modes. Initial tests on a full-scale case show that the methodology can describe route choices in public transport very well. Also, using with Danish SP-analysis, coefficients can be adjusted.

3. Bi-Level Models

Bi-level programming contains an optimization problem in the constraints. When a problem is modeled with bi-level approach, Stackelberg Game Theory is used. According to Game Theory, there is a hierarchy between leader and followers. Followers try to achieve the best objective under the leader's policy (Kunapoli, 2008). Gao et al. (2004) propose a bi-level programming technique to deal with the transit network frequency setting problem. Objective function of the upper level is to minimize travel time and the cost caused by frequencies setting. The lower-level model provides path alternatives to transit users. A heuristic solution with sensitivity analysis is developed to solve the proposed model. Considering variable demand, Yoo et al. (2010) represent frequency design model in urban transit networks. A bi-level mathematical programming is used to describe the problem. The upper problem is formulated as a non-linear optimization model to maximize passenger demand under fleet size and frequency constraints. The lower-level problem is formulated as a capacity-constrained stochastic user equilibrium assignment model with variable demand, considering transfer delays between transit lines. While the upper level problem is solved with gradient projection method, an extant iterative balancing method is used to solve the lower-level problem.

Taking into account route choice, Puchalsky (2007) represents a bi-level mathematical model for identifying optimal transit frequencies in a network. This model analyzes transport system such as; transit provider, passengers, potential passengers, competing modes, etc. While transit provider wants to maximize ridership between multimodals, travelers make choices with some conditions. A solution algorithm for the continuous relaxation of the bi-level program using cutting planes is developed and to allow fast TAPAS (traffic assignment by paired alternative segments) is developed.

Sun & Gao (2007) present a model for urban transit market equilibrium. Passenger's decision making effects are defined as a non-cooperative perfect information static game. The model is based on general economic equilibrium principle. The generalized Nash equilibrium game is applied to describe how passengers adjust their route choices and trip modes. An algorithm is designed to obtain the equilibrium solution.

Table 2.3: Literature survey on frequency setting problems

Type of Models							
Authors	**Frequency setting**			**Network design**	**Capacity constraint**	**Stochastic assignment**	**Bi-level**
	real network	**heuristic methods**	**exact methods**				
Furth & Wilson (1981)		*					
Han & Wilson (1982)	*	*			*		
Van Nes et al. (1988)		*		*			
Marcotte & Blain (1991)		*					*
Constantin & Florian (1995)	*	*					*
Pattnaik et al. (1998)		*		*			
Tong & Wong (1998)	*		*			*	
Shih et al. (1998)	*	*		*			
Nielsen (2000)	*	*				*	
Nuzzolo et al. (2001)	*	*			*		
Bielli et al. (2002)	*	*		*			
Carrese & Gori (2002)	*	*		*			

Table 2.4: Literature survey on frequency setting problems (cont.)

Type of Models							
Authors	Frequency setting			Network design	Capacity constraint	Stochastic assignment	Bi-level
	real network	heuristic methods	exact methods				
Fusco et al. (2002)		*		*			
Lam et al. (2002)		*				*	
Guan et al. (2003)	*		*	*	*		
Kurauchi et al. (2003)		*			*		
Ngamchai & Lovell (2003)		*		*			
Tom & Mohan (2003)		*		*			
Wan & Lo (2003)			*	*	*		
Fan & Machemehl (2004)		*		*			
Poon et al. (2004)	*	*			*		
Borndörfer et al. (2005)	*		*	*	*		
Park (2005)		*				*	

Table 2.5: Literature survey on frequency setting problems (cont.)

Type of Models							
Authors	Frequency setting			Network design	Capacity constraint	Stochastic assignment	Bi-level
	real network	heuristic methods	exact methods				
Cepeda et al. (2006)	*	*			*		
Dell'Olio et al. (2006)		*		*			*
Fan & Machemehl (2006)		*		*			
Gao et al. (2007)		*		*			*
Puchalsky (2007)			*				*
Schmöcker et al. (2008)	*	*			*		
Teklu (2008)		*			*	*	
Cortés (2011)	*	*			*		
Szeto et al. (2011)	*		*		*	*	

In the literature, there are several studies about the frequency setting problems which are categorized in the Table 2.3. Most of them are solved by heuristic methods due to their complexity. With this research, we propose bi-objective bi-level optimization model to determine transit line frequencies regard with minimizing greenhouse gas emission. We provide sustainable solutions for the selected bus network with minimizing travel time and gas emission. The overall model is solved by an adapted genetic algorithm. With these unique features, our work fills an important gap in the literature.

3 MODEL FORMULATION

In this chapter, we present the details of our sustainable transit network frequency setting model. As this model involves bi-level programming and multi-objective programming, we first introduce these concepts. Bi-level programming is a special case of the multi-level programming; hence the general case is also elaborated. The lower level of our model includes frequency assignment, and thus frequency based route choice models are introduced next. Since we aim to reduce emissions, we also investigate several emission modeling approaches. Our frequency setting model is revealed at the final section.

3.1 Multi-level Linear Programming (MLP)

Multi-level linear programming (MLP) is defined as a mathematical programming, which deals with multiple objective functions with their constraints. Multi-level programming models partition control over decision variables among ordered levels within a hierarchical planning structure. Multi-level programming model has some features as indicated below (Saati & Memariani, 2004):

- The model is a hierarchical structure with integrating decision making units.
- Each sub level applies its policies regard with policies of superior levels.
- Each level tries to optimize their policy independently of the others, but may be impacted by the actions and reactions of them.
- The external effect on a superior problem can be reflected in both its objective function and its set of feasible decisions.

Multi-objective programming problems can be applied to a wide range area due to its flexibility such as; economics, statistics, government policy, environment, data bases, game theory, operation research, network design, warfare, transportation, etc.

Multi-objective programming provides to evaluate alternatives considering trade-offs among the objectives. By way of addition, new applications are constantly being introduced (Bialas, 2003).

Many algorithms have been developed to solve multi-level problems for especially linear ones. Solvable of multi-linear programming problems are bi-level programming problems (BLPPs), bi-level decentralized programming problems (PLDPPs) and three-level programming problems (TLPPs). The vertex enumeration approach, the Kuhn-Tucker approach, fuzzy approach, multiple objectives linear programming approach, grid search algorithm, bi-criteria linear programming algorithm can be used to solve BLPP (Saati & Memariani, 2004).

Multi-level mathematical programming is related to non-cooperative game theory. It is assumed that there is no communication among decision makers with the solution concept of Stackelberg equilibrium (Bialas, 2003).

$x \in \mathbb{R}^N$ is decomposed as (x^a, x^b) and $S \subset \mathbb{R}^N$ is defined as closed and bounded region: $\psi_f(S) = \{\hat{x} \subset \mathcal{S} : f(\hat{x}) = max\{f(x) \mid (x^a \mid \hat{x^b})\}\}$. For fixed x^b, there is unique x^a that maximizes $f(x^a, \hat{x^b})$ over $(x^a, \hat{x^b}) \subset \mathcal{S}$, then there induced a mapping $\hat{x^a} = \psi_f(\hat{x}^b)$ and then, $\psi_f(\mathcal{S}) = \mathcal{S} \cap \{(x^a, x^b) : x^a = \psi_f(x^b)\}$. $\mathcal{S} = S^1$ is the level-one feasible region, $\mathcal{S}^2 = \psi_{f1}(\mathcal{S}^1)$ represents the level-two feasible region, and the level-k feasible region is $\mathcal{S}^k = \psi_{fk-1}(\mathcal{S}^{k-1})$.

Note: While $\mathcal{S}^1$ is convex, $\mathcal{S}^k = \psi_{fk-1}(\mathcal{S}^{k-1})$ for $k \geq 2$ are generally non-convex sets.

Applications of bi-level and multi-level programming can be denoted such as (Vicente & Calamai, 1994):

- Transportation
- Management
- Planning
- Engineering Design

3.2 Bi-level Programming (BLP)

Bi-level programming is a branch of hierarchical mathematical optimization. According to bi-level programming, the model has two levels which are the upper level and the lower level. Although, the upper and the lower objective functions conflict each other, the model tries to simultaneously optimize both the upper and the lower problems.

J. Bracken & J. McGill (1973) propose first original formulation for bi-level programming. In addition, designation bi-level and multi-level programming is first used by Candlerand & Norton (1977). After that, bi-level programming takes attention in the literature and the studies that are bi-level programming start to appear. Regard with the game theory of Stackelberg, bi-level programming is studied intensively by many academics. Stackelberg games, which are also called leader-follower games, are initially proposed by Stackelberg in 1952 (von Stackelberg, 1952) based on some economic monopolization phenomena. Stackelberg games, in which the leader first implements a policy and then the follower tries to get best responds to it. For this type of work, refer to Candler & Norton (1977); Bialas & Karwan (1982); Aiyoshi & Shimizu (1981); Bard & Falk (1990).

By improving bi-level programming, algorithms are developed for solving the proposed models. Survey on these algorithms are provided by; Kolstad (1985) and Anandalingam & Friesz (1992).

Many problems require integrated decision variables which can conflict with each others. These groups of problem are designed with a hierarchical system, with individuals being independent. For this reason, bi-level programming has many potential applications in different fields; such as transportation, economics, ecology, engineering and others (Dempe, 2003). Although, a wide range of applications fit the bi-level programming framework (Colson et al., 2005), there is not enough efficient algorithms for solving large scale problems.

The general formulation of a bi-level programming problem is (Colson et al., 2005);

$$\text{minimize} \quad \sum_{x \in \mathcal{X}, y} F(x, y) \tag{3.1}$$

$$\text{s.t.} \quad G(x, y) \leq 0 \tag{3.2}$$

$$\text{minimize}_y \quad f(x, y) \tag{3.3}$$

$$\text{s.t.} \quad g(x, y) \leq 0 \tag{3.4}$$

Where $x \in \mathbb{R}^{n_1}$ and $y \in \mathbb{R}^{n_2}$. The variables of the problem (3.1)-(3.4) are divided into two classes, the upper level variables $x \in \mathbb{R}^{n_1}$ and the lower level variables. The functions of the model $F : \mathbb{R}^{n_1} \times \mathbb{R}^{n_2} \to \mathbb{R}$ and $f : \mathbb{R}^{n_1} \times \mathbb{R}^{n_2} \to \mathbb{R}$ are the upper level and the lower level objective functions respectively, while the vector valued functions $G : \mathbb{R}^{n_1} \times \mathbb{R}^{n_2} \to \mathbb{R}^{m_1}$ and $g : \mathbb{R}^{n_1} \times \mathbb{R}^{n_2} \to \mathbb{R}^{m_2}$ are called the upper level and the lower level constraints, respectively. Upper-level constraints play important role by including variables from both levels. They do not affect directly the lower level decision maker (Colson et al., 2005).

For a sustainable transportation, the model may also have a two level structure. The transit authority determines pricing schemes, frequency of transit lines, quality service objectives including the minimization of congestion, operation cost, emission or maximization of ridership. According to the variables, passengers try to maximize their utilities, such as minimizing travel time, waiting time, travel cost, transfers, etc. Therefore bi-level programming is a suitable structure for modeling sustainability in transportation networks.

The linear bi-level programming problem resembles standard linear programming problem (BLPP). One different point of the bi-level problem is that the constraint region of the linear bi-level problem is designed to provide a linear objective and get optimal solution regard with variables of the model.

Especially, most studies of bi-level programming problems are BLPP in which all functions are linear. Wen & Hsu (1989) and Ben-Ayed (1993) propose linear bi-level programming problem.

According to mathematical definition, x which is the vector of the model can be partitioned between the leader and the follower. While ${x_1}^{N1}$ is the variable of the upper level model, ${x_2}^{N2}$ is the variable of the lower level model. Assume that $N1$ (for the upper level problem), $N2$ (for the lower level problem) show that components of vector x. Then, assume that $f_1, f_2 : \mathbb{R}^{N1} \times \mathbb{R}^{N2} \rightarrow \mathbb{R}$ are linear. Now, BLPPs can be formulated as below (Saati & Memariani, 2004):

$$\text{maximize}_{x_1} \quad f_1(x_1, x_2) \qquad\qquad \text{where } x_2 \text{ solves} \tag{3.5}$$

$$\text{maximize}_{x_2} \quad f_2(x_1, x_2) \tag{3.6}$$

$$\text{s.t.} \qquad (x_1, x_2) \in \mathcal{S} \tag{3.7}$$

$\mathcal{S}$ includes the feasible choices of (x_1, x_2) which can be identified $\mathcal{S} \subset \mathcal{R}^{N(1)+N(2)}$. For specific x_1, the follower tries to maximize the f_2 using x_2, which is the objective function of the lower level problem. From here, for each feasible x_1, the lower level problem will react with an appropriate value of x_2. It is assumed that the reaction function is known by the level-one.

3.3 Multi-Objective Programming (MOP)

Multi-objective programs have several objectives that represent different goals. The multi-objective programs can be named as multi-objective optimization (MOO) or multi-criteria optimization (Rangaiah, 2009). The aim of these programs is to find the optimum of more than one objective. For this property of the multi-objective programs, it differs from single objective optimization or single objective program. While the single objective programs give a unique solution, there are a set of alternative trade-offs which called are Pareto optimal solutions for the multi-objective programs. Hence, solving methods of the multi-objective program are different from single objective ones.

Multi-objective programming problems can be applied to a wide range of areas for private and public sectors. For the public sectors, investment, regulation, control of economic activity and policy problems can be modeled as a multi-objective programming due to their nature. The multi-objective programs have been important over the last two decades. Especially, operation research, economics and psychology area widely use this programming (Cohon, 2003).

From the transportation side, transit planning is a multi-objective problem, where the users' and the authorities' interests conflict. For example; the authorities want to minimize their cost or maximize ridership while the users try to minimize their travel time, cost, transfers and disutility of service, etc.

3.3.1 Multi-Objective Optimization Problem Setting and General Notation

The general form of multi-objective optimization problem is as follow (Marler & Arora, 2004):

$$\text{minimize}_x \quad F(x) = [F_1(x), F_2(x), ..., F_k(x)]^T \tag{3.8}$$

$$\text{s.t.} \qquad g_j(x) \leq 0,\ j = 1, 2, ..., m, \tag{3.9}$$

$$h_l(x) = 0,\ l = 1, 2, ..., e, \tag{3.10}$$

Where k is the number of objective functions, m is the number of inequality constraints, and e is the number of equality constraints. $x \in\ E^n$ is a vector of decision variables, where n represents the number of independent variables x_i. $F(x) \in E^k$ is a vector of objective functions $F_i(x) : E^n \to E1$. $F_i(x)$ can be named as payoff functions, value functions. The gradient of $F_i(x)$ with respect to x is written as $\nabla x F_i(x) \in E^n$. $x_i^\star$ minimizes the objective function $F_i(x)$ which is called an optimal solution. $\mathcal{X}$ is feasible decision space that is defined as the set:
$\{x \mid g_j(x) \leq 0,\ j = 1, 2, ..., m;\ and\ h_i(x) = 0, i = 1, 2, ..., e\}$.

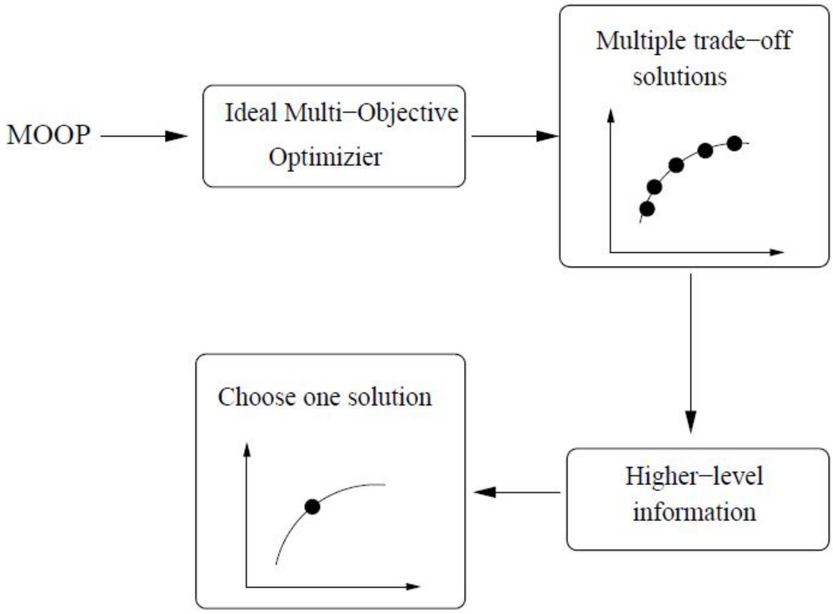

Figure 3.1: Ideal multi-objective procedure (Narzisi, 2008).

Figure 3.1 shows the process of multi-objective optimization problem. First, an appropriate method is selected to solve the problem. Then, a set of solutions are obtained which are Pareto optimal solution. After finding Pareto optimal solutions, decision maker chooses the best solution for his/her problem.

3.3.2 Pareto Optimal Solutions

Multi-objective optimization solutions are defined as the Pareto-optimal solutions that include a set of points. Edgeworth-Pareto (1906) introduced optimal point as a predominant concept which refers to Pareto optimality.

Pareto optimal is illustrated as below (Marler & Arora, 2004):

A point $x^\star \in \mathcal{X}$, is Pareto optimal if there does not exist another point, $x \in \mathcal{X}$, such that $F(x) \leq F(x^\star)$, and $F_i(x) < F_i(x^\star)$ for at least one function.

When a point is weakly Pareto optimal, no other point enhances all of the objective functions simultaneously. Pareto optimal points are weakly Pareto optimal, but weakly Pareto optimal points are not Pareto optimal.

Weakly Pareto optimal is defined as follow:

$x^\star \in \mathcal{X}$ is weakly Pareto optimal for (P) if another vector $x \in \mathcal{X}$ such that $f_i(x) < f_i(x^\star)$ for all $i = 1, ..., k$ does not exist.

All Pareto optimal points can be classified into two classes as either proper or improper. According to Pareto optimality, there is a trade-off between each function and at least one other function be bounded in order for a point. If a Pareto optimal point is not proper, it is improper (Marler & Arora, 2004).

Properly Pareto optimal is implied as below:

$x^\star \in \mathcal{X}$ is properly Pareto optimal for (P) if it is Pareto optimal for (P) and if there is some real number $M > 0$ such that for each f_i and each $x \in \mathcal{X}$ satisfying $f_i(x) < f_i(x^\star)$ there is at least one f_i and each $x \in \mathcal{X}$ satisfying $f_i(x) < f_i(x^\star)$ there is at least one f_j such that $f_j(x^\star) < f_j(x)$ and $\dfrac{f_i(x^\star) - f_i(x)}{f_j(x) - f_j(x^\star)} \leq M$.

3.4 Frequency Based Route Choice Models

Transit passenger route choices are modeled with frequency based transit assignment with information of routes, travel time and frequencies of transit line, which are known by passengers. The focus point of the model is that passengers do not know exact departure times beforehand so the passengers choose a route regard with information of routes. Detailed network representation is used to model a transit trip which includes the walking time, waiting time, in-vehicle time, and the transfers between lines if there is more than one.

Assumptions of frequency based route choice models are as below (Noekel & Wekeck, 2007):

- Service regularity (distribution of inter-arrival times for each transit line),
- Arrival distribution of passengers at stops,
- Capacity constraints,
- Trip information available to passengers,
- The structure of the choice set.

The ordered assumptions are taken into account with Optimal Strategies Framework which is developed Nguyen & Pallottino (1988); Spiess & Florian (1989). Each assumption can generate different type of frequency based route choice models. It is not correct to assume the result of one model will be a good approximation in a network where another set of assumptions holds true. There can be more than one true answer to route choice in frequency-based assignment.

There are three main models for transit route choices. If the travel time and the frequencies are constant, this is the linear case model which is the simplest model in the route choice models. When the travel time is not fixed, the non linear cost model occurs. If there is congestion in the network, passengers cannot get in the first vehicle and the variable frequency or capacitated model is used. It is the most complex transit route choice model.

3.4.1 The Linear Cost Model

The linear cost model is based on optimal strategies which is detailed by Spiess & Florian (1989). The transit network is represented by nodes and links. A set of nodes $i \in \mathcal{I}$ is connected by a set of links $a = (i, j) \in \mathcal{A}$. The links are separated main four classes, such as boarding, alighting, in-vehicle and walking links.

Assumed that waiting links have a finite frequency f_a, the other links are served continuously $(f_a = \infty)$. Wait links do not have travel time, in vehicle links do not have waiting time, alighting links do not have travel and waiting time, and walk links have travel time but do not have waiting time.

Each walk link and transit line segment which can be defined as an arc, is fixed. At each node which belongs a transit line, the distribution of the interarrival time of the vehicles is known for that transit line. From here, expected arrival time of the first vehicle can be calculated. The objective is to minimize expected waiting and travel time or expexted total generalized cost.

$\mathcal{A}$ is the set of links and $\mathcal{N}$ is the set of nodes. $\bar{\mathcal{A}} \in \mathcal{A}$ shows that the solution of the model. For a single destination, the solution is $b_s = (N, \bar{A})$ where b_s is a subgraph. g_i is presented the demand from nodes $i, i \in \mathcal{N}$ to the destination s. A travelers gets in the first vehicle at each node in a solution $\bar{\mathcal{A}}$. $\mathcal{A}_i^+$ shows that the set of links going out of node i (forward star), $\mathcal{A}_i^-$ is identified that the set of incoming links (backward star). $\mathcal{A}_i^+$ is represented that will be chosen by the traveler to board from i to q. At each node i, $\mathcal{A}_i^+$is defined the set of attractive lines, $\bar{\mathcal{A}}_i^+ (\bar{\mathcal{A}} = \cup_i \mathcal{A}_i^+)$.

$W(\bar{\mathcal{A}}_i^+)$ is the expected waiting time at a node i for the arrival of the first vehicle, $a \in \bar{\mathcal{A}}_i^+$. Assuming that distribution of interarrival time is exponential then,

$$W(\bar{\mathcal{A}}_i^+) = \frac{1}{\sum\limits_{a \in \bar{\mathcal{A}}_i^+} f_a} \tag{3.11}$$

Where f_a is the frequency of the link a.

$P_a(\bar{\mathcal{A}}_i^+)$ is the probability that, a link is the first served line among the links $\bar{\mathcal{A}}_i^+$.

$$P(\bar{\mathcal{A}}_i^+) = \frac{f_a}{\sum\limits_{a' \in \bar{\mathcal{A}}_i^+} f_{a'}}, \;\; a \in \bar{\mathcal{A}}_i^+ \tag{3.12}$$

$\bar{\mathcal{A}}$ to the unknown, the single model is formulated with using binary variables x_a.

$$x_a = \begin{cases} 0 \text{ if } a \notin \bar{\mathcal{A}} \\ 1 \text{ if } a \in \bar{\mathcal{A}} \end{cases}, \;\; a \in \mathcal{A} \tag{3.13}$$

The model has one destination which is denoted s. For simplicity formulation of the model, s is not used with mathematical formulation.

The optimization model is as below (Florian, 2008):

$$\text{minimize} \quad \sum_{a \in \mathcal{A}} s_a v_a + \sum_{i \in \mathcal{N}} \frac{v_i}{\sum_{a \in \mathcal{A}_i^+} f_a x_a} \tag{3.14}$$

$$\text{s.t.} \quad v_a = \frac{x_a f_a}{\sum_{a' \in \mathcal{A}_i^+} f_{a'} x_{a'}} \qquad a \in \mathcal{A}_i^+, i \in \mathcal{N} \tag{3.15}$$

$$v_a = \sum_{a \in \mathcal{A}_i^+} v_a + g_i \qquad i \in \mathcal{N} \tag{3.16}$$

$$v_i \geq 0 \qquad i \in \mathcal{N} \tag{3.17}$$

$$x_a = 0 \text{ or } 1 \qquad a \in \mathcal{A} \tag{3.18}$$

s_a is the travel cost on link a and v_i is the total volume at node i of the model. The proposed problem (3.14)-(3.18) is a mixed integer nonlinear optimization problem.

To obtain simple formulation, the problem can be formulated as a linear programming problem. Constraint (3.17) can be rewritten $v_a \geq 0, a \in \mathcal{A}$ since $\sum_{a \in \mathcal{A}_i^+} v_a = v_i, i \in \mathcal{N}$ with new variables w_i, which corresponds the total waiting time at node i,

$$w_i = \frac{v_i}{\sum_{a \in \mathcal{A}_i^+} f_a x_a}, i \in \mathcal{N} \tag{3.19}$$

Then the new formulation is obtained as below:

$$\text{minimize} \quad \sum_{a \in \mathcal{A}} s_a v_a + \sum_{i \in \mathcal{N}} w_i \tag{3.20}$$

$$\text{s.t.} \qquad v_a = x_a f_a w_i, a \in \mathcal{A}_i^+ \qquad \text{i} \in \mathcal{N} \tag{3.21}$$

$$\sum_{a \in \mathcal{A}_i^+} v_a - \sum_{a \in \mathcal{A}_i^-} v_a = g_i \qquad \text{i} \in \mathcal{N} \tag{3.22}$$

$$v_a \geq 0 \qquad \text{a} \in \mathcal{A} \tag{3.23}$$

According to the optimal strategy, the model aims to minimize the total expected cost. The total expected cost includes sum of link travel times s_a multiplied by probability of traveling on link a, and the total waiting time at node i weighted by the probability of traveling through node i.

Objective function is linear and binary variables are used in constraint (3.21), which is the single non linear constraint of the model. Constraint (3.21) can be relaxed with

$$v_a \le f_a w_i, a \in \mathcal{A}_i^+, i \in \mathcal{N} \tag{3.24}$$

3.4.2 The Nonlinear Cost Model

When the link travel times c_a are not fixed, $c_a(v), a \in \mathcal{A}$ and, $v = \{v_a\}, a \in \mathcal{A}$ discomfort exists which can be defined as cost of passengers in overload vehicles. If $c_a(v) = c_a(v_a), a \in \mathcal{A}$ there is an equivalent convex cost optimization problem, in the other words transit equilibrium assignment. The total volume on link a:

$$v_a = \sum_{s \in \mathcal{S}} v_a^s, a \in \mathcal{A} \tag{3.25}$$

Where s represents destination nodes, $s \in \mathcal{S}$.

The nonlinear cost problem cannot be decomposed anymore because the link costs depend on the total flow of passengers. g_i^s denotes that the demand from node $i, i \in \mathcal{I}$ to destination $s, s \in \mathcal{S}$. h_i^k is the part of the demand g_i^s with using travel strategy $k, k \in \mathcal{K}_s$ and then flow equation is;

$$\sum_{k \in \mathcal{K}_s} h_i^s = g_i^s, i \in \mathcal{I}, k \in \mathcal{K}_s, s \in \mathcal{S} \tag{3.26}$$

The expected cost of strategy is not constant; depend on the total volumes so the optimal strategies are defined by Wardrop's (Wardrop, 1952) second principle. According to Wardrop's principle, passengers do not choose strategies which lead to larger cost. Thus, equilibrium condition exists. When S_i^k presents the expected travel times of strategy $k \in \mathcal{K}_s$ from node i to destination s, the equilibrium condition is defined:

$$\begin{cases} {s_i}^{k\star} = {u_i}^{s\star}, \text{ if } {h_i}^{k\star} > 0 \\ {s_i}^{k\star} \geq {u_i}^{s\star}, \text{ if } {h_i}^{k\star} = 0 \end{cases}, \; i \in \mathcal{I}, \; k \in \mathcal{K}_s, \; s \in \mathcal{S} \tag{3.27}$$

Taking into account similar development with used by Smith (1979), the general cost can be defined. $c_a(v) = c_a(v_a), a \in \mathcal{A}$. From here, convex cost optimization problem is formulated (Florian, 2008):

$$\text{minimize} \quad \sum_{a \in \mathcal{A}} \int_0^{v_a} c_a(x)dx + \sum_{i \in \mathcal{I}} \sum_{s \in \mathcal{S}} w_i^s \tag{3.28}$$

$$\text{s.t.} \quad v_a^s \leq f_a w_i^s \qquad \text{a}\in \mathcal{A}_i^+, i \in \mathcal{I}, s \in \mathcal{S} \tag{3.29}$$

$$\sum_{a \in \mathcal{A}_i^+} v_a^s - \sum_{a \in \mathcal{A}_i^-} v_a^s = g_i^s \qquad \text{i}\in \mathcal{I}, s \in \mathcal{S} \tag{3.30}$$

$$v_a^s \geq 0 \qquad \text{a}\in \mathcal{A}, s \in \mathcal{S} \tag{3.31}$$

The problem can be solved with using convex cost optimization problems' algorithms.

3.4.3 The Variable Frequency Model

Regard with congested transit network, passengers may not board the first vehicle at a stop due to vehicles have the rigid capacity. At each stop, travelers board the first vehicle whose residual capacity is nonzero to minimize their expected cost. Hence, there is an equilibrium problem; travelers prefer strategies which are minimizing expected travel cost or travel time.

Effective frequency is the main part of the variable frequency model. It is the frequency which is perceived by passengers at a stop. The variable frequency model is used for more complex problems, such as the analysis and planning of congested transit systems.

Congestion has been taken into account as an externality by Wu et al. (1994); De Cea & Fernández (1993). To analyze the effect of reducing frequency without rigid capacities in the equilibrium models, Cominetti & Correa (2001) propose a model.

Florian (2008) represents an algorithm for variable frequency model. For solving the variable frequency models, the solution of the linear cost model is used as a sub-problem in the developed algorithm.

3.5 Emission Models

Vehicle growth rates has been raised rapidly in the last years and expected that number of vehicles will increase in the transportation area. With this exponential growth effect of transportation has been an important issue in the world. To measure environmental impact of transportation comprehensive studies are proposed with emission models. These models take into account to evaluate emission vehicle technology distributions, power-based driving factors, vehicle soak distributions, and meteorological factors. Result of the studies help to make regulations and decisions about emission for future transportation (Davis et al., 2005).

For forecasting emission impacts of transit systems, there are main criteria, such as trip-end versus vehicle miles travelled (VMT, distance-based emission factors), traffic speed/flow, time-of-day shifting and vehicle type (FHA, 2000).

Trip-End Versus VMT (Distance)-Based Emission Factors: At beginning of a vehicle trip emissions are higher than later in the trip which means that vehicle has warmed up. For this reason, some of emission forecasting approaches regards with separate trip-based, the others apply VMT.

There are few approaches which also consider emissions from work and non-work trips separately in order to measure different between the two types of trips.

Traffic Speed/Flow Impacts On Emissions: Characteristics of traffic flow, such as idle time and acceleration rates have an important effect on emissions. When vehicle has high acceleration, emit higher pollution than before. Hence, speed of the vehicles directly effects emission. By applying speed-based emission factors, emissions can be calculated under at different speeds.

Time-Of-Day Shifting: In peak period, travel time is longer than off peak period due to traffic congestion with low speed of vehicles. For modeling this situation, vehicle speed characteristics should be known during the peak and off-peak periods.

Vehicle Type: Age and types of fleet effect pollution rates. Old vehicles emit higher pollution than the new ones due to advanced technologies. Moreover, long vehicles affect more badly than short ones.

Improved emission models should have three main features (Janssen & Wang, 2003):

1. Quality Control: Critical and non-critical errors in the inputs and outputs must be defined by the model with the effective way.

2. Transparency: Data sets of future expected models which are related to on-road mobile, off-road mobile, biogenic, electric utility are easy to model. Data transparency allows to survey with new data about emission.

3. Performance: Performance consists of hardware and software. With improved model both of them should run on similar platforms as the photochemical models with minimum modifications.

Emission levels vary with many parameters. These parameters categorize vehicle and operational based. For vehicle based parameters are fuel type, age of vehicle, size of vehicle, technology level. Regard with operational based speed, acceleration, gear selection, road gradient, and area temperature are taken into account. Emission sources and pollutants for vehicle are shown in Table 3.1.

Table 3.1: Vehicle emission sources and pollutants (Boulter, 2007).

Source/process	**Pollutant(s) emitted**
Hot and cold-start exhaust emissions	Regulated pollutants *CO *VOC_s *NO_x *PM Unregulated pollutants
Evaporative emissions	VOC_s (regulated)
Tyre and brake wear Road surface wear Resuspension	PM (unregulated)

Emission models classify emission calculation approach, generic model type, and geographical application with continuous emission functions or discrete values. Table 3.2 summarizes the emission models.

Table 3.2: Models for estimating emissions from light-duty vehicles[2] (Boulter, 2007).

Generic type	Example	Type of emission factor/function	Type of input data	Typical application
Aggregated emission factors	NAEI	Discrete trip-based	Road type	Emission inventories, EIA[3], SEA[4]
Average speed	COPERT, DMRB	Continuous, trip or link-based	Average trip speed	Emission inventories, dispersion modeling
Adjusted average speed	TEE	Continuous, link-based	Average speed, congestion level	Emission inventories, dispersion modeling
Traffic situation	HBEFA	Discrete link-based	Road type, speed limit, level of congestion	Inventories, EIA, SEA, area-wide assessment of urban traffic management schemes, dispersion modeling
Multiple linear regression	VERSIT+	Discrete link-based	Driving pattern	Emission inventories, dispersion modeling

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[2] Most of the models listed also address other types of vehicle, such as heavy good vehicles and buses.

[3] EIA: Environmental impact assessment.

[4] SEA: Strategic environmental assessment.

Table 3.3: Models for estimating emissions from light-duty vehicles[5] (cont., Boulter, 2007).

Generic type	Example	Type of emission factor/function	Type of input data	Typical application
Simple modal	"UROPOL"	Discrete link-based	Distribution of driving modes	Local assessment of urban traffic management schemes
Instantenous speed based	Modem-DGV	Discrete link-based	Driving pattern	Detailed temporal and spatial analysis of emissions, dispersion modeling
Instantenous power based	VeTESS, PHEM	Discrete link-based	Driving pattern, gradient, vehicle data	Detailed temporal and spatial analysis of emissions, dispersion modeling

Generic type of models are categorized as below (Boulter, 2007):

- **Aggregated Emission Factor Models:** Aggregated emission factor models use a single emission factor to present specific type of vehicle and general type of driving. Therefore, this model is the simplest one among the others.

- **Average Speed Models:** The model calculates average emission for a given type of vehicle with average speed during the trip. The average speed model is used by Ntziachristos & Samaras (2000).

[5] Most of the models listed also address other types of vehicle, such as heavy good vehicles and buses.

- **'Corrected' Average Speed Models:** Correction factor is made of average speed, link length, traffic density and green time percentage. The model defines the effect of congestion at a specific speed on environmental with correction factor. This model is studied by Negrenti (1998).

- **Traffic Situation Models:** Traffic situation models integrate both speed and cycle dynamics for emission calculation.

- **Multiple Linear Regression Models:** The VERSIT+ model which is developed by Smit et al. (2005) provides a weighted least squares regression approach to calculate emission.

- **Modal Models:** For specific analysis, for instance a mode of vehicle operation during a trip is evaluated by the modal models. The models classify simple modal models and instantaneous models.

Figure 3.2 indicates that generic physical model diagram. Using generic model, emission of vehicle can be calculated under different type of parameters.

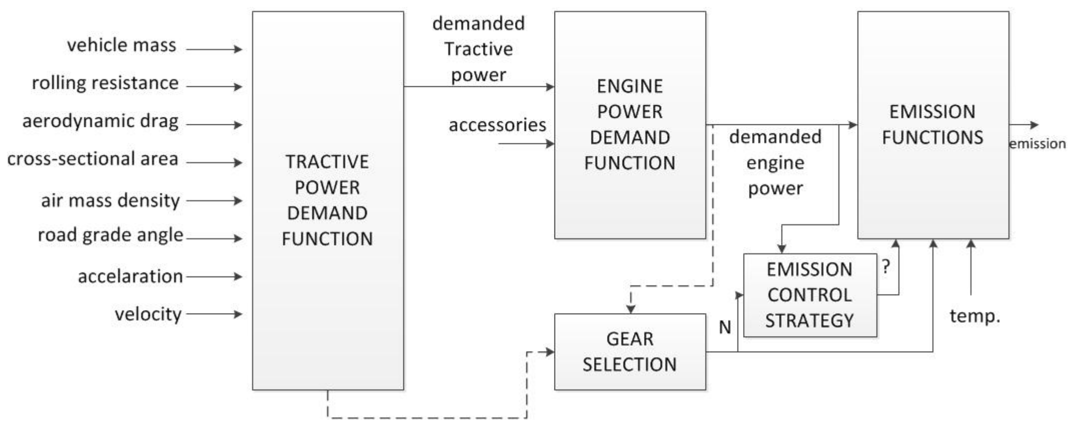

Figure 3.2: Methodology of power demand emissions modeling (Barth et al., 1996).

3.6 Sustainable Transit Frequency Setting

Sustainable transit planning has become significant issue in the world due to negative effect on especially environments such as, global warming. Government makes decisions to provide sustainable transportation, but this process takes long time because of high cost. At this point transit authorities have responsibility for sustainability of transit systems. The transit authorities have a chance to decrease greenhouse gas emissions by optimizing transit system in the network. While they have reduced negative effect of transportation, they have also improved the quality of life regard with service quality. Hence, effective solutions of transit sustainability lead to a more livable community (Feng, 2009).

In this section, a mathematical formulation for the problem of finding sustainable transit frequency on a transit network is developed. The transit route choice mathematical formulation comes from the idea of linear cost model which is proposed by Florian (2008) and general formulation of the line frequency optimization model which is presented by Constantin & Florian (1995). We improve existing models with bi-level approach regarding sustainable transportation. We propose bi-objective and bi-level optimization model to determine transit line frequencies. The upper level problem is related to optimizing transit line frequency taking into account emission.

For the upper level problem, two objectives are considered which are minimization of mean passenger travel time and total CO_2 emission. The lower level problem is frequency based transit route choice. At the lower level problem, we aim to reduce the total passenger travel times at given passenger demand and existing transit lines. Finally sustainable transit frequency setting problem is obtained.

Let us denote $G(\mathcal{N},\mathcal{A})$ the directed graph with $\mathcal{N}$ as the set of nodes and A is the set of links. Let also $\mathcal{S}$ denote the set of destination nodes, $\mathcal{A}_i^+$ and $\mathcal{A}_i^-$ the forward and backward star of node i respectively, and $\mathcal{L}$ the set of transit lines.

1. Upper Level Problem

For improving service quality of transportation system transit authorities try to optimize transit line frequencies given passenger demand and the other constraints. Especially, peak hours are taken into account for analyzing the transit system due to passenger overloading. The first aim of the authorities is to minimize the total travel time spent by the travelers in the network under the fleet size and line constraints.

In our upper level problem, we have two objective functions which optimize simultaneously minimizing mean passenger travel time and total CO_2 emission due to the operating vehicles. If transit line frequencies are increased, the total travel time decreases. Meanwhile, increasing bus frequencies also leads to an increase in the total emission. In other words, these two objectives are in conflict.

$$\text{minimize} \quad \frac{1}{D}\sum_{s\in\mathcal{S}}\left(\sum_{a\in\mathcal{A}} t_a v_a^s + \sum_{i\in N} w_i^s\right) \tag{3.32}$$

$$\text{minimize} \quad \sum_{l\in\mathcal{L}} e_l f_l \tag{3.33}$$

$$\text{s.t.} \quad \sum_{l\in\mathcal{L}} t_l f_l \leq M \tag{3.34}$$

$$f_l \geq \underline{f}_l \qquad l \in \mathcal{L} \tag{3.35}$$

Here, D denotes the total travel demand between zones, t_a the fixed travel time on link a, v_a^s the flow on link a with destination s, w_i^s the total waiting time for passengers on node i with destination s, e_l the total CO_2 emission for a vehicle operating on line l, and t_l the fixed in-vehicle travel time of line l, M the fleet size, and $\underline{f}_l$ the required minimum frequency for line l. The variable of this model is f_l which denotes the vehicle frequency for line l. In (3.32), we aim to minimize mean passenger travel time; including in vehicle and waiting time in the network, while in (3.33) we aim to minimize the total CO_2 emission for the operating vehicles. Constraint (3.34) limits available total vehicles to be operated and constraint (3.35) is the lower bound for frequency of a line. Finally, in (3.32)-(3.35) the bi-objective model is obtained.

2. Lower Level Problem

Travelers make strategies to minimize expected travel time, cost or number of transfers at known travel information, such as travel time, frequency of transit line, etc. There are two main criteria to make travel decision. These are shortest travel time route and route that allows the respondent to arrive earliest. The traveler decisions are optimized with transit route choice problem.

In our lower level problem, we extend the linear cost model to formulate transit route choice problem which is proposed for a single destination by Florian (2008) is improved for multiple destinations. With the lower level problem, the total travel time is minimized under demand and flow constraints.

The transit route choice problem is:

$$\text{minimize} \quad \sum_{s\in\mathcal{S}}\left(\sum_{a\in\mathcal{A}} t_a v_a^s + \sum_{i\in N} w_i^s\right) \tag{3.36}$$

$$\text{s.t.} \quad \sum_{a\in\mathcal{A}_i^+} v_a^s - \sum_{a\in\mathcal{A}_i^-} v_a^s = g_i^s \tag{3.37}$$

$$v_a^s \leq \left(\sum_{l\in\mathcal{L}} \delta_{al} f_l\right) w_i^s \qquad a \in \mathcal{A}_i^+,\ i \in \mathcal{N},\ s \in \mathcal{S} \tag{3.38}$$

$$v_a^s \geq 0 \qquad a \in \mathcal{A},\ s \in \mathcal{S} \tag{3.39}$$

Here g_i^s is the passenger demand at node i willing to reach destination s. The objective in (3.36) is to reduce the total passenger travel times in the network. Constraint in (3.37) is the general flow balance constraint for network flows: the number of passengers leaving node i must be equal to the sum of the passenger incoming to and waiting at node i. Assuming that the passengers waiting at a node get in the first vehicle, constraint (3.38) relates links flows and nodes waiting times. δ_{al} =1 if link a belongs to line l; 0 otherwise. Constraint (3.39) is for non-negative flows. Then, in (3.36)-(3.39) the transit route choice model is formulated.

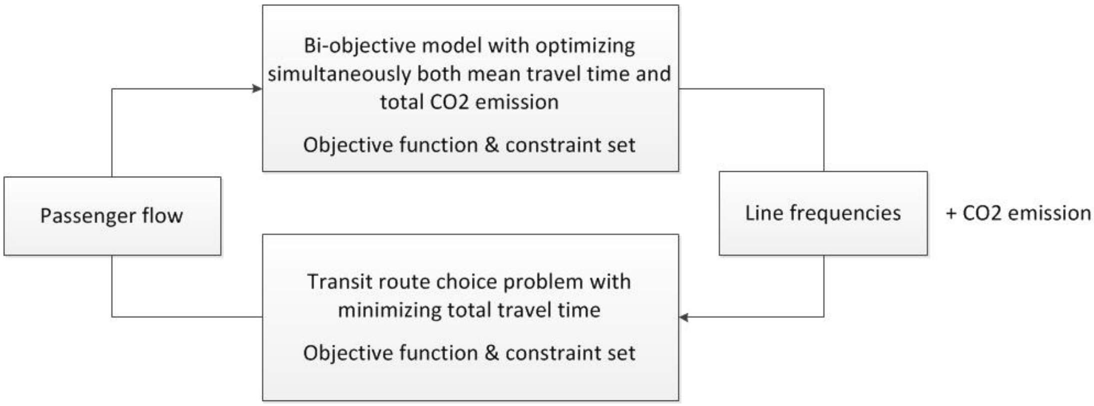

Figure 3.3: Sustainable transit frequency setting problem

Logic of sustainable transit frequency setting problem is summarized in Figure 3.3. For given frequencies, the lower level problem finds passenger flow regard that with minimizes total travel time. Then, the upper level problem optimizes the frequencies and also calculates total CO_2 emission due to operating vehicles with optimized line frequencies. When transit line frequencies are increased, the total travel time decreases. At this point, increasing transit line frequencies also causes to an increase in the total emission. Hence, these two objectives are in conflict.

4 SOLUTION METHODOLOGY

Bi-level and multi-objective programming models differ from conventional models due to their complexity. Bi-level and multi-objective models are used a wide range area, such as transportation, economics, ecology, engineering and others (Pieume et al., 2011). There is a growth of using these models in the literature because of adapting flexibility to the problems. Therefore, several methods are developed for solving bi-level and multi-objective programs. While some of them are exact approaches, the others are heuristics. In this chapter, we outline exact and heuristic methods for bi-level and multi-objective programs.

4.1 Solving Bi-level Programming Models

Bi-level programming is a special case of multi-level programming which is used to solve different type of problems. Most of the mathematical programming models cope with a single objective function to obtain optimal solution. The bi-level programming models differ from conventional models due to having two objective functions. At each level, the decision maker attempts to optimize its own objective function without considering the objective of the other level. At this point, decision of each level affects the objective value of the other level.

Bi-level programming problems are difficult by its nature. For this reason, there are lots of studies on the simplest cases of bi-level programs which have nice properties, such as linear, quadratic or convex objective and/or constraint functions. In the literature, there are lots of studies about linear case which is defined as bi-level linear programming problem (BLLP).

Hsu & Wen (1989); Ben-Ayed (1993) studies are the example of linear case. Over the years, more complex models are studied. Vicente et al. (1996) take into account discrete variables; Anandalingam & Friesz (1992) propose general survey about complex ones.

Colson (1999) deals with both nonlinear bi-level programming problems and mathematical programs with equilibrium constraints and Dempe (2003) studies on these same topics. Savard et al. (2005) investigate the combinatorial nature of bi-level programming.

For solving bi-level programming problem, there are main approaches. These approaches are classified as below (Colson et al., 2007):

4.1.1 Extreme-Point Approaches For The Linear Case

Linear bi-level programming problems which have linear functions and the set $\mathcal{X}$ is polyhedral which is their solution set. Due to their solution set is polyhedron, the solution sets are nonempty.

$$\Omega = \{(x, y) : x \in \mathcal{X}, G(x, y) \leq 0 \wedge g(x, y) \leq 0\} \tag{4.1}$$

For this property, lots of methods are used to solve bi-level linear programming problem (BLPP) with based on vertex enumeration.

Candler & Townsley (1982) propose an algorithm which explores a decreasing number of bases of the lower-level problem for solving BLPP with no upper-level constraints and with unique lower-level solutions.

The K th best method is presented by Bialas & Karwan (1984). The method stops at the lowest index of K corresponding to a rational basis which is globally optimal. Also, Wen & Bialas (1986) study with K-best algorithm. Papavassilopoulos (1982) represents all extreme points assumed belong to the induced region IR and the adjacent vertices are discovered by separation techniques. Chen & Florian (1992); Tuy et al. (1993) make a contribution to extreme point approaches.

4.1.2 Branch-and-Bound Approach

If the lower level problem is regular and convex, it can be modified with Karush-Kuhn-Tucker (KKT) conditions in order to obtain single level problem which is the Lagrangean function associated with the lower-level problem. While the Lagrangean constraint is linear, enumeration algorithms which can be branch-and-bound are used to solve the problem by Bard & Falk (1982). McCarl, et al. (1981) propose algorithms to solve linear bi-level programming problems. Hansen et al. (1992); develop branch-and-bound algorithm to solve bi-level programming problem. They present a code which can solve medium-sized linear bi-level programming problems. Bard & Moore (1990) use the branch and bound method to cope with linear-quadratic problems and Al-Khayal et al. (1992) study quadratic case with the approach.

4.1.3 Complementary Pivoting

Lemke algorithm which is developed by Lemke (1965) is a complementary pivoting algorithm. The Lemke algorithm is a path-following algorithm and generates a piecewise linear path either towards a solution to the linear complementarily problem or towards infinity. There is a trouble with the algorithm due to the fixed starting point z=0 (Kremers & Talman, 1994).

Bialas et al. (1980) use complementary pivots algorithms and develop Parametric Complementary Pivot (PCP) Algorithm to solve BLPPs. Correspondingly, Ben-Ayed & Blair (1990) state that this algorithm does not always converge to the optimal solution. Júdice & Faustino (1992) propose sequential linear complementarily problem (LCP) for solving linear and linear-quadratic bi-level programming problems.

4.1.4 Descent Methods

Steepest Descent is the simplest method among the gradient methods. The choice of direction is where f decreases most quickly, which is in the direction opposite to $\nabla f(x_i)$.

The search starts at an arbitrary point x_o and then slide down the gradient, until you close enough to the solution. [6]

Although, Steepest Descent method is stable and easy to implement, it has a drawback due to slow convergence. The convergence of the method is shown in Figure 4.1.

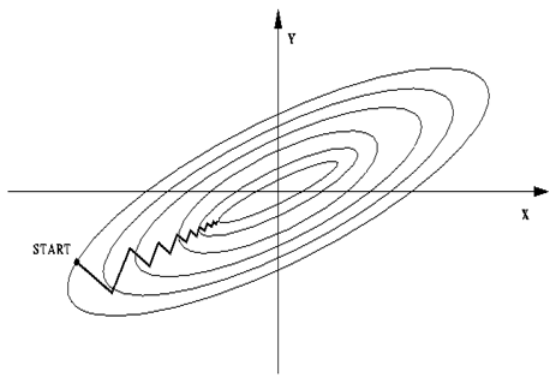

Figure 4.1: The convergence of the method of Steepest Descent

[6] http://trond.hjorteland.com/thesis/node26.html

Vicente et al. (1994) develop a proposed a descent method for convex quadratic bi-level programs.

4.1.5 Penalty Function Methods

Penalty method which is one of the preferred methods among the others solves nonlinear BLPPs with developed algorithms. In general, the developed algorithms are used to find stationary points and local minima (Colson et al., 2007).

Aiyoshi & Shimizu (1981) make a first contribution in this topic. With more complexity, Ishizuka & Aiyoshi (1992) present a double penalty method which means that two objective functions of their model are penalized. In addition, White & Anandalingam (1993) propose a penalty function approach for solving bi-level linear programs. Aiyoshi & Shimizu (1984) study a new computational method for Stackelberg and min-max problem by use of a penalty method. They present a solution method for the static constrained Stackelberg problem via penalty method. A more recent contribution is made by Case (1999) which is related to solving linear bi-level programs.

4.1.6 Trust-Region Methods

Gertz (2003) defines, "Trust-region methods produce a trial step by minimizing a quadratic model of the objective function subject to a constraint on the length of the trial step. Because of this restriction, trust-region methods are sometimes known as restricted-step methods." For helping convergence to local minima, trust-region methods are generally used in local optimization problems.

Liu et al. (1998) propose a trust-region method for the problems which do not contain upper-level constraints and the lower-level program is strongly convex and linearly constrained. Conn et al. (2000) introduce a comprehensive study about trust-region methods. Savard et al. (2005) develop a trust-region algorithm for solving nonlinear bi-level programs.

4.1.7 Evolutionary Methods

Many researchers have represented evolutionary algorithm for solving single-objective bi-level optimization problems. Yin (2000) proposes another GA based nested approach where the lower level problem is solved with the Frank-Wolfe gradient based linearized optimization method. Oduguwa & Roy (2002) represent co-evolutionary GA approach which is the first step for co-evolutionary procedure solving with single-objective bi-level optimization problems deal with variable vectors x_u and x_l independently. Wang et al. (2008) solve bi-level programming problems involving a single objective function in upper and lower levels with using evolutionary algorithms.

Deb & Sinha (2010) represent hybrid evolutionary-cum-local-search based algorithm as a solution methodology. They show that hybrid approach performs better than a number of existing methodologies with 40-variable difficult test problems. In addition they indicate that "a clear niche of evolutionary algorithms in solving such difficult problems of practical importance compared to their usual solution by a computationally expensive nested procedure". Also, Deb & Sinha (2009) propose evolutionary multi-objective optimization (EMO) studies. Their developed approaches can be used to linear/nonlinear, convex/nonconvex, differentiable/nondifferentiable and single-objective/multi-objective problems at both levels.

4.2 Solving Multi-Objective Models

Multi-objective, also known as multi-criteria models provide more than on objective. With this features, multi-objective models differ from single objective models which give a unique solution. For solving multi-objective models, the special methods are introduced (Rangaiah, 2009). Improved multi-objective methods play an important role due to several problems with multi-objective in the literature. Abraham et al. (2004), propose a book whose name is evolutionary multi-objective optimization. Coello Coello (2009) introduce some current research trends and topics for evolutionary multi-objective optimization.

Multi-objective models are categorized with two classes, such as generating methods and preference-based methods in Figure 4.2.

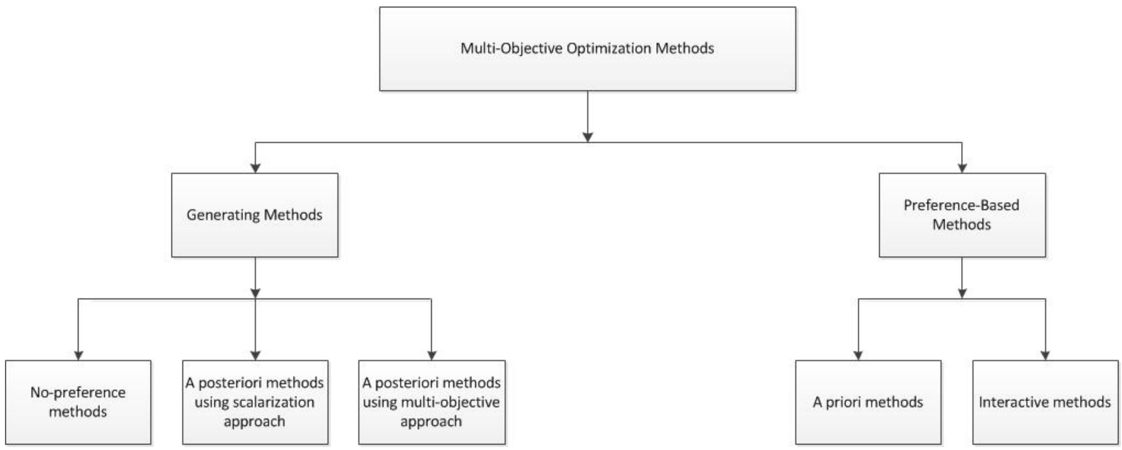

Figure 4.2: Multi-objective methods classification (Rangaiah, 2009).

4.2.1 Generating Methods

The generating methods consist of three sub-groups; no-preference methods, a posteriori methods using the scalarization approach and a posteriori methods using the multi-objective approach.

1. No Preference Methods

Rangaiah (2009) states that "No-preference methods, do not require the relative priority of objectives whatsoever". When the specific method gives one Pareto-optimal solution, using different no-preference methods, a few Pareto-optimal solutions can be found.

The no preference methods are divided into two sub-groups; global criterion and multi-objective proximal bundle method.

A. Global Criterion Method (GC)

The global criterion method is a popular approach among scalarization methods to solve multi-objective optimization. All objective functions of the model are combined to form a single function with the global criterion method and the scalarized function is obtained. The global criterion method is also known as the compromise programming method.

B. Multi-Objective Proximal Bundle Method (MPB)

Multi-objective proximal bundle method is improved by using single objective bundle methods of nondiferentiable optimization (Miettinen, 1999). According to MPB method, all objective functions enhance simultaneously with moving in a direction. The MPB method denotes indirectly the use of a scalarizing function. An unconstrained improvement function is utilized for the approach.

2. A Posteriori Methods Using The Scalarization Approach

A posteriori methods provide to find all or most of the Pareto optimal solutions for a given multi-objective program. The ε-constraint and weighting methods are used as a posteriori methods using the scalarization approach. Using these methods, multi-objective problems convert into single objective problems which present Pareto-optimal solution (Rangoaga, 2009).

A. The ε-constraint Method

One objective function is optimized while the others are required to have specified upper bounds by using the ε-constraint method. Clearly, the method minimizes one objective function and simultaneously goes on the maximum acceptable levels for the other objective functions (Sunar & Kahraman, 2001).

In the literature, Messac, et al. (2003) propose the normalized normal constraint method for generating the Pareto frontier. Ehrgott (2005) represent the approach in his Multicriteria optimization study.

B. Weighting Methods

In this method, the objective functions are converted into a single objective one by creating a new objective from the weighted sum of the k objectives. At this point, the decision maker does not provide targets for each objective. For the problem Pareto optimal solutions are obtained if the weights are strictly positive (Rangoaga, 2009).

3. A Posteriori Methods Using The Multi-Objective Approach

Meta-heuristic methods have been important approach with multi-objective programming over the past years. This leads to expanding the scope of multi-objective programming and solving complex problems efficiently. There are several reasons prefer meta-heuristics to conventional methods for solving multi-objective problems. The reasons are computing power, flexibility and importance of multiple objectives in different disciplines (Jones et al., 2002).

A posteriori methods include meta-heuristic methods which based on rank trial solutions, such as genetic algorithm, simulated annealing and tabu search methods. These approaches are used to solve multi-objective programs. Using with aforementioned methods, many Pareto-optimal solutions are obtained, then decision maker select one of them which is the most appropriate for the problem (Rangoaga, 2009).

We briefly summarize genetic algorithm, simulated annealing and tabu search methods for solving multi-objective programs.

A. Genetic Algorithm

Genetic algorithm approach is based on the mechanisms of natural selection and natural genetics. Using with the approach, multi-objective program can be converted into single objective ones. Although, the genetic algorithm can solve non-convex multi-objective programs, it cannot guarantee the Pareto optimality for the solution (Rangoaga, 2009).

In the literature, several genetic algorithms are developed for the multi-objective programs which are defined as multi-objective evolutionary algorithms (MOEAs). The MOEAs algorithms are (Coello Coello et al., 2009)

Multi-Objective Genetic Algorithm (MOGA): Fonseca & Fleming (1994) present Multi-objective genetic algorithm (MOGA) which is a variation of Goldberg's technique. With this algorithm, a certain individual's rank corresponds to the number of chromosomes in the existing population by which it is dominated.

Non-dominated Sorting Genetic Algorithm (NSGA): NSGA is the another approach of the ranking procedure that is introduced by Srinivas & Deb (1994). The NSGA is composed of several layers with classifications of the individuals. Deb et al. propose NSGA-II that is an improved version of NSGA.

Niched-Pareto Genetic Algorithm (NPGA): Horn et al. (1994) represent NPGA. The idea of NPGA comes from tournament selection.

Pareto Archived Evolution Strategy Algorithm (PAES): The PAES is developed by Knowles & Corne (2000). The approach has historical archive to record some of non-dominated solutions that are previously found.

Strength Pareto Evolutionary Algorithm (SPEA): Zitzler & Thiele (1999) introduce the SPEA algorithm which uses an external archive for previously found non-donimated solutions. A strength value is calculated in the external set for each individual.

Multi-Objective Messy Genetic Algorithm (MOMGA): The MOMGA is proposed by Van Veldhuizen & Lamont (2000). This approach is developed to extend the messy genetic algorithm for solving multi-objective programs. MOMGA-II which is the version of MOMGA (MOMGA-II) is presented by Zydallis et al. (2001).

Pareto Envelope-Based Selection Algorithm (PESA): Corne et al. (2000) propose PESA that has a small internal and a larger external population. PESA-II is also introduced to reduce computational cost associated with Pareto ranking.

The Micro-Genetic Algorithm: Coello Coello & Toscano Pulido (2005) study a micro genetic algorithm. The approach has a small population and a reinitialization process.

Multi-Objective Struggle Genetic Algortihm (MOSGA): MOSGA integrated the struggle crowding approach with Pareto ranking scheme. The logic of approach is similar to struggle algorithm.

Orthogonal Multi-Objective Evolutionary Algorithm (OMOEA): OMOEA is related to a strict definition of the multi-objective program constraints included for a specific problem to solve. With the modification of OMOEA, OMOEA-II is presented.

General Multi-Objective Evolutionary Algorithm (GENMOP): GENMOP is a general form of MOEA which is developed by US Air Force Institute of Technology (AFIT).

B. Simulated Annealing

Simulated annealing approach is used both single objective programs for an optimal solution and multi-objective programs for Pareto solutions. The idea of the method comes from analogy of thermodynamics with the way metals cool and anneal. The approach is not effective as genetic algorithm due to its search-from-a-point nature. Gemand & Gemand (1984) provide a proof which takes long time to converge to the global optima if annealed sufficiently slowly. For this reason, simulated annealing method is usually preferred for single objective programs (Suman & Kumar, 2006).

Czyzak & Jaszkiewicz (1998) propose Pareto simulated annealing (PSA) algorithm that is integrated unicriterion simulated annealing with a genetic algorithm to provide efficient solutions.

The PSA algorithm is based on neighbourhood, such as acceptance of new solutions with some probability and annealing schedule from simulated annealing and the concept of using a sample population of interacting solutions from genetic algorithm (Suman & Kumar, 2006).

C. Tabu Search

Glover (1989) introduces first tabu search form which is widely used for the optimization problems. The tabu search is an optimization tool with repeatedly moving from a current solution to the best in the list of neighboring solutions regard with keeping a tabu-list of forbidden moves. With the modifications, the method is used to generate non-dominated alternatives to multi-objective combinatorial optimization problems. Hansen (1997) defines the multi-objective tabu search procedure (MOTS) “The multi-objective tabu search procedure, MOTS, works with a set of current solutions which simultaneously are optimized towards the non-dominated frontier.

The points of the current solutions are sought to cover the whole frontier and repeatedly for each solution, an optimization direction is made so that it tends to move away from the other points while moving towards the non-dominated frontier. The solutions take turn in applying one move according to a tabu search heuristic and each solution keeps its own tabu list (Hansen, 1997)."

In the literature, Chelouah & Siarry (2005) study a hybrid method which includes tabu search and nelder-mead simplex algorithms for the global optimization of multi-minima functions. Jaeggi et al. (2005) introduced a book whose name is a multi-objective tabu search algorithm for constrained optimization problems. Takahashi & Kurahashi (2007) introduce algorithm of tabu-GA for a multimodal function problem. For the recent studies, Thakur & Dhiman (2011) represent a tabu search algorithm for multi-objective purpose of feeder reconfiguration. They develop tabu search based algorithm for multi-objective network reconfiguration problem.

4.2.2 Preference Based Methods

Composite objective function as the weighted sum of the objectives are obtained by using preference based methods. Preference-based methods divide into two sub-groups: a priori methods and interactive methods.

1. A Priori Methods

Decision maker's opinion is taken into account with the priori methods before solving the multi-objective program. The most used a priori methods are goal programming and lexicographic goal programming methods (Rangoaga, 2009).

A. Goal Programming

The generalized goal programming method is presented by Ignizio (1976). The main aim of the approach is to find solutions which are close to predefined targets. For this reason, the decision maker identifies the targets for each objective functions. And then, the decision maker solves a single objective function with finding solutions that have minimum deviation for each target. Although, the approach is simple, there are some difficulties for it, such as it does not always produce Pareto optimal solutions for the problem due to finding weights for each objective can be difficult (Rangoaga, 2009).

B. Lexicographic Goal Programming Methods (LGP)

In the lexicographic method, the objective functions of multi-objective programs are arranged according to their importance while a target is not given for each objective function. With this idea, the most important function is minimized first, and then the second function is minimized and go on until all the specified functions are minimized. Hence, having higher priority function must be met before than lower priority ones (Rangoaga, 2009).

2. Interactive Methods

In the interactive methods, the decision maker plays an important role for solving multi-objective programs. The weights of the objective functions can be changed the analysis as the decision maker's knowledge of the decision problem changes.

For solving multi-objective programming problems, interactive methods have main three steps (Rangoaga, 2009):

- Find an initial solution.
- The solution is discussed with the decision maker. If the decision maker is pleased, stop. Otherwise decision maker identifies new targets for the objectives and then, go to the next step,
- Find a new solution and go back to step 2.

The iterative methods can be classified into two sub-groups that are interactive surrogate worth trade-off method (ISWT) and nondifferentiable interactive multi-objective bundle-based optimization system method (NIMBUS).

A. Interactive Surrogate Worth Trade-off Method (ISWT)

With the interactive surrogate trade-off method, there are two main to levels which are the decision and the analysis level. After decision maker gets solution, he/she analyzes and then makes a new decision to obtain best solution.

As an example application of this method is; Chen et al. (2002) propose the interactive surrogate worth trade-off method for multi-objective decision-making in reactive power sources planning.

B. Non differentiable Interactive Multi-Objective Bundle-based Optimization System Method (NIMBUS)

The method is improved to deal with non differentiable functions of the multi-objective programs efficiently.

For each iteration, decision maker sorts the objective functions into up to five different classes: those to be improved, those to be improved till some aspiration level, those to be accepted as they are, those to be impaired till some bound, and those allowed to change freely (Miettinen & Mäkelä, 1995). After the classification, new multi-objective problem is formulated which is solved with multi-objective proximal bundle method (MPB).

For more detailed information of the NIMBUS method, we refer readers to Miettinen (1999).

Methods of solving multi-objective programs can be also categorized as below:

- In no-preference methods, decision maker does not provide information.
- In a posteriori methods, the posteriori information is used.
- In a priori methods, priori information is used.
- In interactive methods, progressive information is used (Rangaiah, 2009).

For detailed information about the methods, we refer readers to comprehensive book which was written by Miettinen (1999) includes many methods with its features and difficulties.

4.3 On Solving Lower-Level Problem

The proposed lower level problem is transit route choice problem. Passengers on a transit network with common lines are often faced with the problem of choosing the best combination of displayed waiting time and expected travel time to destination. At this point, the transit route choice problems are used to model such situations. The lower level problem copes with passenger route choice behavior so the decision variables of the model are the set of flow which are result of the passenger optimal route choice. For improving quality of transit systems, it is important to analyze the route choice behavior of passengers.

The earliest studies transit route choice problems for public transport can be found in the late 1960s. These studies are solved using with heuristic algorithms. The early methods for finding passengers' routes in transit network propose the least-cost route finding algorithm. This type of algorithm is developed to find the shortest transit route with assumptions which are fixed in vehicle travel cost and expected travel time (Liu et al., 2010).

The proposed lower level problem is solved by the way of using transit route choice algorithm which is developed by Florian (2008). Dual problem of the linear cost model is formulated to solve the transit route choice problem.

The problem (3.20-3.23) in which chapter 3.4.1 is linear with both objective function and also all constraints. The dual problem of the linear program can be formulated:

$$\text{maximize} \quad \sum_{i \in \mathcal{N}} g_i u_i \tag{4.2}$$

$$\text{s.t.} \quad u_j + s_a + \mu_a \geq u_i \qquad \text{a} \in \mathcal{A} \tag{4.3}$$

$$\sum_{a \in \mathcal{A}_i^+} f_a \mu_a = 1 \qquad \text{i} \in \mathcal{N} \tag{4.4}$$

$$\mu_a \geq 0 \qquad \text{a} \in \mathcal{A} \tag{4.5}$$

u_i, u_j are the dual variables and respond to the constraint (3.22). By way of addition μ_a are the dual variables corresponding to constraint (3.21).

While $(v^\star, w^\star)$ denotes optimal solution of the primal problem, $(u^\star, \mu^\star)$ infers optimal solution of dual problem. From complementary slackness conditions, we can write them as below:

$$(v_a^\star - f_a w_i^\star)\mu_a^\star = 0, a \in \mathcal{A}_i^+, i \in \mathcal{N} \tag{4.6}$$

and

$$(u_i^\star + s_a^\star + \mu_a^\star - u_i^\star)v_a^\star = 0, a \in \mathcal{A} \tag{4.7}$$

Primal and dual formulations look like the shortest path route choice model. The dual formulation corresponds to the shortest path problem for $f_a \to \infty$ and $w_i \to 0$ conditions, which mean that there is no waiting time on the links in the network.

The transit route choice algorithm is closed to the label setting algorithm for solving shortest paths. The solution algorithm has two stages. At the first stage, from the destination nodes to all origins, the arcs which carry flow, $\bar{A}^\star$ and the expected travel times $u_i^\star$ are computed with from each node, $i, i \in \mathcal{N}$ to the destination nodes. At the second stage, from all origins to the destination, the passenger demand is assigned to the links. $a, \in \bar{\mathcal{A}}^\star$.

The algorithm provided below efficiently solves the lower level problem related to destination node q.

Transit route choice algorithm (Florian, 2008):

1. $u_i = \infty$ for all $i \in \mathcal{N}/\{q\}$, $u_q = 0$, $\bar{f}_i = 0$ for all $i \in \mathcal{N}$, $\mathcal{B} = \mathcal{A}$, $\bar{\mathcal{A}} = \emptyset$.

2. If $\mathcal{B} = \emptyset$ then go step 3

Otherwise

Find $a = (i, j)$ such that $u_j + t_a$ is the smallest value of $\mathcal{B}$

$\mathcal{B} = \mathcal{B}/\{a\}$

If $u_i \geq u_j + t_a$ then

$u_i = \left(\bar{f}_i u_i + f_a(u_j + t_a)\right) / (\bar{f}_i + f_a)$

$\bar{f}_i = \bar{f}_i + f_a$

$\bar{\mathcal{A}} = \bar{\mathcal{A}} \cup \{a\}$

Go back step 2

3. $V_i = g_i^q$ for all $i \in \mathcal{N}$

4. For every link $a \in \bar{\mathcal{A}}$ in decreasing order of $(u_j + t_a)$ do

$v_a^q = \left(f_a/\bar{f}_i\right) V_i$

$V_j = V_j + v_a^q$

For all others arcs $a \in \mathcal{A}/\bar{\mathcal{A}}$ set $v_a^q = 0$.

5. $w_i^q = V_i/\bar{f}_i$ for all $i \in \mathcal{N}$

$\bar{f}_i$ are the auxiliary variables, $i \in \mathcal{N}$ which is identified as combined frequencies for all selected links at node i. The primal and dual problems can be solved optimally if each of the destination decomposed sub-problem is solved optimally. For improving the transit route choice algorithm, Wu & Florian (1993); Wu et al. (1994) propose algorithmic variations for solving transit route choice problem.

4.4 Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)

There are several methods to handle the multi-objective optimization problems. One of them is non-dominated sorting genetic algorithm (NSGA-II) which is proposed by Srinivas & Deb (1994) and is a popular method among the others.

The NSGA-II is a ranking and niching method. In the other words, the method highlights current non-dominated solutions and progresses diversity in the population

For non-dominated sorting genetic algorithm studies, Srinivas & Deb (1994) propose multi-objective optimization using non-dominated sorting in genetic algorithms. While, Michielssen & Goldberg (1996) introduce genetic algorithm design of Pareto-optimal broad band microwave absorbers. A fast elitist non-dominated sorting genetic algorithm (NSGA-II) is developed by Deb et al. (2000). Similiarly, Deb et al. (2002) present a fast and elitist multi-objective genetic algorithm (NSGA-II). Deb (2001) proposes a book whose name is multi-objective optimization using evolutionary algorithms, also includes NSGA approach.

The NSGA-II is one of evolutionary algorithms that can find multiple optimal solutions (Pareto solutions) in one single simulation because of its population approach. Non-dominated sorting genetic algorithm approach has been criticized mainly three topics (Deb et al., 2000):

1. Computational Complexity: The non-dominated sorting algorithm deals with large size population so the population needs to be sorted in every generation.

2. Nonelitism Approach: Elitism can quicken the performance of the algorithm and protects the loss of good solutions that they have been found.

3. The Need for Specifying a Sharing Parameter: To get wide variety population, the approach needs to the specification of a sharing parameter σshare. The approach tries to choose the optimal parameter value for sharing parameter σshare. Having diversity population without parameterless mechanism is desirable.

Deb et al. (2000) moderate these difficulties in NSGA-II. The elitist non-dominated sorting genetic algorithm for that there is need fewer parameters than other approaches. Shimamoto et al. (2005) show that elitism helps in achieving better convergence in multi-objective evolutionary algorithms (MOEAs) in the their study.

4.4.1 General Description of NSGA-II Approach

Firstly, the population is created and sorted based on non-domination into each front. The first front is non-dominant set in the existing population and the second front is dominated by the individuals in the first front only and the front carries on like this. Each individual in the each front are assigned according to its fitness value. In the first front, individuals take a fitness value as 1 and in the second front are given a fitness value as 2 and keep on. For each individual, crowding distance which is a parameter for fitness value is calculated. The crowding distance is denoted that what is the distance between individual with its neighbors. If there is a big crowding distance, this leads to better diversity in the population (Seshadri, 2006). Parents are selected from the population by the way of binary tournament selection which is based on rank and crowding distance. An individual is selected regard with its range and crowding distance. In the other words, if the range is less than the others or crowding distance is greater than the others, the individual is selected. The crowding distance is calculated if only the rank is the same both individuals. Offsprings are generated by using selected parents with simulated binary crossover (SBX) and polynomial mutation. The current population and offsprings are sorted according to non dominated approach and the best individuals are selected which size is N. In this case, N represents the population size. After that there is a selection that is based on range and crowding distance on the last front.

4.4.2 Procedure of NSGA-II

NSGA-II algorithm is presented below as a general form (Shimamoto et al., 2005).

1. Initialization part

$t = 0$;

Set a random size of N population; P_0

2. Create offspring population part
   Create offspring population Q_t from P_t using binary tournament selection which size of N according to binary crossover and polynomial mutation.

3. Match P_t and Q_t part
   Match parent and offspring populations and create; $R_t = P_t \cup Q_t$;

4. Use non-dominated sorting approach for R_t and define fronts: $F_i, i = 1, 2, ...$
   Selection part
   $i = 1$;

5. Set a new population $P_{t+1} = \psi$;
   While $| P_{t+1} | + | F_i | < N$, perform
   $P_{t+1} = P_{t+1} \cup F_i$ and $i = i + 1$;
   Crowding distance sorting part
   When $| P_{t+1} | + | F_i | > N$ then
   Use the crowding-sort approach and eliminate $(| P_{t+1} | - N)$ solutions which include worse value for crowding distance.

6. Iteration part
   $t = t + 1$;
   Repeat (2) to (6) until t reaches the predetermined number of iterations.
   Elitism is guaranteed in NSGA-II by R_t in 3 part which includes all previous and current members in.

4.4.3 Non-dominated Sorting

The aim of multi-objective programs is to find Pareto front that is the other name of set of non-dominated solutions.

For a set of objective functions, such as $1, ..., \psi_m$ with assuming the minimization of all objectives; $x(1)$ is a solution that dominate another solution, $x(2)$ when the two main conditions are satisfied (Shimamoto et al., 2005):

Solution $x(1)$ is no worse than $x(2)$ for all objectives. In mathematical definition is $\psi_m(x^{(1)}) \leq \psi_m(x^{(2)})\ for\ all\ m.$ Solution $x(1)$ is strictly better than $x(2)$ for all objectives. In mathematical definition is $\psi_m(x^{(1)}) < \psi_m(x^{(2)})\ for\ at\ least\ one\ m.$

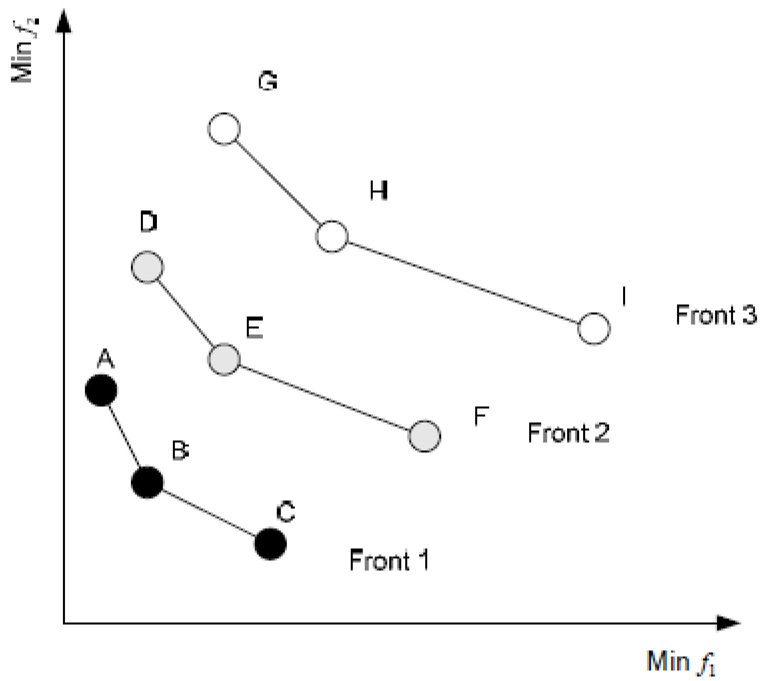

Figure 4.3: Levels of non-dominating (Shimamoto et al., 2005).

Figure 4.3 is an example of different non-dominated levels with two objective functions in NSGA-II. While horizontal axis shows value of objective function 1, vertical axis represents value of objective function 2. Chromosomes A, B, and C which imply solutions are not dominated by any other chromosomes. These chromosomes correspond to front 1 that are highest level of non-domination and the others refer to front 2 and front 3 which are at second and third level of non-domination.

4.4.4 Crowding Distance and Crowding-sort

Although the others methods have parameters to define solutions, the NSGA-II do not use any parameter to obtain the solutions. For this property of the approach, there is a wide space for searching. The main indicator in the solution space is analyzing of how well the solution performs on the Pareto Front.

Assuming that i is a particular solution in the population, the average distance of two solutions on either side of solution i along each axis of the objectives is adopted. It is represent by d_i which is an estimate of the perimeter of the cuboid formed by using the nearest neighbours as called the crowding distance in Figure 4.4.

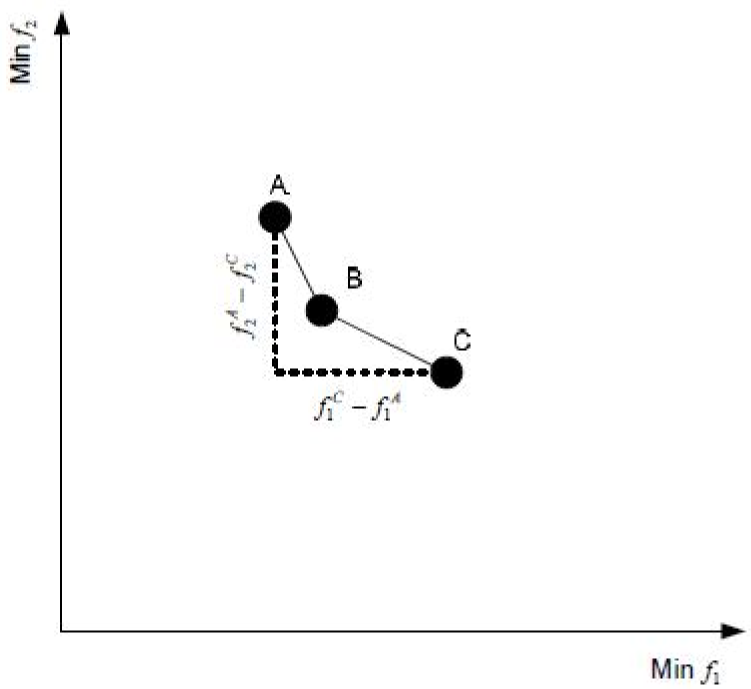

Figure 4.4: Crowding distance (Shimamoto et al., 2005).

For each point in set F, crowding distance calculating algorithm is proposed as follow (Shimamoto et al., 2005):

1. Initialization part

   Count the number of populations in F as $l =| F |$;

   Set $d_i = 0 \; for \; i = 1, 2, 3, ..., l$;

2. Calculating part

   for each objective function $m = 1, 2, ..., M$

   Range the set in worse order of f_m;

   for each populations $j = 1, 2, ..., l$

   if $j = 0, \; or \; j = 1$ then

   $d_{I_j^m} = \infty$;

   else

   $$d_{I_j^m} = d_{I_j^m} + \frac{f_m^{(I_{j+1}^m)} - f_m^{(I_{j-1}^m)}}{f_m^{\max} - f_m^{\min}}$$

where, f_m implies the value of the objective function and ψ_m and I_j imply the solution index which belong to the jth member in the sorted list.

4.4.5 Crowded Tournament Selection Operator

Two solutions are evaluated and returned the winner of the tournament by using the crowded comparison operator. Assuming that i solution is the winner towards another solution j, two conditions must be satisfied:

- when solution i has a better range than solution j, that is, $r_i < r_j$;
- when two solutions have the same range, but solution i has a better crowding distance than solution j, that is, $r_i = r_j$ and $d_i > d_j$.

4.4.6 Genetic Operators

Using generic operators, new offspring is created, and then new population is selected by the way of tournament. The generic operators are introduced below (Kannan et al., 2009).

1. Simulated Binary Crossover (SBX)

The SBX operator runs with two parent solutions and obtains two offspring from the selected parents. Crossover index "η_c" leads to difference between offspring and parents.

The crossover index is any nonnegative real number. When "η_c"is a large number, there is a higher probability for creating "near-parent" solutions. For the result of small number, distant solutions are found as offspring. The created two offspring are symmetric about the parent solutions. If "η_c" is a constant, offspring takes proportional value from the parent solutions. This difference is comprised by decision variables of created offspring and parent solutions. When"η_c"is fixed, there are two properties:

- decision variables of the created offspring is proportional to decision variables of the parent solutions.
- decision variables of created offspring which are nearer to the parent solutions are more likely to be selected.

2. Polynomial Mutation

There is a higher chance to create offspring which is nearer to the parent. It is controlled by the shape of the probability distribution with an external parameter. For a fixed parameter, the distribution does not change during the iterations.

4.4.7 Recombination and Selection

The offspring population is matched with the current generation population, and then individuals are selected for the next generation. All the previous and current best individuals are in the population so elitism is guaranteed. The population is sorted based on non-dominated approach and the new generation is composed of each front till the population size is N. If the population size exceeds N due to adding individuals in front F_j, the individuals are selected based on crowding distance approach with decreasing range to the population size is N. This process repeats for following generations.

4.5 Overall Solution Method

For solving multi-objective programming problem, NSGA approach is the most used in the literature. We propose bi-level and bi-objective model that is a type of multi-objective programs due to having bi-objective. We develop NSGA-II (Deb et al., 2002) algorithm to solve the proposed model given in (3.32-3.35 & 3.36-3.39). Using the NSGA-II algorithm, the frequency for each transit line regard with emission is found as a set of solutions whose name is Pareto optimal solutions. After finding the Pareto optimal solutions, we can determine what the best solution for our case is.

We apply problem solving procedure instead of going directly from specific problem toward specific solution. The procedure is defined as Four-Box Scheme (Nakagawa, 2005) that is given below in Figure 4.5.

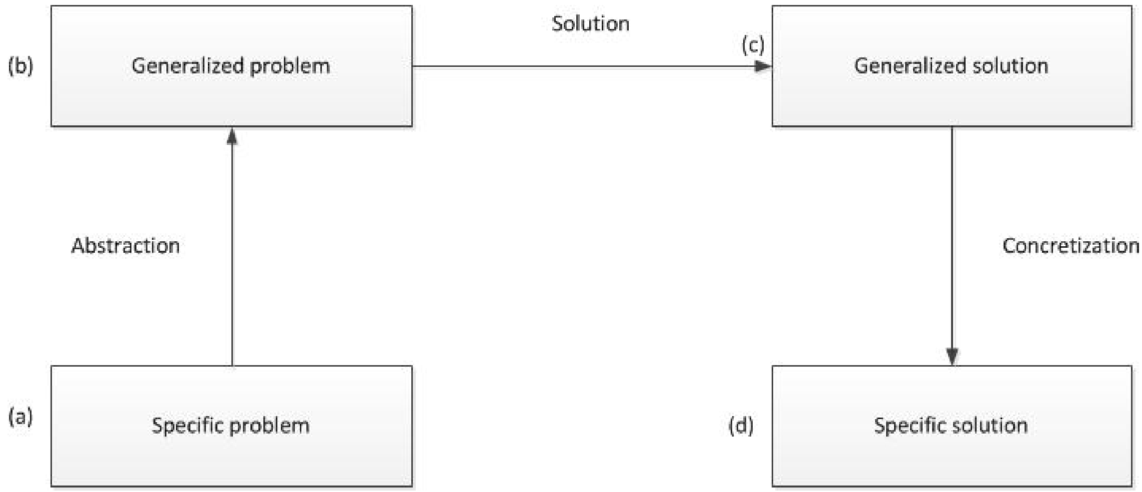

Figure 4.5: Four-box scheme of problem solving in general (Nakagawa, 2005).

According to the Four-Box Scheme, firstly existing problem is described, and then the problem is converted into generalized problem to find suitable method for solving the generalized problem efficiently. When generalized method is characterized, the method is modified to solve specific problem. With applying modified method, the specific solution is obtained. The Four-Box Scheme is a general procedure; this procedure can be customized for any solving methodology.

When the NSGA-II method is used for solving overall problem, existing population is sorted based on the level of non-domination. At this point, each solution must be compared with every other solution in the population to find if it is dominated. This process is maintained until finding the members of the first non-dominated class for all population members. With the finding all individuals in the first non-dominated front, is passed to find the individuals in the next front by applying the process that is based on the solutions of the first front are temporarily discounted (Deb et al., 2000).

We present procedure of developed NSGA-II method which is described in part 4.4 of this chapter. Within the general framework of genetic algorithm, every individual is represented with a vector of size $|\mathcal{L}|$ of real numbers. Based on this idea, our objective is to identify what must be the frequency for each transit line regard with emission.

Procedure of developed non dominated sorting genetic algorithm (NSGA-II):

1. Create the initial population by randomly selecting line frequencies that satisfy constraints (3.34) and (3.35) for each individual that made the population.

2. Find objective function values for the existing population. For each individual, first calculate the objective in (3.33). Then given line frequencies, use the transit route choice algorithm to find optimum line flows and waiting times. With this solution, the objective in (3.32) can be calculated.

3. Based on the objective functions values, calculate the non-dominance ranking and crowding distance of each individual.

4. To form the new population, first conduct a tournament among individuals to form the mating pool. The tournament is played by two or more individuals that are selected from the existing population and the one that has the lowest non-dominance ranking is added to the mating pool. If there are two or more players that have the lowest ranking score, the one with the largest crowding distance is added to the pool. If there is a tie, the individual to be added to the pool is selected at random. The tournament process continues until the mating pool is filled.

5. Form the new population with the crossover and mutation of the individuals at the mating pool. Two parents are selected from the mating pool, and two children are created with their crossover. Then mutation occurs with a given probability. While parents return to the mating pool, the children are added to the new population. This process continues until the new population reaches to a determined size.

6. Here it is ensured that constraints (3.34) and (3.35) are satisfied while genetic operators are applied.

7. If the maximum number of iterations is not reached, then go to step 2. Otherwise, identify non-dominated solutions from the existing population and display as a result.

5 CASE STUDY

5.1 Istanbul Transportation Network

Istanbul is the largest city of Turkey which has 13.483.052 population in 2011 (TUIK, 2011). Approximately, half of population of Istanbul is women.[7] 98 percent of the population is urban, the others are rural (TUIK, 2011). It has 39 districts and it includes 17.8 percent of the population of Turkey.[8] It has 5.512 km^2 areas and its density population is 2.400 per km^2.[1]

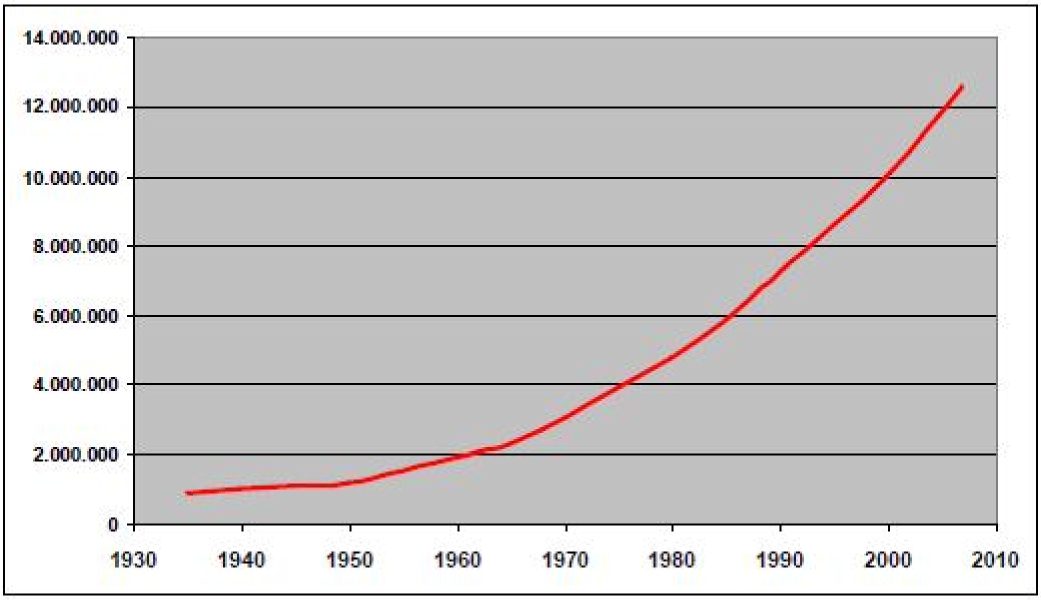

Figure 5.1: Population growth in Istanbul (Gerçek & Demir, 2008).

[7] http://www.ibb.gov.tr/sites/ks/tr-TR/0-Istanbul-Tanitim/konum/Pages/Sayilarla_Istanbul.aspx
[8] http://www.tuik.gov.tr/dig/biliyormusunuz.html

Figure 5.1 shows that population of Istanbul has grown rapidly since 1950. The main reason of rapid growth is extraordinary migration from rural areas.

Istanbul is a megacity in terms of cultural, economic, and financial. It is selected in the top ten of the world's fastest growing metro areas as in position 7th regard with employment and per capita income by the Brookings Institution in 2011[9]. Istanbul contributes 40 percent to Turkey budget.[1] For all reasons, Istanbul has always been important situation for Turkey.

The two Bosphorus Bridges are in the Istanbul that connects between the Asian and European sides of Turkey. In addition, the third Bosphorus Bridge has been proposed due to the high volume of traffic.

Istanbul has improved transportation system and it continues to develop. The two sides of Istanbul's metro will ultimately be connected under, the Bosphorus when the Marmaray tunnel, the first rail connection of any kind between Thrace and Anatolia, is completed in 2015[10]. Moreover, new bus line and metro lines are planned to open due to traffic congestion. Because of increasing passenger demand new bus lines are opened to service. According the plans; more than 600 kilometers of railway is planned to open, nearly 200 km of urban roads and 300 kilometers of highway and third Bridge is planned to finish by 2023. Hence, 42% of travelers will choose public transportation which was 35% in 2006 (Yardım, 2012).

Istanbul has 25.000 km line network and average trip time is approximately 49 minutes. Istanbul transportation system is composes of several transport modes. In Istanbul, three main transport modes are used; such as road, rail and sea. Each of them includes several sub-modes.

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[9] http://www.istanbulview.com/istanbul-ranks-worlds-7th-fastest-growing-metro-area/
[10]Turkey: Connecting Contients".

Components of road transport system:

- Bus
- Minibus
- Istanbul Metrobus (Bus rapid transit)
- Private service
- Taxi
- Private vehicle

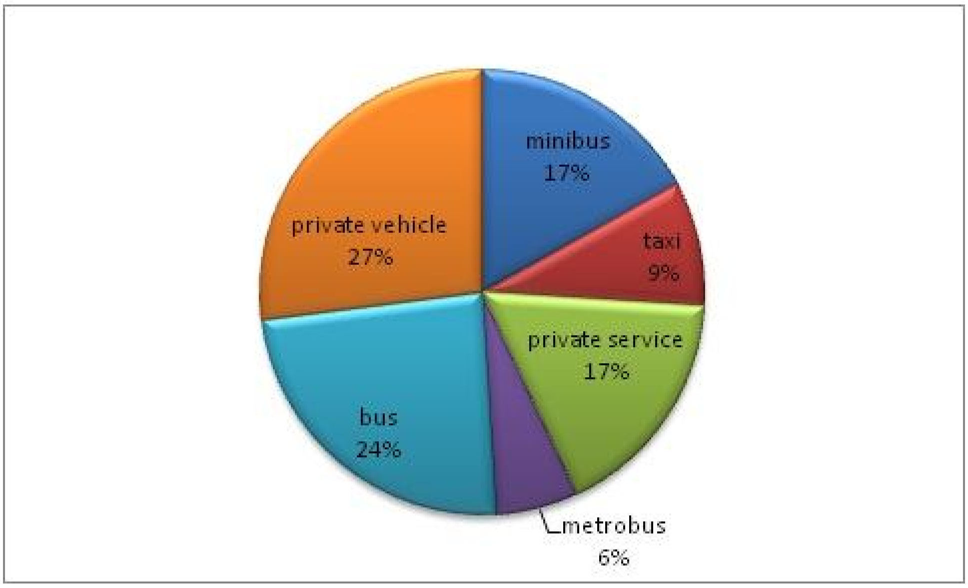

Figure 5.2: Types of road transportation for Istanbul (IETT, 2012a).

The main reason of traffic congestion is high rate of private car owned; which is shown in Figure 5.2.

Components of rail transport system is indicated in Figure 5.3:

- Train
- Metro
- Light rail system (LRT)
- Tram
- Teleferic (cable-car)
- Funicular

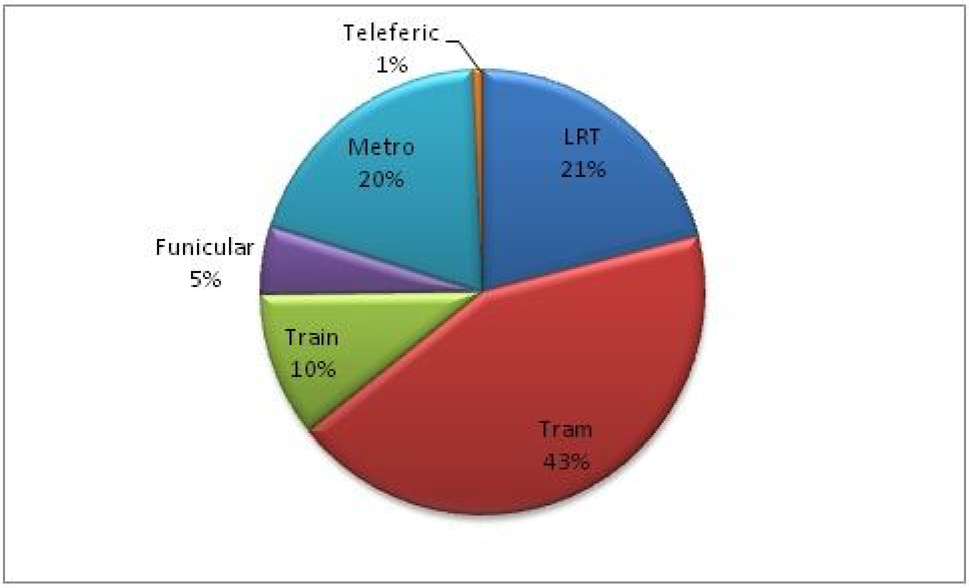

Figure 5.3: Types of rail transportation for Istanbul (IETT, 2012a).

Components of sea transport system:

- Ferry
- Private motor boat
- Seabus

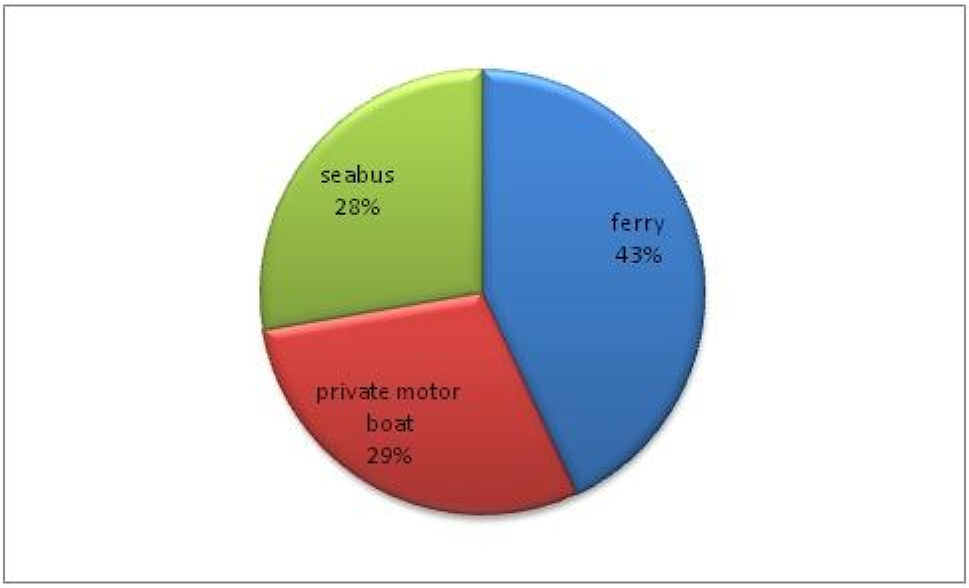

Figure 5.4: Types of sea transportation for Istanbul (IETT, 2012a).

Figure 5.4 shows that overall transport system of Istanbul including road, rail and sea transport.

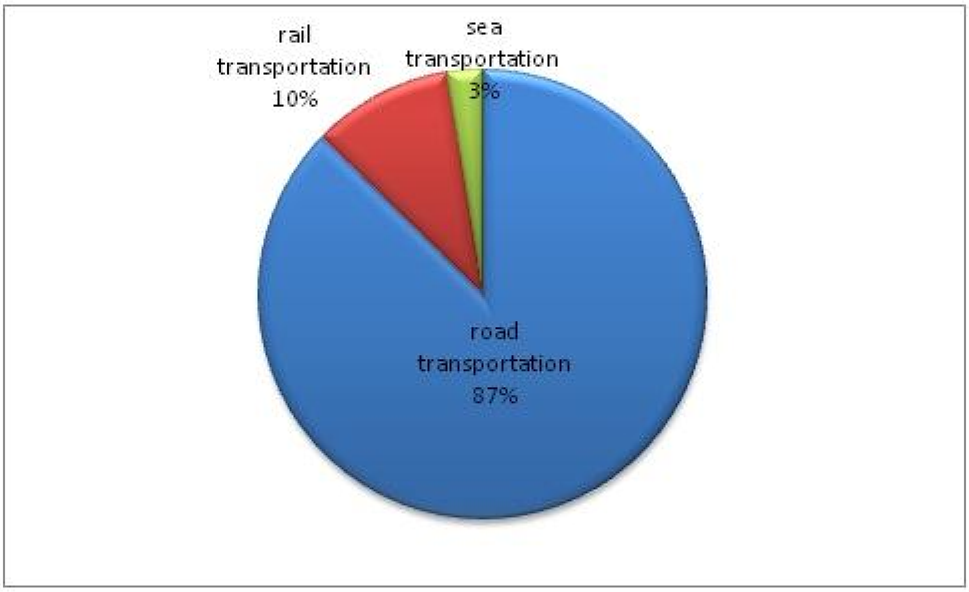

Figure 5.5: Istanbul transportation system (IETT, 2012a).

The most used transportation mode is road with 87%. For the road transportation, Istanbul BRT (bus rapid transit) is the most popular among the other sub-modes. While rail system is 10%, sea transportation is 3% in Figure 5.5. Istanbul transport system is integrated with all modes. For transportation passengers use contactless Istanbulcard. Benefits of Istanbulcard are ticket integration development, e-identification, bus fleet follow up, passenger mobility tracking, customer satisfaction.

There are three main authorities for transport. While Istanbul electricity, tramway and tunnel general management (IETT) is responsible for road transport and authority of rail system is Ulaşım A.Ş, Şehir Hatları A.Ş provides sea transportation. IETT is the oldest organization among the others. All authorities depend on Istanbul Metropolitan Municipality (IBB). IBB is responsible to provide transportation system for Istanbul. IBB makes policies and the related authorities perform these policies to increase transport quality. Istanbul faces with traffic congestion especially morning and evening peak hour. To decrease congestion, public transport is encouraged with effective transport modes, such as Istanbul Metrobus.

By using Istanbul metrobus one gains 117 minutes a day. The Metrobus contributes to Istanbul transport system. It helps reduce travel time, travel cost, use of private car, emission and it increases service quality of transportation system.

5.2 Istanbul Bus Network

Istanbul has a comprehensive bus network with all parts of the city serviced. Public transportation of Istanbul is strongly dependent on bus transportation like most of the cities in the world.

Bus transport has a critical importance for public transport of Istanbul. Therefore, IETT which is responsible for road transport including with bus and metrobus generates new methods to improve the bus transportation. The IETT has 140 years of transportation experience. The IETT operates, manages and controls in total 4.792 buses that are public and private buses. 2.315 of them belong to IETT and 2.477 of them are owned by private companies. For operating IETT buses, the IETT has 9 garages, 4 parking garage and 1 engine renewal unit. The IETT and private buses are transporting daily; 3 million passengers with total of 4.792 buses, 1.097.760 km and 26 thousand trips on the 593 lines. IETT bus fleet is shown in Table 5.1.

Table 5.1: Type and number of buses of IETT (IETT, 2012a).

Type of buses	Number of buses
MAN	325
IKARUS	930
MERCEDES	561
MERCEDES CITARO	493
***MERCEDES CAPACITY**	250
***PHILEAS**	50
TOTAL	2.609

*Mercedes, Capacity and Phileas buses are only used for Istanbul Metrobus.

In Figure 5.6 and 5.7 indicates that the brand of IETT bus fleet.

Figure 5.6: MAN

Figure 5.7: Mercedes

The bus lines are categorized as urban, rural and social lines. The urban lines service centre of the city and they are the most intensive lines for passengers. The rural lines have lower density of passenger and greater line km than the urban lines. The social lines have the least density among them. 48.52% of bus lines are serviced by only public buses. 24.6% of them are serviced by only private buses and 26.88% of them are serviced by both public and private buses.

General numerical information of bus lines is as follow:

- Average bus line km is 17,
- Average trip number for a line is 19,
- Average daily passengers for a line are nearly 3.800,
- Average daily operated km is 250.

Istanbul has three main regions for bus transport. These are Istanbul, Anatolia and Europe region. The regions are managed by IETT as a general form, for specific management there are eight operation branch managements.

The number of buses ise increased to provide quality of public transport with respect to EN 13.816 which is a service quality standard for public transport. With increasing number of buses, also passengers demand increase as indicated in Figure 5.8.

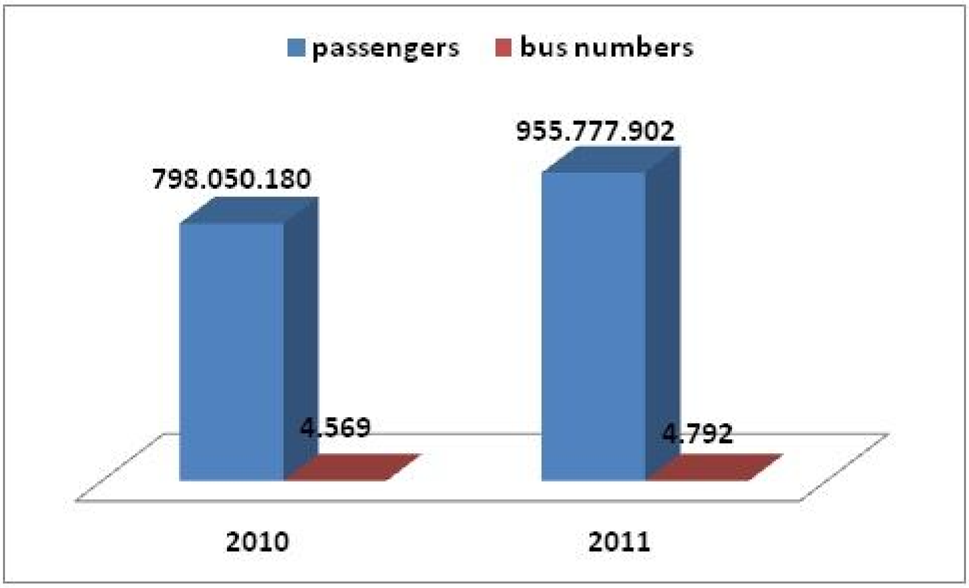

Figure 5.8: Total bus passengers buses for 2010-2011years (IETT, 2012a).

Traffic congestion is a big problem especially in the morning and evening. This leads to decrease commercial speed of buses. Travel time increases and comfort of transportation reduces. In addition, there is bus needs to satisfy passenger demand.

According to the traffic congestion, commercial speeds of the buses change during different time intervals. These changes are shown in Figure 5.9-5.11.

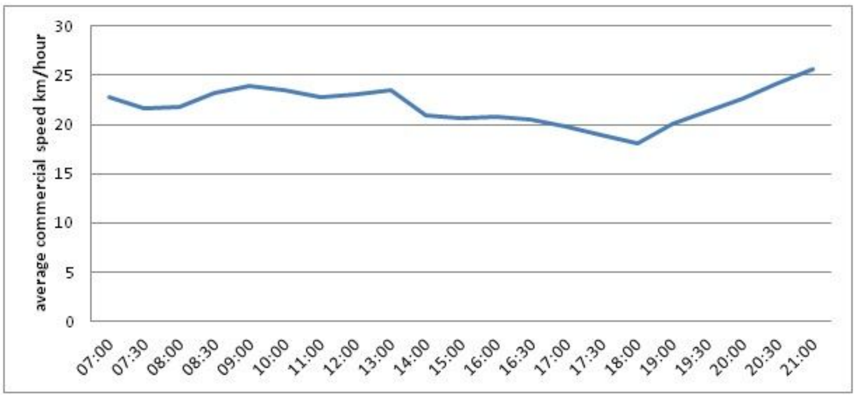

Figure 5.9: Bus commercial speed for weekdays (IETT, 2012b).

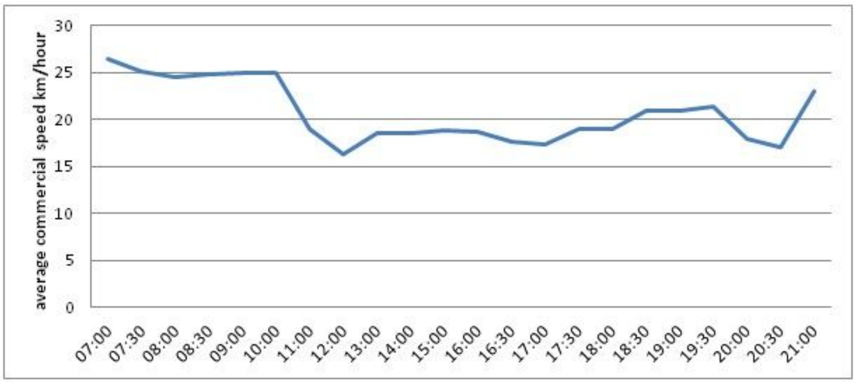

Figure 5.10: Bus commercial speed for Saturdays (IETT, 2012b).

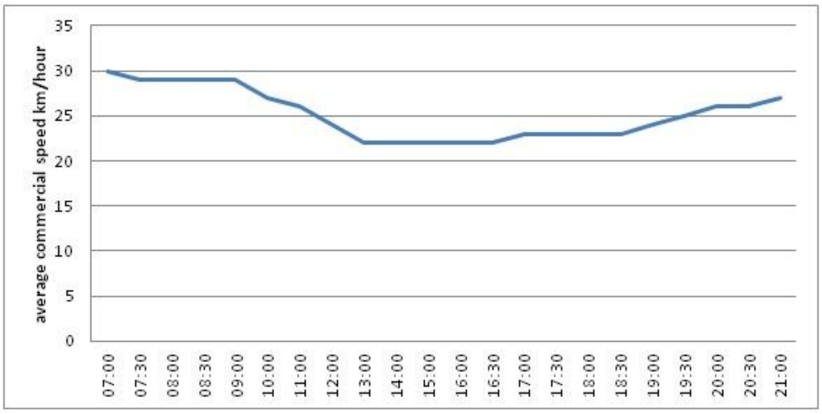

Figure 5.11: Bus commercial speed for Sundays (IETT, 2012b).

To manage the traffic efficiently, Istanbul has a traffic control centre that is operational 7/24 that is managed by Director of Traffic of IBB. The control center has command and control, decision support, and geographic information systems (GIS). Moreover, the center includes a call centre a broadcasting room, web services, a mobile phone application, and road and weather observation stations.

Istanbul bus network is operated by different schedules for weekdays, Saturdays and Sundays due to difference of passenger characteristics in Figure 5.12-5.14. For weekdays, passenger demand is higher than Saturdays and Sundays. In weekdays, especially Monday and Friday is higher than the other days. The least passenger demand is for Sundays.

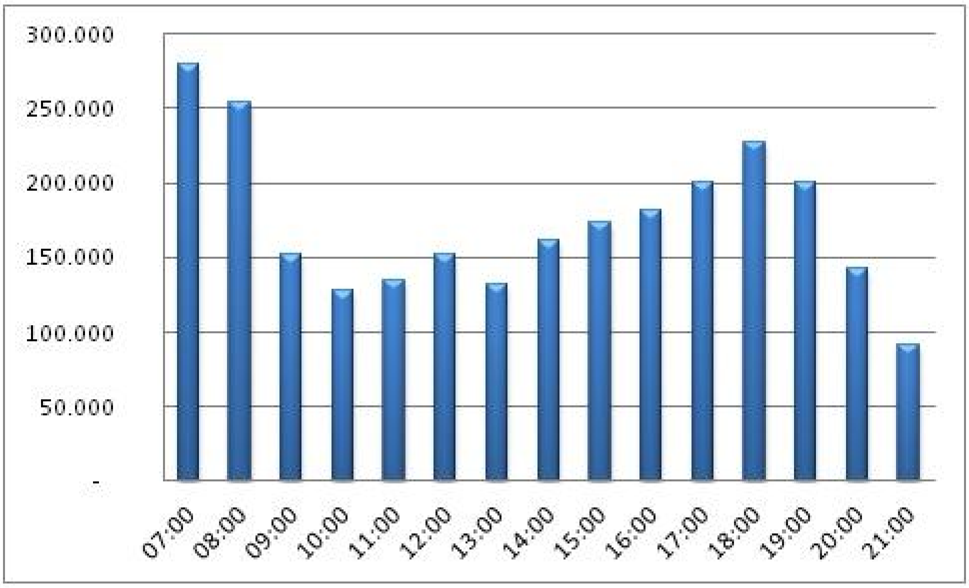

Figure 5.12: Daily passenger demand for weekdays (IETT, 2012a).

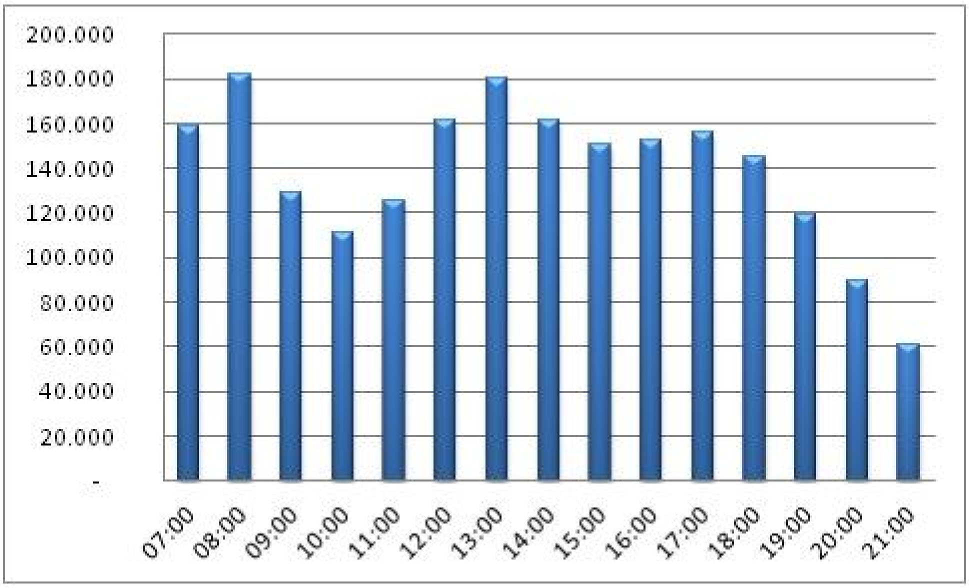

Figure 5.13: Daily passenger demand for Saturdays (IETT, 2012a).

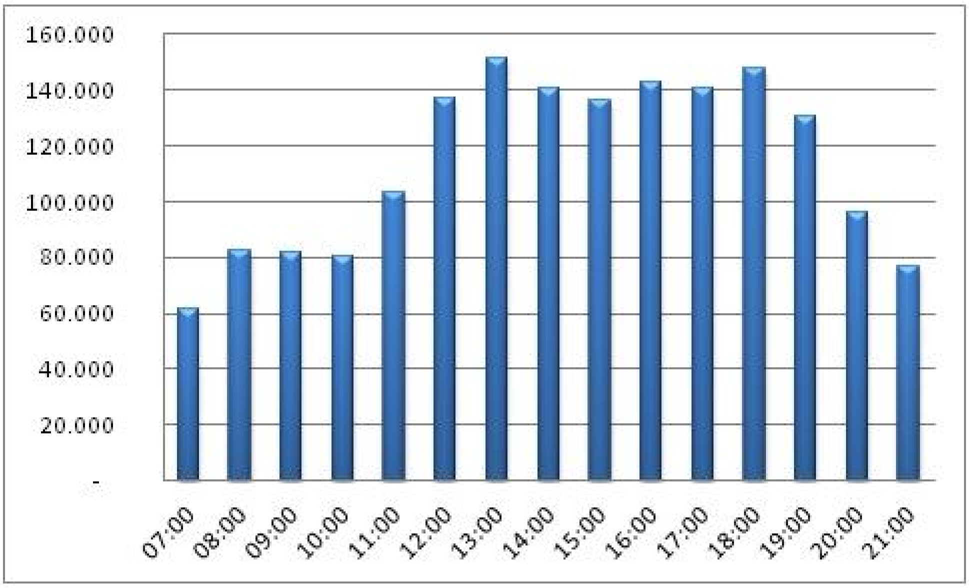

Figure 5.14: Daily passenger demand for Sundays (IETT, 2012a).

5.3 Demand Data

While 14 zones of Istanbul are located in Asia, and 25 of them are in Europe. According to population survey, the highest density population belongs to Bağcılar zone. The least density is in Adalar zone. 64.66% population of Istanbul is inhabited in Europe and 35.33% of them in Asia (IBB, 2010). The zones of Istanbul are introduced with their population in Table 5.2 as below.

Table 5.2: Population of zones of Istanbul in 2010 (IBB, 2010).

Zones of Istanbul	Population
Adalar	14.221
Arnavutköy	188.011
Ataşehir	375.208
Avcılar	364.682
Bağcılar	738.809
Bahçelievler	590.063
Bakırköy	219.145
Başakşehir	248.467
Bayrampaşa	269.481
Beşiktaş	184.390
Beykoz	246.136
Beylikdüzü	204.873
Beyoğlu	248.084
Büyükçekmece	182.107
Çatalca	62.001
Çekmeköy	168.438
Esenler	461.072
Esenyurt	446.777
Eyüp	338.329
Fatih	431.147
Gaziosmanpaşa	474.259
Güngören	309.624
Kadıköy	532.835
Kağıthane	414.515
Kartal	432.199
Küçükçekmece	695.998
Maltepe	438.257
Pendik	585.196
Sancaktepe	256.442

Table 5.3: Population of zones of Istanbul in 2010 (cont., IBB, 2010).

Zones of Istanbul	Population
Sarıyer	280.802
Silivri	138.797
Sultanbeyli	291.063
Sultangazi	468.274
Şile	28.119
Şişli	317.337
Tuzla	185.819
Ümraniye	603.431
Üsküdar	526.947
Zeytinburnu	292.430

For modeling transit frequency setting problem, demand data is needed between zones of Istanbul. The demand data is taken by director of transportation planning department of IBB. The director of transportation planning department propose integrated urban transportation master plan for Istanbul metropolitan area (IUAP) in 2011. The demand data of zones of Istanbul is forecasted based on study of passenger surveys and analyzed of traffic data with forecasting of passenger demand with four stages model. It is modeled using with TransCAD software.

The process of forecasting of passenger demand is shown in Figure 5.15. Forecasting passenger demand composes of five main steps which are survey and analysis, passenger demand modeling, socio-economic structure, data of input and output and future plan of road and public transportation.

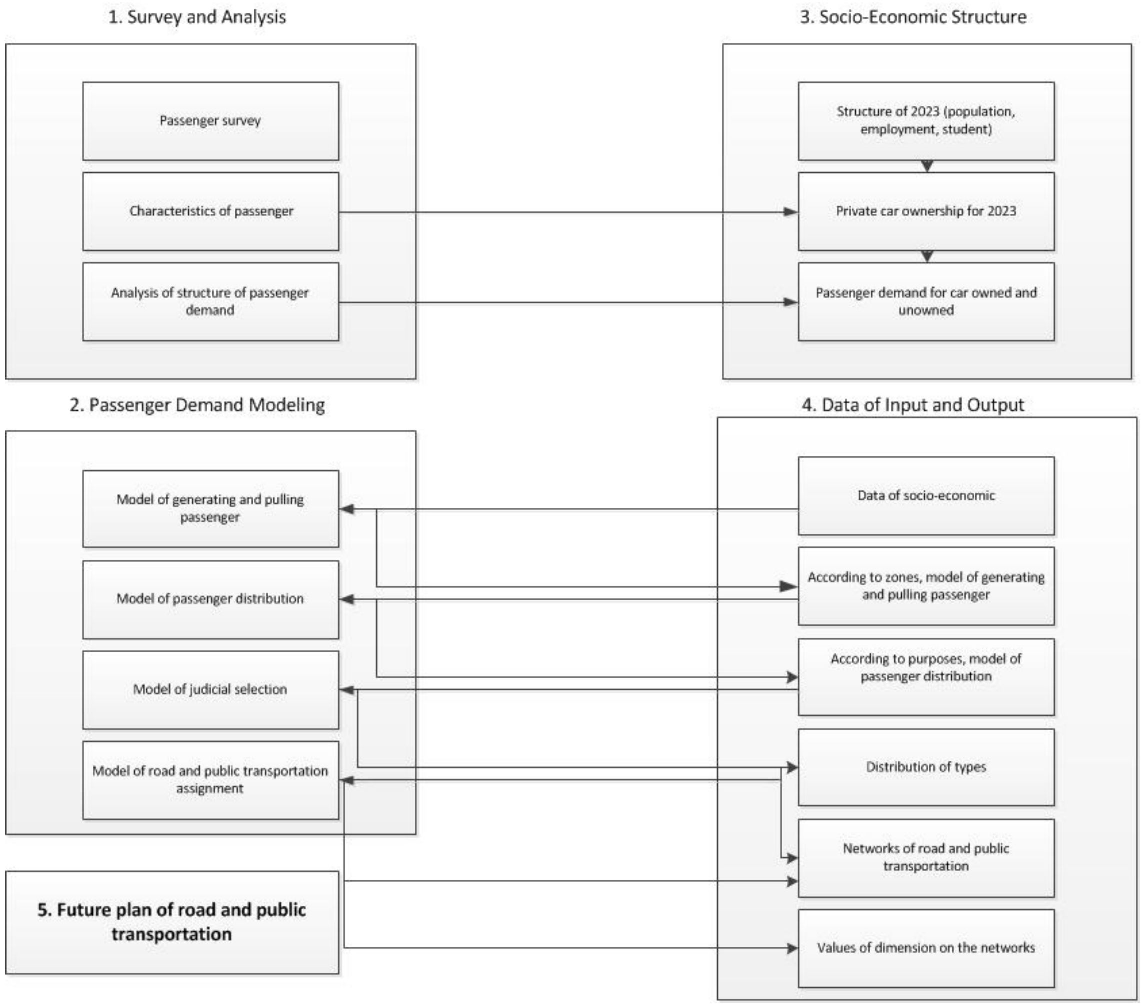

Figure 5.15: Process of forecasting of transportation demand (IMP, 2011).

The forecasting of passenger demand is categorized as daily private vehicle, private service, public transport, total journeys.

Between 07:00-09:00 am time interval is presented as morning peak hour and 17:00-20:00 pm is introduced as evening peak hour. Morning peak hour is a greater problem than evening peak hour due to short time interval. Therefore, we take into account morning peak hour case to formulate the problem. Passenger demand of the morning peak hour is nearly 25% of daily total bus passengers. We apply this idea to our data which is used for the proposed model.

5.4 Emission Measurement for Istanbul

Transportation has a significant bad effect on environment. Emissions from the transport have a high proportion of total emissions which is man-made emissions. The main pollutants of transportation are defined as carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxides (NOx), particulate matter (PM) and volatile organic compounds (VOC) (Gerçek and Demir, 2008). Many older uncontrolled vehicles are in Turkey. This leads to a disproportionate contribution to air pollution problems.

A study which is related to calculating of emissions for Istanbul is proposed in 2007 (Lents et al., 2007). The emissions were measured on 31 October-17 November 2006 with a series of 42 diesel vehicles in Istanbul. The vehicles are categorized as light duty truck, truck, minibus, passenger car, bus (public), bus articulated (public), bus (private). We take into account bus (public), bus articulated (public), bus (private) ones for our model. Table 5.3 denotes only tested buses for calculating emissions.

Table 5.3: Tested diesel buses during the study (Lents et al., 2007).

Test Number	**Date**	**Vehicle Type**	**Model**	**Year**	**Engine Size (cm^3)**	**Odometer (km)**	**Weight (kg)**
1	11/7/2006	Bus(public)	Mercedes Citaro	2006	6374	2449	111000
2	11/7/2006	Bus(public)	MAN SL200	1986		>100000	
3	11/7/2006	Bus articulated(public)	Mercedes 0345	2000		>100000	
4	11/8/2006	Bus(private)	Belde 220CB	2004		>100000	10150
5	11/8/2006	Bus(private)	Belde Euro2	2005		>100000	10150

The study is performed by EMBARQ and ISSRC. EMBARQ is an organization that helps to provide sustainable transportation for quality of life in cities.

Similarly, SSRC has a mission for finding ways to provide environmentally sustainable development in growing cities and countries. While ISSRC is responsible of test equipment and testing expertise, EMBARQ provides personnel for the study.

Firstly, vehicles are prepared to test with test equipment installation. During the testing, the vehicles are warmed up. After the installation the vehicles are operated over a prescribed driving circuit. Time of this circuit can be varied from 36 to 50 minutes due to traffic conditions. The typical time is 38 minutes for completing driving circuit.

For the testing process, Semtech Sensor D and Dekati DMM testing units are used. The Semtech Sensor D testing unit is an integrated emissions testing device improved to be used with operating vehicles, in other words, it is used as on road testing programs.

Using with Sensor D emissions of CO, CO_2, total Hydrocarbons (THC), NO_x, and NO_2 are measured. Moreover, The Sensor D has a GPS device to measure location and speed of the vehicles.

Dekati DMM testing unit is used to measure particle concentration which is collected by the Sensor D unit. Particulate mass flow rates are determined with the DMM. The DMM can measure size range of from 0 to 1.5 micron that is enough the size range for the particulars.

Figure 5.16: Integrated exterior emission testing for buses (Lents et al., 2007).

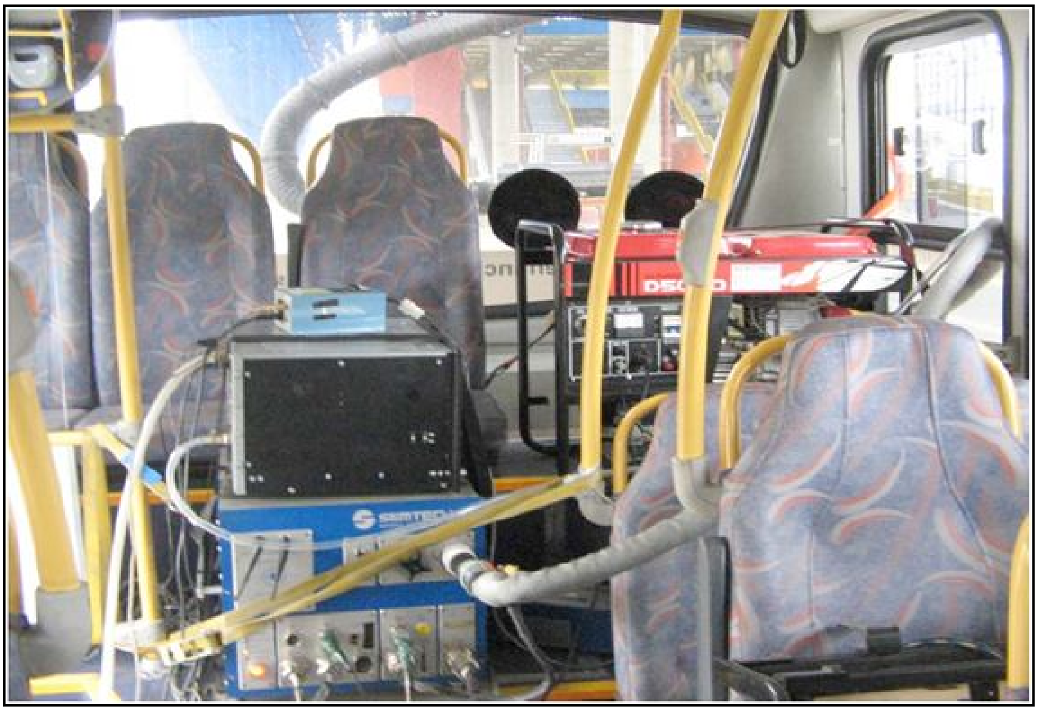

Figure 5.17: Integrated interior emission testing for buses (Lents et al., 2007).

As shown in Figure 5.16 and 5.17, emissions testing can be performed as exterior and interior. During the emissions testing in order to provide passenger weight, 70 liter plastic water containers are used. Each of them weighs nearly 64 kilograms. Numbers of located container change depend on size of the tested bus.

Testing process maintain 2-3 week period. For the limited testing, results may not represent actual urban fleet. According to ISSRC data collected in similar gasoline emissions studies, the collection of data from a fleet of randomly selected gasoline fueled vehicles resulted in 90% confidence interval of plus or minus 20%.

Finally, average emissions for the buses are obtained in Table 5.4 with 90% confidence limits. Lents et al., (2007) state that “The vehicles tested should be somewhat representative of the Istanbul fleet, thus, the measured values are likely within 20-25% of the true mean of the Istanbul fleet”.

Table 5.4: Overall emission results for the tested diesel buses of Istanbul fleet (Lents et al., (2007).

Test Number	Data Tested	Vehicle Type	Year	Measured Emissions (grams/kilometer)					FTP Normalized Emissions (grams/kilometer)				
				CO_2	NO_x	PM	CO	THC	CO_2	NO_x	PM	CO	THC
1	11/7/2006	Bus(public)	2006	1.198	11.41	0.105	6.75	0.67	857	10.09	0.076	4.85	0.41
2	11/7/2006	Bus(public)	1986	949	14.33	0.413	4.26	2.46	674	13.33	0.299	3.13	1.47
3	11/7/2006	Bus Articulated (public)	2000	1.574	20.88	0.025	1.60	1.06	1212	19.66	0.020	1.24	0.71
4	11/8/2006	Bus(private)	2004	1.089	13.43	0.665	2.33	1.34	669	11.66	0.413	1.45	0.66
5	11/8/2006	Bus(private)	2005	701	7.09	0.533	3.71	0.44	579	7.11	0.446	3.12	0.32

5.5 Results and Discussion

To demonstrate the efficiency of our approach, we applied it to Istanbul bus network. Istanbul bus network is very large with 39 zones connected through 593 bus lines. We take into account 39 zones and 463 bus lines of the network. Remaining zone and the bus lines cannot represent our model due to having different characteristics than the others.

We assume that travel time of bus lines does not change due to the traffic congestion. In the morning and evening peak hours and non-peak hours travel time on the bus line is fixed in other words, stochastic travel times are not considered for our model.

Passenger demand of 07:00-09:00 time interval is taken into account for having greater problem than the evening peak hour. In the morning peak hour demand corresponds to the 25% of daily passenger demand of the Istanbul bus network. In our model we suppose that there is no capacity constraint for operating vehicles. Passengers get on the first vehicle at each bus stop of the network.

The bus fleet is composed of very different vehicles. However, we did not consider this fact keep our model simple. Instead, we assumed that the network is served with an average vehicle. The CO_2 emission of this average vehicle is set to 0.850 kg/km (Federal Test Procedure normalized, Lents et al. (2007).

Assumptions of the model are summarized as follow:

- Bus lines with low frequency is not considered.
- Travel time is fixed, does not change depend on traffic congestion.
- Passenger demand of morning peak hour is taken into account.
- There is no capacity restraint with buses.

NSGA-II algorithm is developed for our model which is introduced in section 4. The NSGA-II is run for a population size 100, tournament size 2, crossover rate 0.80, Pareto front population fraction 0.20. As it can be observed from Figure 5.18, the population average of objective function values start to stabilize around 120 iterations. Hence, the maximum number of iterations for the NSGA-II is set to 120. For the crossover operator, we first where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child. For the mutation operator, a small number of solution vector elements are selected at random and the values of these elements are randomly increased or decreased. Both operators are arranged such that the produced children are always feasible. As we do not want to discontinue any existing line, the lower bound on the minimum frequency of each line is set to one.

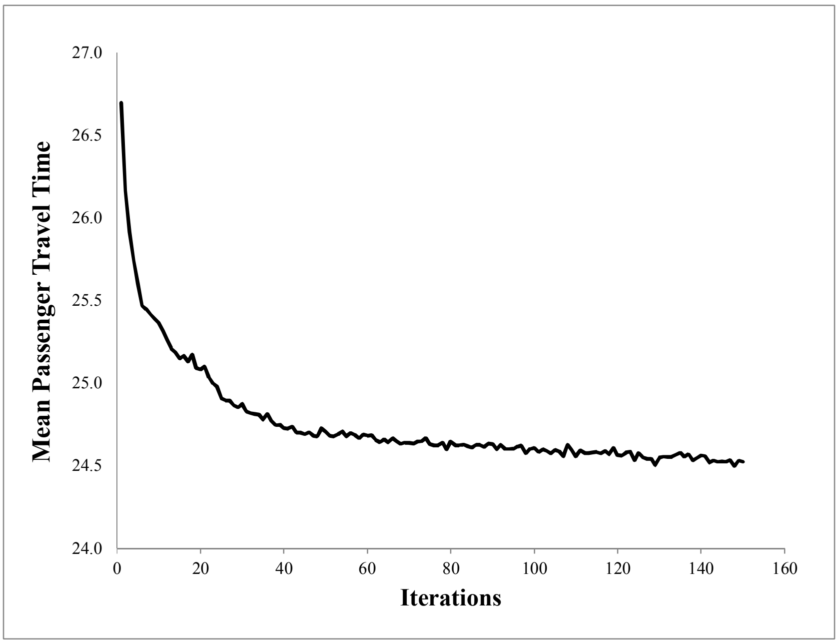

Figure 5.18: Average of mean travel time objective during the iterations of NSGA-II

Final results for 5 different runs of the NSGA-II are pooled and the final Pareto frontier is obtained after removing dominated solutions from this pool.

These solutions are shown in Figure 5.19. The current frequency assignment is also shown in that figure. This solution is dominated by the Pareto optimum solutions of our algorithm. While it is possible to reduce mean passenger travel time for the same CO_2 level around 15%, it is interesting to observe that there is a room to cut more than a half of the total CO_2 emission for the same mean travel time level. This result is not difficult to explain because most of these types of transit networks are designed to minimize the total or mean passenger travel time. Moreover, many lines of the network are not operated harshly on the efficiency principle. Instead, many lines are continued despite low ridership or long travel distances.

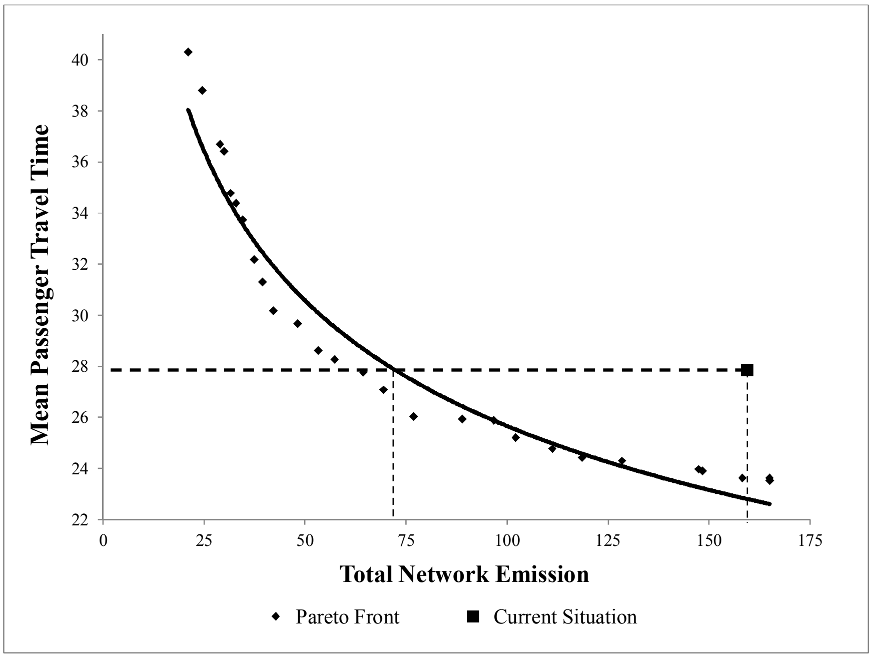

Figure 5.19: Pareto optimal solutions depicted in the objective functions space

The Pareto optimal solutions are provided but which one of them is sustainable is not fully answered. Surely solutions lying on the two extreme of the trend curve in Figure 5.19 are not sustainable: they ignore the passengers in favor of environment or vice versa. We can ignore them. However, identifying the sustainable solution is not simple.

In our case, if we had a specific figure of what is sustainable in terms of per capita CO_2 emission and per capita transport time, we could then detect easily which of the Pareto optimal solutions is sustainable or how much these solutions are far from the sustainable solution. As these numbers are non-existing (in fact there is no common understanding on these numbers), we should make an assumption and accept the solution that is "good enough" in both objectives as the most appropriate. Here we adopt the following convention: the solution that is "good enough" in both objectives is the one with minimal distance to the origin at the objective functions space. As the origin in this space corresponds to the ideal solution (yet impossible to attain), the closest Pareto optimal solution to the ideal solution can be considered as satisfactory. The distance is measured with Euclidean norm and paying equal importance (equal weights) to both upper level objectives. In our case, the solution which results in 28.61 minutes for the mean passenger travel time and 53.24 tones of CO_2 emission is a good solution. Compared to the current situation, the adaptation of this solution may lead to a slight decrease (3%) in mean travel time but also to a significant emission reduction (66%).

6 CONCLUSION AND FUTURE RESEARCH

In the cities, public transportation consists of road, rail and sea transport. The road and rail transportation is used more than sea transport. For this reason, transit authorities pay attention to present quality transportation service regard with improving of road and rail systems. In the recent years, sustainable transportation has been most popular issue due to environmental effect. Governments and authorities build new policies to provide sustainable transportation.

While frequencies of transit systems lines are planned, minimization of the total travel time spent by the passengers is the most preferred objective. Unfortunately, this planning approach is not sufficient today. Fossil fuels are the primary energy sources for transport systems and accordingly, the emission of greenhouse gases especially carbon dioxide is accredited to transportation industry. Hence, it is impossible to ignore environmental requirements in the transit planning phase.

In this study, we develop a bi-level optimization model to provide sustainable transit assignment. The proposed model identifies the optimum line frequencies with two objectives: minimizing CO_2 emission which is a significant element for the greenhouse gas emission, and minimizing the mean travel time of the passengers. A genetic algorithm, namely NSGA-II, is adopted to solve this mathematical programming problem. A large instance related to Istanbul bus network involving 39 zones and 463 bus lines is investigated with the help of the mathematical model. After solving the model, Pareto optimal solutions are obtained and the sustainable solution is selected among these solutions

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This study has the potential of being a starting point for many future researches. We can only conceive of apparent ones. As for example, the model can be extended to include limited capacity of the buses and the behavior of the passengers under congestion (SUE).

Thus, perceived travel and waiting time, travel cost and disutility can be minimized in regard with constraints. Another line of research is to satisfy in-day and day-to-day demand by taking into account dynamic frequency assignment.

With this approach morning, evening peak hours and non-peak hours can be analyzed in detailed. Moreover, both transit design and line frequency can be optimized. According to such a model, the opening or closing decisions on transit stops and lines can be made currently with the line frequency assignment.

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Appendix

Table A.1: Daily private vehicle trips for zones[11]

	ARNAVUTKÖY	AVCILAR	BAĞCILAR	BAHÇELİEVLER	BAKIRKÖY	BAŞAKŞEHİR	BAYRAMPAŞA	BEŞİKTAŞ	BEYLİKDÜZÜ	BEYOĞLU	BÜYÜKÇEKMECE	ÇATALCA	ESENLER	ESENYURT	EYÜP	FATİH	GAZİOSMANPAŞA	GÜNGÖREN	KAĞITHANE	KÜÇÜKÇEKMECE
ARNAVUTKÖY	10,872	626	1,076	822	954	2,656	854	800	882	699	1,392	1,056	547	1,258	1,305	1,906	541	499	591	1,923
AVCILAR	1,449	18,672	2,615	2,529	4,232	2,127	1,428	839	5,917	970	2,854	671	1,005	9,825	800	3,335	874	1,198	597	5,393
BAĞCILAR	1,139	1,553	40,458	19,330	7,007	5,301	6,149	2,523	1,308	2,272	1,329	542	7,703	1,992	3,053	6,812	4,628	7,963	2,081	13,989
BAHÇELİEVLER	1,382	2,271	20,005	32,861	16,568	5,404	5,025	2,809	1,704	3,004	1,476	616	3,819	2,158	2,600	9,983	3,087	7,263	1,948	17,033
BAKIRKÖY	721	4,439	7,072	16,488	47,529	2,487	3,166	1,606	1,610	2,138	1,108	380	2,149	2,153	1,574	7,902	1,763	5,964	1,104	12,546
BAŞAKŞEHİR	2,448	873	4,042	2,302	1,799	6,530	1,412	633	1,092	564	956	368	1,139	1,820	806	1,784	1,039	816	521	4,372
BAYRAMPAŞA	687	451	4,269	1,997	2,356	1,421	12,974	2,121	512	1,957	637	465	4,134	757	3,364	5,733	8,490	2,705	1,740	2,843
BEŞİKTAŞ	453	304	1,627	1,047	1,509	655	2,349	64,891	291	5,022	352	222	1,195	411	2,798	4,821	2,105	1,273	9,439	1,395
BEYLİKDÜZÜ	1,258	4,837	1,710	1,288	1,987	1,634	1,105	607	18,406	590	3,925	661	762	9,702	617	1,998	686	699	452	2,892
BEYOĞLU	239	259	1,349	850	1,301	433	1,902	7,080	193	31,923	218	127	993	296	3,291	4,994	2,150	1,079	4,664	968
BÜYÜKÇEKMECE	2,043	2,456	2,100	1,458	1,945	1,926	1,465	796	5,323	748	15,337	2,193	1,002	5,102	827	2,539	902	850	588	3,082
ÇATALCA	1,244	460	803	551	656	658	622	360	610	313	1,835	7,073	424	872	378	1,079	390	339	256	1,095
ESENLER	838	703	10,358	3,800	4,016	2,422	7,728	2,515	797	2,417	877	410	12,874	1,151	3,025	7,281	6,031	7,949	1,983	4,594
ESENYURT	2,282	9,665	3,164	2,184	2,792	3,682	1,945	1,019	11,960	967	4,996	943	1,300	30,820	1,045	3,118	1,170	1,176	778	4,966
EYÜP	1,181	352	2,927	1,588	1,961	1,223	4,988	3,958	399	3,728	472	265	2,200	588	18,211	6,401	10,774	1,832	4,571	2,272
FATİH	510	1,065	5,516	3,633	7,419	1,377	8,711	5,051	655	9,608	661	355	4,117	1,034	6,951	80,850	5,710	4,123	3,685	3,410
GAZİOSMANPAŞA	1,112	709	6,271	3,303	3,672	2,542	10,188	6,390	847	5,291	988	509	4,795	1,214	10,560	10,212	26,935	3,352	5,937	4,927
GÜNGÖREN	791	916	6,677	4,468	7,215	1,702	5,026	2,276	717	2,437	769	420	5,755	911	2,111	8,143	2,591	17,267	1,527	3,894
KAĞITHANE	473	238	1,752	1,069	1,459	764	2,763	11,967	265	5,487	311	173	1,293	375	5,340	5,064	3,335	1,428	24,311	1,480
KÜÇÜKÇEKMECE	3,789	7,062	12,425	11,235	12,505	8,517	6,218	3,659	4,916	3,726	3,993	1,636	4,181	6,387	3,589	12,802	3,926	4,205	2,614	33,114
SARIYER	1,421	416	2,265	1,517	1,952	1,334	2,984	9,729	529	3,389	682	497	1,561	664	3,532	7,023	2,142	1,541	4,271	2,628
SİLİVRİ	1,013	585	1,059	739	883	876	822	472	945	434	3,316	2,012	554	1,098	488	1,496	504	465	340	1,440
SULTANGAZİ	1,363	395	4,187	2,037	1,748	1,653	3,840	2,707	423	2,174	477	246	2,073	620	3,533	3,783	10,488	1,461	2,678	3,057
ŞİŞLİ	415	301	1,708	1,046	1,393	625	2,355	15,043	285	7,556	331	204	1,214	418	3,587	4,235	2,597	1,326	11,298	1,331
ZEYTİNBURNU	287	691	2,712	3,785	10,645	848	3,712	1,483	416	1,948	365	159	1,876	560	1,782	8,956	1,905	5,275	1,119	2,522
ADALAR	98	41	166	136	208	91	226	218	45	216	68	74	129	54	162	764	129	115	114	235
ATAŞEHİR	445	144	697	510	667	468	913	1,500	200	1,083	262	222	459	235	690	2,745	473	547	767	927
BEYKOZ	566	210	1,043	724	916	627	1,301	2,340	261	1,324	347	274	714	328	1,099	3,099	886	688	1,212	1,288
ÇEKMEKÖY	168	57	270	195	258	173	345	545	73	384	99	87	182	89	266	988	196	195	282	358
KADIKÖY	941	321	1,449	1,083	1,427	973	1,905	3,177	436	2,230	573	503	967	505	1,439	5,766	972	1,154	1,589	1,943
KARTAL	391	119	587	431	535	403	742	1,196	174	913	225	196	372	201	559	2,444	377	461	622	798
MALTEPE	801	247	1,191	894	1,133	811	1,541	2,578	360	1,814	471	421	787	411	1,190	4,864	820	913	1,279	1,651
PENDİK	392	119	584	431	549	395	746	1,181	170	901	224	200	378	198	563	2,468	386	454	613	802
SANCAKTEPE	131	42	210	152	195	138	270	436	58	319	76	64	138	69	204	815	144	159	226	278
SULTANBEYLİ	174	54	271	199	262	179	356	551	74	415	98	86	181	88	265	1,098	186	209	284	367
ŞİLE	116	42	164	127	179	98	206	263	49	182	73	81	119	60	158	551	129	106	134	240
TUZLA	141	47	211	154	203	128	254	356	62	270	87	86	138	76	200	748	151	149	199	284
ÜMRANİYE	627	220	1,045	756	951	688	1,320	2,178	288	1,454	373	306	691	341	1,025	3,659	741	763	1,125	1,371
ÜSKÜDAR	844	301	1,397	1,012	1,317	932	1,805	2,910	391	2,034	504	416	921	460	1,367	5,097	928	1,105	1,561	1,791
GEBZE	268	85	394	284	379	248	482	686	115	537	157	153	255	139	376	1,487	275	288	388	534

	SARIYER	SİLİVRİ	SULTANGAZİ	ŞİŞLİ	ZEYTİNBURNU	ADALAR	ATAŞEHİR	BEYKOZ	ÇEKMEKÖY	KADIKÖY	KARTAL	MALTEPE	PENDİK	SANCAKTEPE	SULTANBEYLİ	ŞİLE	TUZLA	ÜMRANİYE	ÜSKÜDAR	GEBZE
ARNAVUTKÖY	488	822	1,075	1,721	755	40	110	286	64	678	95	142	111	37	47	77	68	273	253	145
AVCILAR	346	1,060	649	1,664	1,779	32	121	300	68	581	99	150	115	40	51	71	71	290	261	142
BAĞCILAR	1,054	731	2,608	4,591	3,689	59	322	843	160	1,220	232	373	251	97	117	113	148	784	675	283
BAHÇELİEVLER	1,010	851	1,813	5,188	6,483	70	299	767	159	1,312	227	349	253	99	112	133	167	739	653	303
BAKIRKÖY	555	585	950	3,026	7,489	37	225	507	111	956	169	270	190	65	86	95	110	501	525	232
BAŞAKŞEHİR	313	507	804	1,193	879	24	107	272	55	463	82	131	92	33	42	49	52	254	219	110
BAYRAMPAŞA	917	553	2,355	4,133	2,466	73	318	812	164	1,518	241	381	275	96	128	179	147	736	721	329
BEŞİKTAŞ	4,912	296	1,134	22,780	1,741	81	1,138	3,519	406	3,404	596	1,114	579	249	302	167	291	2,494	2,896	576
BEYLİKDÜZÜ	293	1,145	513	1,190	1,039	28	110	257	61	547	92	141	106	35	45	64	64	257	226	136
BEYOĞLU	943	162	983	17,223	1,524	25	446	933	157	1,325	253	465	259	96	133	77	117	875	1,107	263
BÜYÜKÇEKMECE	380	4,154	658	1,611	1,189	40	123	315	71	689	105	159	122	42	53	80	73	301	268	156
ÇATALCA	212	1,885	321	733	470	23	75	176	43	447	66	102	78	24	34	55	42	171	163	104
ESENLER	915	541	2,114	4,807	3,581	57	252	703	131	1,107	185	289	202	81	93	101	125	638	594	230
ESENYURT	429	1,380	850	2,014	1,563	39	137	354	76	677	111	167	126	46	54	74	82	339	288	155
EYÜP	1,653	333	3,636	7,746	2,146	57	375	1,104	172	1,349	244	411	254	104	123	102	142	913	882	274
FATİH	1,517	451	1,936	9,155	12,214	45	792	1,615	307	2,329	489	868	518	179	263	171	229	1,552	1,831	539
GAZİOSMANPAŞA	2,522	676	12,437	11,047	3,763	117	603	1,871	297	2,234	410	673	428	183	208	185	255	1,551	1,311	475
GÜNGÖREN	734	564	1,104	4,521	6,109	64	236	589	126	1,273	183	282	206	76	93	119	125	572	631	251
KAĞITHANE	2,887	224	1,763	19,568	1,752	57	551	1,922	224	1,664	305	539	298	139	154	94	168	1,358	1,323	291
KÜÇÜKÇEKMECE	1,592	2,340	2,646	7,266	6,274	164	491	1,291	285	2,710	412	614	477	171	209	324	296	1,225	1,076	601
SARIYER	45,245	627	1,513	10,798	2,425	152	728	2,214	371	2,906	495	777	529	231	246	272	359	1,910	1,514	614
SİLİVRİ	255	14,996	398	981	650	30	91	217	53	546	80	122	94	30	41	66	53	213	197	124
SULTANGAZİ	1,082	309	20,383	4,512	1,524	47	283	867	133	958	187	311	194	82	94	78	114	710	571	209
ŞİŞLİ	2,915	262	1,307	54,729	1,646	48	773	1,862	278	2,355	429	784	435	169	222	132	209	1,606	1,989	442
ZEYTİNBURNU	457	222	677	2,919	17,199	24	184	426	84	686	126	210	137	49	67	58	70	405	461	151
ADALAR	90	83	81	418	210	0	198	211	101	1,236	219	375	233	63	84	119	128	386	412	279
ATAŞEHİR	500	269	369	2,769	980	564	34,111	2,290	3,033	23,118	5,060	12,965	3,743	3,858	2,583	606	2,327	21,195	10,748	2,812
BEYKOZ	870	330	616	3,586	1,119	279	2,854	31,374	1,518	6,771	1,457	2,583	1,374	846	781	505	822	8,334	6,031	1,360
ÇEKMEKÖY	206	103	150	1,005	342	155	2,055	1,332	6,027	3,475	1,615	1,638	1,438	2,970	1,275	586	843	5,416	2,097	1,118
KADIKÖY	1,055	616	744	5,783	2,068	1,466	21,864	4,048	3,495	138,172	7,588	26,833	5,410	3,256	2,800	1,102	3,399	21,716	31,361	4,514
KARTAL	404	228	309	2,337	855	479	2,843	1,335	1,745	7,065	39,540	12,574	15,788	3,184	3,165	691	5,064	4,764	2,747	3,904
MALTEPE	938	494	646	4,790	1,661	1,272	8,787	2,752	2,284	22,205	13,392	45,144	8,119	2,557	2,475	1,101	4,213	9,605	7,848	4,648
PENDİK	408	231	313	2,324	847	437	2,168	1,289	1,631	5,930	13,381	5,972	55,067	2,209	5,915	832	12,475	4,029	2,315	7,519
SANCAKTEPE	151	75	113	826	286	130	2,270	776	3,319	2,813	3,366	2,399	2,222	9,020	3,505	340	1,154	4,627	1,406	1,209
SULTANBEYLİ	190	100	147	1,070	379	176	1,698	773	1,393	3,067	3,541	2,211	5,433	3,164	15,039	436	2,756	2,834	1,350	2,648
ŞİLE	142	90	101	496	184	69	251	393	449	1,254	297	345	369	171	203	6,990	228	565	461	549
TUZLA	159	98	120	699	267	147	697	486	543	2,175	2,266	1,575	8,024	511	1,137	395	13,122	1,287	880	7,828
ÜMRANİYE	827	364	571	3,910	1,318	591	12,145	4,366	5,017	16,817	4,155	6,920	3,514	3,649	2,194	781	2,202	43,022	13,872	3,057
ÜSKÜDAR	966	507	706	5,396	1,903	773	10,163	5,326	2,801	38,945	3,592	7,753	3,086	1,941	1,646	820	2,141	28,606	89,650	2,914
GEBZE	275	173	220	1,393	524	235	1,040	836	787	3,127	2,067	1,654	4,903	646	1,232	798	8,483	2,129	1,387	42,849

[11] This data is obtained from Center of Transportation Coordination (UKOME) of IBB.

Table A.2: Daily private service trips for zones[12]

	ARNAVUTKÖY	AVCILAR	BAĞCILAR	BAHÇELİEVLER	BAKIRKÖY	BAŞAKŞEHİR	BAYRAMPAŞA	BEŞİKTAŞ	BEYLİKDÜZÜ	BEYOĞLU	BÜYÜKÇEKMECE	ÇATALCA	ESENLER	ESENYURT	EYÜP	FATİH	GAZİOSMANPAŞA	GÜNGÖREN	KAĞITHANE	KÜÇÜKÇEKMECE	SARIYER	SİLİVRİ	SULTANGAZİ	ŞİŞLİ	ZEYTİNBURNU	ADALAR	ATAŞEHİR	BEYKOZ	ÇEKMEKÖY	KADIKÖY	KARTAL	MALTEPE	PENDİK	SANCAKTEPE	SULTANBEYLİ	ŞİLE	TUZLA	ÜMRANİYE	ÜSKÜDAR	GEBZE
ARNAVUTKÖY	9,369	695	978	934	837	4,767	819	1,437	1,280	923	1,710	1,017	484	1,311	1,013	2,463	372	532	712	2,156	749	923	763	2,543	896	30	92	233	63	388	78	98	103	43	33	95	132	245	181	212
AVCILAR	927	12,009	1,364	1,441	1,868	1,587	776	734	4,200	697	1,774	437	479	5,644	428	2,290	357	700	414	2,509	259	690	318	1,300	1,057	15	58	148	38	208	47	58	62	27	21	53	73	153	104	96
BAĞCILAR	1,289	1,422	37,450	17,897	5,082	6,056	5,086	3,450	1,619	2,444	1,524	653	6,084	1,939	2,502	7,492	3,167	6,410	2,161	11,899	1,402	953	1,992	5,307	3,332	43	218	592	130	676	158	205	195	93	69	128	230	591	393	292
BAHÇELİEVLER	1,265	1,748	14,205	26,306	7,474	5,202	3,320	3,187	1,759	2,525	1,404	648	2,344	1,751	1,780	8,667	1,744	3,425	1,620	11,843	1,241	913	1,203	4,811	4,092	42	179	488	114	606	136	173	171	81	60	130	213	483	332	293
BAKIRKÖY	140	715	1,035	3,951	7,663	495	555	401	316	458	203	77	338	350	272	1,632	243	1,280	232	1,734	112	120	141	676	1,394	5	35	81	19	118	26	38	32	12	13	21	28	82	73	45
BAŞAKŞEHİR	1,443	577	1,435	1,005	680	4,691	641	533	974	411	731	297	404	1,259	363	1,266	319	406	325	1,875	214	435	327	940	561	12	47	116	30	169	38	48	48	21	16	39	56	125	82	74
BAYRAMPAŞA	470	245	2,105	1,181	956	1,070	8,670	1,745	417	1,293	438	308	2,359	466	1,716	3,808	4,123	1,654	1,088	1,577	651	405	1,090	2,915	1,456	24	121	323	73	403	91	121	116	50	43	98	127	308	233	194
BEŞİKTAŞ	93	53	266	182	204	143	367	12,791	65	1,018	76	53	171	81	397	896	244	240	1,286	243	664	77	156	4,608	316	10	153	388	58	410	85	141	91	39	41	35	67	324	345	106
BEYLİKDÜZÜ	466	1,617	560	463	552	734	379	328	7,774	268	1,385	234	229	3,033	206	872	178	258	194	907	133	389	154	584	404	8	33	79	21	124	28	36	35	14	12	29	37	84	58	56
BEYOĞLU	139	96	550	399	443	278	898	4,184	110	15,080	119	72	381	137	1,458	2,854	648	577	3,315	441	491	104	364	9,474	705	9	111	269	47	316	67	105	76	32	33	34	61	245	259	94
BÜYÜKÇEKMECE	1,266	1,531	1,279	1,030	987	1,751	956	913	3,882	651	9,589	1,717	578	2,919	524	2,162	436	584	487	1,936	393	2,451	360	1,573	895	20	68	174	45	265	56	71	73	31	25	64	87	180	125	130
ÇATALCA	965	373	645	616	513	893	636	796	650	458	1,136	5,028	379	626	364	1,685	273	344	310	1,161	373	1,249	231	1,319	572	17	50	129	36	233	45	60	58	23	22	59	66	127	106	141
ESENLER	1,026	685	8,060	3,826	2,753	2,844	6,408	3,551	1,104	2,614	1,088	543	13,132	1,239	2,575	8,023	4,547	7,919	2,128	4,209	1,336	778	1,716	5,604	3,306	41	194	540	118	645	142	180	176	85	61	122	219	534	383	277
ESENYURT	1,610	7,923	2,050	1,570	1,685	2,889	1,308	1,081	10,263	867	4,141	708	769	23,420	689	2,693	597	865	670	3,090	404	1,065	511	1,934	1,264	24	87	223	56	319	69	85	90	40	30	73	109	236	152	137
EYÜP	741	244	1,738	1,142	978	1,117	2,831	3,772	395	2,736	416	235	1,143	456	10,707	4,879	4,446	1,272	3,346	1,557	1,427	337	1,942	5,899	1,488	28	185	526	99	536	121	166	142	70	52	79	162	485	360	203
FATİH	243	339	1,697	1,338	2,283	635	3,112	2,242	278	3,851	276	163	1,166	370	2,329	39,096	1,409	1,717	1,481	1,189	454	234	532	4,022	5,147	14	183	412	83	506	123	192	143	52	65	73	93	386	393	176
GAZİOSMANPAŞA	968	555	4,011	2,582	2,016	2,414	6,404	7,280	937	4,287	952	507	2,834	1,030	6,878	8,466	16,144	2,464	4,806	3,638	3,172	731	8,468	9,699	2,830	58	348	1,019	199	981	231	315	273	141	101	159	334	943	629	437
GÜNGÖREN	639	588	3,358	3,943	3,326	1,421	2,844	2,349	661	1,841	627	367	3,790	648	1,247	6,393	1,198	10,245	1,107	2,409	722	507	572	3,756	3,784	29	112	296	72	455	87	112	111	50	39	89	135	297	264	196
KAĞITHANE	401	169	1,109	787	752	707	1,707	10,525	269	3,866	291	177	702	310	2,680	3,841	1,285	1,071	18,678	1,054	2,806	258	899	14,464	1,284	29	272	883	127	715	153	218	170	93	64	76	191	710	555	210
KÜÇÜKÇEKMECE	2,594	5,348	8,244	8,520	6,815	7,605	3,710	3,767	4,598	2,922	3,111	1,244	2,281	4,518	2,108	9,923	1,838	2,767	1,989	23,948	1,550	1,837	1,441	6,187	4,272	71	255	673	169	929	206	257	268	119	91	234	329	684	459	464
SARIYER	682	203	985	750	707	772	1,227	5,718	349	1,594	401	310	601	360	1,325	3,303	650	745	1,924	1,260	17,518	424	550	5,219	1,180	47	253	667	141	765	173	229	206	101	73	130	248	672	445	324
SİLİVRİ	906	523	976	806	689	1,240	847	904	1,050	616	2,406	1,443	497	960	476	2,094	367	498	438	1,501	395	8,788	321	1,605	801	22	68	171	47	294	59	75	77	31	27	73	89	177	131	150
SULTANGAZİ	1,071	370	3,308	1,820	1,264	1,876	2,865	3,327	553	2,207	564	296	1,438	645	2,428	3,851	5,642	1,333	2,505	2,660	1,283	437	16,197	4,687	1,474	33	202	574	111	554	134	177	160	80	56	90	190	546	334	219
ŞİŞLİ	161	88	509	343	366	268	765	5,560	115	3,108	129	84	332	143	1,046	1,756	563	496	4,063	438	807	122	339	22,309	585	12	162	395	67	458	96	152	107	45	47	46	82	358	378	128
ZEYTİNBURNU	235	400	1,348	3,259	4,850	691	1,728	1,255	336	1,438	267	124	834	363	853	6,530	653	3,223	736	1,442	275	189	292	2,134	11,383	11	69	172	37	224	49	66	60	26	23	38	59	170	153	79
ADALAR	66	24	80	81	77	76	109	193	42	133	49	51	56	35	75	451	42	65	68	140	65	60	32	308	128	0	52	68	34	199	50	80	55	23	20	44	73	108	108	160
ATAŞEHİR	380	103	452	353	363	392	558	1,162	187	709	231	228	265	190	407	1,755	225	374	507	661	374	289	213	1,959	669	169	14,534	920	1,326	8,796	1,752	4,814	1,390	1,705	829	322	1,600	8,313	4,472	1,904
BEYKOZ	567	191	839	694	643	722	1,043	2,741	338	1,225	391	320	536	330	824	2,917	515	621	1,032	1,219	909	420	417	3,452	1,045	114	1,374	14,934	857	2,828	671	1,156	666	495	326	291	817	4,024	2,722	1,294
ÇEKMEKÖY	247	67	291	225	229	257	346	716	121	430	149	149	168	123	249	1,093	142	227	309	432	235	185	137	1,214	409	74	1,247	779	5,069	1,754	858	1,182	772	1,887	602	339	905	3,322	1,149	1,108
KADIKÖY	370	107	451	361	372	384	569	1,263	188	717	233	234	274	190	421	1,777	230	380	528	659	409	297	206	2,051	675	208	4,547	895	891	29,232	1,423	4,173	1,095	845	557	314	1,238	4,660	6,934	1,660
KARTAL	553	134	601	461	472	527	716	1,420	257	930	322	348	341	260	526	2,430	291	487	647	905	464	424	286	2,604	899	225	1,691	869	1,188	3,505	21,805	6,698	7,878	2,178	1,516	583	4,499	3,014	1,569	3,681
MALTEPE	779	207	880	750	718	811	1,115	2,671	409	1,406	492	500	546	383	855	3,703	473	704	1,015	1,417	1,020	611	435	4,265	1,293	426	4,120	1,433	1,381	8,211	5,837	18,097	3,424	1,606	1,186	719	3,483	4,551	3,698	4,600
PENDİK	727	176	782	609	623	693	937	1,863	336	1,211	423	456	448	339	680	3,243	376	634	831	1,198	604	552	372	3,422	1,188	255	1,587	1,028	1,283	3,523	8,498	3,920	36,008	1,774	3,441	793	12,708	3,178	1,620	8,231
SANCAKTEPE	262	67	302	228	237	262	357	695	123	453	154	156	170	128	254	1,152	143	242	318	442	213	194	141	1,252	439	84	1,815	579	3,721	1,864	2,243	3,397	1,461	8,545	2,097	317	1,447	3,889	978	1,436
SULTANBEYLİ	418	104	467	360	373	412	561	1,060	194	702	243	252	266	198	391	1,842	217	380	477	702	326	309	218	1,948	696	127	1,476	675	1,227	2,230	2,814	2,379	4,670	2,933	12,607	469	3,938	2,617	1,093	3,863
ŞİLE	143	49	162	173	156	172	230	567	89	250	104	102	122	74	163	778	96	124	164	330	233	119	85	851	241	30	128	217	234	464	135	188	167	104	92	3,051	249	289	258	689
TUZLA	163	40	176	133	140	150	204	375	75	258	96	107	99	78	148	695	85	140	180	263	124	129	84	718	263	49	301	223	251	731	729	518	2,475	253	369	204	9,302	638	348	4,696
ÜMRANİYE	830	245	1,034	839	813	935	1,262	2,779	442	1,483	530	494	628	430	943	3,755	545	798	1,143	1,568	1,049	623	502	4,381	1,395	295	8,078	2,743	4,283	9,467	2,452	5,064	2,124	2,828	1,228	646	2,596	29,164	8,163	3,852
ÜSKÜDAR	621	184	785	610	633	673	962	1,932	316	1,151	387	373	464	322	702	2,850	389	649	888	1,110	630	478	356	3,265	1,119	231	3,628	1,925	1,220	13,612	1,280	2,422	1,210	873	544	432	1,467	10,080	32,667	1,889
GEBZE	520	122	540	391	427	459	609	1,045	225	781	291	333	290	239	437	2,086	246	431	546	794	321	398	255	2,151	808	131	690	598	542	1,652	1,059	815	2,459	481	545	603	6,703	1,650	831	28,710

[12] This data is obtained from Center of Transportation Coordination (UKOME) of IBB.

Table A.3: Daily public transportation trips for zones[13]

	ARNAVUTKÖY	AVCILAR	BAĞCILAR	BAHÇELİEVLER	BAKIRKÖY	BAŞAKŞEHİR	BAYRAMPAŞA	BEŞİKTAŞ	BEYLİKDÜZÜ	BEYOĞLU	BÜYÜKÇEKMECE	ÇATALCA	ESENLER	ESENYURT	EYÜP	FATİH	GAZİOSMANPAŞA	GÜNGÖREN	KAĞITHANE	KÜÇÜKÇEKMECE
ARNAVUTKÖY	19,475	1,048	1,667	1,437	2,111	4,182	1,764	1,824	1,379	1,615	2,164	1,362	997	1,640	2,270	5,272	912	917	902	3,301
AVCILAR	1,873	36,969	3,073	3,488	7,881	3,098	2,290	1,759	8,112	2,015	4,127	933	1,398	13,419	1,208	7,769	1,063	1,780	832	8,454
BAĞCILAR	1,903	2,650	73,954	32,611	14,462	9,155	11,028	5,396	2,028	5,012	2,069	786	13,612	2,874	4,803	17,074	6,811	13,137	3,225	22,945
BAHÇELİEVLER	1,982	3,553	26,660	48,400	24,547	7,263	7,308	5,334	2,443	5,424	2,251	897	4,935	2,830	3,471	20,028	3,574	7,790	2,465	23,772
BAKIRKÖY	326	2,521	3,070	10,494	40,578	1,104	1,972	1,086	747	1,511	541	166	1,200	990	897	6,001	857	4,023	571	6,637
BAŞAKŞEHİR	2,980	1,411	3,593	2,126	2,512	8,422	1,733	968	1,431	949	1,283	463	1,243	2,480	875	3,503	974	945	567	4,884
BAYRAMPAŞA	1,752	1,103	6,333	4,111	6,349	2,718	24,555	5,211	1,144	4,657	1,517	1,132	7,134	1,381	5,922	16,705	13,268	4,824	2,751	6,223
BEŞİKTAŞ	178	163	680	520	960	283	1,163	39,129	126	3,320	153	79	559	175	1,256	3,143	818	594	3,900	668
BEYLİKDÜZÜ	795	3,940	918	852	1,763	1,024	773	506	12,958	532	2,714	432	461	6,074	391	2,046	351	469	266	2,107
BEYOĞLU	264	286	1,358	1,038	2,082	507	2,618	10,569	204	53,167	236	112	1,150	289	4,501	9,616	2,301	1,371	6,726	1,156
BÜYÜKÇEKMECE	2,171	3,347	1,948	1,712	3,007	2,099	1,790	1,270	6,115	1,232	18,843	2,734	1,055	5,389	922	4,738	796	1,006	620	3,842
ÇATALCA	1,391	612	703	652	1,068	696	751	614	738	565	2,030	11,099	433	895	407	2,291	320	411	263	1,371
ESENLER	1,738	1,550	18,469	7,539	10,232	4,790	15,546	6,373	1,555	5,976	1,761	806	27,140	2,047	5,624	20,459	10,204	15,892	3,505	8,873
ESENYURT	2,507	16,892	3,332	2,635	4,830	4,539	2,479	1,611	16,226	1,658	7,024	1,152	1,553	41,980	1,237	6,070	1,147	1,489	869	6,588
EYÜP	1,550	555	3,513	2,401	3,778	1,553	8,133	6,678	552	6,737	655	319	2,977	722	30,426	12,944	15,352	2,737	6,755	3,238
FATİH	625	1,333	5,878	4,713	13,452	1,676	12,845	7,957	741	18,194	769	338	4,931	1,109	9,922	157,022	6,275	5,448	4,361	4,392
GAZİOSMANPAŞA	1,745	1,207	7,852	5,152	7,313	3,626	16,669	11,265	1,244	9,358	1,467	693	6,760	1,597	17,012	20,802	42,823	4,993	8,022	7,358
GÜNGÖREN	1,137	1,394	8,495	7,973	12,925	2,322	7,485	4,473	990	4,475	1,120	571	8,682	1,147	3,004	16,794	3,084	23,580	1,980	5,573
KAĞITHANE	605	362	2,089	1,527	2,679	1,006	3,978	21,222	364	9,451	436	221	1,723	472	7,253	10,040	3,820	2,027	40,664	2,049
KÜÇÜKÇEKMECE	5,518	14,359	17,572	18,375	27,290	14,206	10,681	8,064	8,340	8,171	6,933	2,518	6,485	10,152	5,536	31,720	5,216	6,886	3,858	62,081
SARIYER	1,194	462	1,963	1,594	2,597	1,238	3,162	11,633	499	4,325	654	432	1,578	594	3,245	9,987	1,703	1,560	4,040	2,629
SİLİVRİ	1,215	937	1,154	1,020	1,641	1,143	1,193	927	1,330	909	4,353	2,048	679	1,407	633	3,554	497	673	436	2,138
SULTANGAZİ	2,614	717	6,540	3,366	3,818	2,763	7,253	4,907	684	4,378	788	363	3,497	903	6,049	9,005	16,737	2,520	3,991	5,117
ŞİŞLİ	286	246	1,184	870	1,546	483	2,135	14,443	202	9,124	238	118	973	280	3,030	5,341	1,788	1,121	9,707	1,074
ZEYTİNBURNU	532	1,274	4,101	8,161	27,737	1,455	7,081	3,423	699	4,764	639	254	3,240	863	3,251	23,216	2,872	9,920	1,880	4,567
ADALAR	277	148	407	430	750	296	718	950	133	767	202	195	381	144	467	3,126	317	317	295	756
ATAŞEHİR	525	224	741	644	1,066	574	1,174	2,076	245	1,545	332	271	569	276	809	4,746	470	663	803	1,169
BEYKOZ	751	347	1,323	1,132	1,798	903	2,074	4,592	377	2,654	505	359	1,063	435	1,559	7,225	1,009	1,045	1,703	1,956
ÇEKMEKÖY	333	132	457	391	647	343	710	1,176	150	916	207	175	351	169	490	2,885	303	390	477	730
KADIKÖY	668	321	995	885	1,477	750	1,571	2,866	329	2,016	446	360	780	374	1,068	6,033	633	875	1,057	1,563
KARTAL	880	346	1,122	966	1,532	921	1,704	2,735	401	2,217	541	480	829	443	1,116	7,110	646	997	1,078	1,832
MALTEPE	1,347	574	1,799	1,714	2,593	1,503	2,919	5,372	645	3,588	873	741	1,445	693	1,913	11,642	1,133	1,561	1,759	3,132
PENDİK	954	372	1,191	1,024	1,638	994	1,805	2,785	429	2,377	579	519	874	474	1,165	7,769	661	1,071	1,113	1,964
SANCAKTEPE	312	123	418	350	574	328	638	1,037	141	863	191	162	309	158	435	2,701	255	371	434	660
SULTANBEYLİ	477	185	613	518	860	489	942	1,501	211	1,280	289	254	456	236	639	4,123	372	549	625	989
ŞİLE	167	72	212	205	347	158	348	536	72	383	108	104	182	81	228	1,425	151	168	184	393
TUZLA	242	103	313	264	454	237	468	623	107	561	151	139	235	123	302	1,873	191	264	270	507
ÜMRANİYE	1,167	479	1,695	1,518	2,339	1,305	2,658	4,851	563	3,312	756	598	1,326	624	1,865	10,227	1,139	1,436	1,815	2,748
ÜSKÜDAR	959	414	1,434	1,254	2,034	1,068	2,250	3,914	468	2,835	625	491	1,104	527	1,570	8,601	922	1,287	1,551	2,209
GEBZE	903	333	1,113	906	1,482	883	1,619	2,171	386	2,057	536	507	795	435	1,052	6,780	629	968	994	1,769

	SARIYER	SİLİVRİ	SULTANGAZİ	ŞİŞLİ	ZEYTİNBURNU	ADALAR	ATAŞEHİR	BEYKOZ	ÇEKMEKÖY	KADIKÖY	KARTAL	MALTEPE	PENDİK	SANCAKTEPE	SULTANBEYLİ	ŞİLE	TUZLA	ÜMRANİYE	ÜSKÜDAR	GEBZE
ARNAVUTKÖY	703	1,233	1,918	3,500	1,739	105	136	381	92	2,115	136	188	147	56	55	122	119	389	422	250
AVCILAR	518	1,616	752	3,083	3,246	80	149	377	89	1,719	140	202	148	53	55	99	116	400	429	234
BAĞCILAR	1,652	1,268	4,062	9,027	7,398	155	386	1,125	212	3,170	318	481	317	131	125	167	250	1,046	1,037	461
BAHÇELİEVLER	1,451	1,400	2,196	8,169	9,641	155	320	893	187	3,121	280	408	288	114	108	171	245	888	918	460
BAKIRKÖY	293	283	420	1,862	5,566	29	118	248	56	958	97	162	95	31	37	41	58	276	356	133
BAŞAKŞEHİR	321	750	867	1,803	1,387	50	91	248	54	1,034	83	123	86	32	33	57	67	247	253	133
BAYRAMPAŞA	1,781	1,558	3,561	9,220	5,786	292	461	1,264	284	6,556	442	661	477	157	188	403	313	1,202	1,438	818
BEŞİKTAŞ	1,929	128	433	13,612	996	56	499	1,370	175	2,355	288	566	249	103	118	65	123	1,084	1,508	281
BEYLİKDÜZÜ	171	792	253	921	863	28	57	134	33	677	54	81	55	19	20	34	41	148	161	87
BEYOĞLU	1,021	180	978	25,302	2,223	47	331	802	126	1,740	214	396	195	75	87	60	103	734	1,024	232
BÜYÜKÇEKMECE	403	5,203	567	2,291	1,791	72	111	291	69	1,509	108	155	114	41	42	82	90	308	330	188
ÇATALCA	196	1,917	283	1,125	783	43	57	140	37	973	59	85	64	21	23	53	48	155	179	112
ESENLER	1,819	1,268	3,605	10,922	8,479	187	399	1,201	232	3,824	339	500	345	144	137	204	276	1,110	1,188	523
ESENYURT	484	1,901	819	2,953	2,510	75	137	360	82	1,523	127	180	132	50	48	86	112	382	380	207
EYÜP	2,166	501	4,958	12,621	3,726	128	402	1,311	204	2,793	297	483	279	125	124	123	192	1,104	1,170	371
FATİH	1,592	539	1,927	14,009	19,619	80	722	1,437	282	3,693	501	929	479	156	204	153	232	1,533	2,107	595
GAZİOSMANPAŞA	3,536	1,108	19,203	17,677	6,711	263	673	2,268	367	5,110	532	825	503	226	219	245	366	1,900	1,875	708
GÜNGÖREN	1,058	879	1,331	7,309	9,976	141	255	691	150	3,186	230	341	237	88	91	152	183	694	922	386
KAĞITHANE	4,665	353	1,994	32,786	3,028	139	672	2,600	303	3,365	413	720	369	190	175	130	253	1,782	1,833	442
KÜÇÜKÇEKMECE	2,471	4,136	3,604	13,567	12,633	388	625	1,723	389	7,920	596	856	631	230	238	454	495	1,734	1,844	1,036
SARIYER	47,926	645	1,202	12,588	2,985	242	619	1,932	326	4,876	482	766	469	201	194	243	358	1,614	1,543	696
SİLİVRİ	295	19,384	391	1,768	1,261	62	87	217	55	1,352	88	124	95	32	34	75	74	238	261	160
SULTANGAZİ	1,546	573	36,285	8,129	3,189	122	342	1,108	181	2,352	261	406	248	113	106	116	186	965	861	334
ŞİŞLİ	2,172	191	863	62,888	1,675	63	495	1,240	185	2,466	306	582	275	108	125	80	144	1,089	1,479	323
ZEYTİNBURNU	695	417	956	6,080	40,438	67	222	563	109	1,727	174	284	173	64	70	80	115	560	740	237
ADALAR	307	251	212	1,480	707	3,541	292	346	157	4,270	377	658	365	97	116	188	226	586	853	591
ATAŞEHİR	544	371	375	3,580	1,471	743	31,005	1,704	2,530	27,779	4,565	12,077	2,979	3,173	2,022	516	1,948	17,615	11,290	3,034
BEYKOZ	1,459	521	709	6,474	2,166	490	2,672	47,083	1,448	11,027	1,485	2,623	1,246	769	646	493	859	8,969	7,369	1,623
ÇEKMEKÖY	325	237	239	2,083	875	320	2,587	1,470	9,732	6,522	2,238	2,168	1,731	4,244	1,662	824	1,074	7,223	2,925	1,603
KADIKÖY	795	497	494	4,687	1,917	1,192	12,518	1,996	1,814	119,448	4,632	17,202	2,989	1,654	1,336	536	1,926	11,767	24,357	3,186
KARTAL	724	628	567	5,068	2,274	996	3,690	1,516	2,287	15,191	71,243	20,073	23,356	4,601	4,275	916	7,650	5,869	4,109	7,803
MALTEPE	1,472	980	938	8,587	3,516	2,192	9,018	2,408	2,281	35,224	17,432	58,712	9,495	2,533	2,319	1,073	5,524	9,190	9,525	8,467
PENDİK	716	675	599	5,340	2,489	903	2,582	1,380	1,962	13,119	21,175	8,921	87,703	2,742	7,399	993	20,452	4,772	3,254	15,371
SANCAKTEPE	272	217	212	1,930	842	304	3,366	956	5,899	6,106	5,659	4,223	3,199	15,732	5,671	558	1,745	6,974	2,205	2,175
SULTANBEYLİ	390	335	313	2,857	1,276	428	2,618	1,071	2,342	7,503	6,442	3,804	9,568	5,558	28,307	758	4,727	4,579	2,333	5,371
ŞİLE	168	134	125	914	395	114	222	324	493	2,169	279	301	294	172	175	8,363	197	579	493	471
TUZLA	186	182	166	1,237	601	247	629	378	474	3,774	2,709	1,764	9,531	496	1,079	293	18,846	1,152	904	13,303
ÜMRANİYE	1,405	818	876	7,861	3,166	1,098	15,683	5,145	7,469	28,346	5,174	8,998	3,925	4,966	2,665	1,113	2,700	60,313	19,236	4,570
ÜSKÜDAR	1,104	681	704	6,636	2,796	921	7,931	4,263	2,259	40,083	2,959	6,461	2,283	1,465	1,168	672	1,701	24,692	93,138	2,842
GEBZE	604	651	573	4,570	2,208	642	1,589	1,163	1,076	9,838	4,122	3,138	8,851	1,022	1,675	894	17,079	3,217	2,431	126,973

[13] This data is obtained from Center of Transportation Coordination (UKOME) of IBB.

Table A.4: Daily passenger trips for zones[14]

	ARNAVUTKÖY	AVCILAR	BAĞCILAR	BAHÇELİEVLER	BAKIRKÖY	BAŞAKŞEHİR	BAYRAMPAŞA	BEŞİKTAŞ	BEYLİKDÜZÜ	BEYOĞLU	BÜYÜKÇEKMECE	ÇATALCA	ESENLER	ESENYURT	EYÜP	FATİH	GAZİOSMANPAŞA	GÜNGÖREN	KAĞITHANE	KÜÇÜKÇEKMECE
ARNAVUTKÖY	124,499	2,384	3,771	3,220	3,917	12,702	3,490	4,078	3,571	3,250	5,490	3,498	2,058	4,317	4,866	9,690	1,865	1,960	2,220	7,483
AVCILAR	4,268	280,875	7,337	8,024	15,514	7,009	4,558	3,340	21,064	3,699	9,096	2,043	2,950	37,536	2,453	13,529	2,323	3,787	1,849	19,351
BAĞCILAR	4,361	5,953	708,547	110,169	32,204	25,040	30,186	11,764	5,000	10,363	4,941	1,982	46,678	6,968	12,156	35,028	19,683	43,585	7,883	67,216
BAHÇELİEVLER	4,645	8,233	92,055	482,071	67,723	19,697	18,686	11,724	5,989	11,567	5,152	2,161	14,579	6,889	8,669	43,453	9,739	26,325	6,245	71,249
BAKIRKÖY	1,189	8,384	12,220	40,695	313,112	4,195	6,176	3,137	2,705	4,237	1,857	623	4,056	3,554	2,868	16,734	3,005	13,754	1,941	24,437
BAŞAKŞEHİR	7,278	2,954	10,675	5,909	5,184	99,591	3,972	2,144	3,594	1,939	3,013	1,129	3,063	6,127	2,094	6,636	2,471	2,271	1,426	12,969
BAYRAMPAŞA	2,935	1,827	16,639	8,730	10,989	5,669	260,784	9,974	2,081	9,366	2,597	1,905	22,221	2,631	15,959	33,412	45,577	12,759	6,426	11,659
BEŞİKTAŞ	724	521	2,617	1,779	2,719	1,086	4,093	288,995	483	11,623	581	354	1,991	668	4,825	9,917	3,379	2,166	18,039	2,320
BEYLİKDÜZÜ	2,534	11,819	3,209	2,633	4,371	3,453	2,262	1,441	142,510	1,391	8,920	1,331	1,458	22,852	1,216	4,924	1,218	1,434	912	6,069
BEYOĞLU	645	644	3,501	2,459	4,094	1,247	6,860	28,978	507	356,575	573	311	2,918	723	12,661	24,493	6,684	3,420	23,116	2,629
BÜYÜKÇEKMECE	5,631	7,593	5,343	4,214	5,964	5,829	4,217	2,979	17,164	2,631	151,178	7,055	2,641	15,046	2,274	9,444	2,137	2,444	1,695	8,936
ÇATALCA	3,723	1,446	2,151	1,819	2,237	2,249	2,009	1,770	2,004	1,336	5,215	56,050	1,237	2,402	1,149	5,055	983	1,094	829	3,629
ESENLER	3,626	3,024	60,605	20,590	20,355	11,546	46,718	13,183	3,473	12,225	3,737	1,759	309,240	4,508	14,525	42,368	33,680	54,535	8,355	20,776
ESENYURT	6,516	48,452	8,724	6,561	9,631	11,937	5,779	3,716	50,341	3,498	19,616	2,813	3,677	363,342	2,984	11,925	2,943	3,571	2,321	15,629
EYÜP	3,683	1,158	9,130	5,516	7,148	4,031	22,607	16,432	1,348	16,012	1,544	820	7,835	1,772	266,440	29,235	52,409	6,678	19,944	7,312
FATİH	1,379	2,760	14,196	10,795	26,533	3,771	30,845	17,287	1,677	41,977	1,707	856	11,764	2,521	24,738	814,814	15,912	13,571	10,696	9,281
GAZİOSMANPAŞA	3,864	2,498	22,030	12,406	14,076	9,176	52,007	27,767	3,035	22,534	3,412	1,709	20,600	3,871	55,747	48,194	452,057	12,935	23,490	17,056
GÜNGÖREN	2,577	3,040	28,217	27,836	32,161	5,919	21,199	9,600	2,389	9,595	2,523	1,358	31,642	2,742	7,614	37,646	8,698	227,934	4,902	14,011
KAĞITHANE	1,484	772	5,173	3,517	5,069	2,511	9,697	64,343	898	25,977	1,039	570	4,083	1,158	20,401	21,769	10,694	4,812	356,328	4,650
KÜÇÜKÇEKMECE	11,974	33,568	50,261	50,819	57,720	36,012	22,438	15,683	18,556	15,116	14,195	5,401	14,942	22,492	11,712	56,621	11,915	15,709	8,592	518,303
SARIYER	3,299	1,081	5,244	3,882	5,280	3,353	7,515	34,935	1,377	9,711	1,737	1,238	3,788	1,618	8,489	20,779	4,654	3,876	11,862	6,534
SİLİVRİ	3,135	2,046	3,190	2,565	3,214	3,259	2,862	2,303	3,330	1,958	10,922	5,822	1,730	3,467	1,597	7,144	1,368	1,636	1,214	5,080
SULTANGAZİ	5,720	1,493	15,778	7,667	7,077	6,693	17,757	11,645	1,662	9,443	1,831	906	8,564	2,181	15,497	17,945	51,931	5,826	10,575	11,397
ŞİŞLİ	864	636	3,517	2,330	3,407	1,390	5,872	48,468	601	28,611	699	406	2,697	841	9,139	13,357	5,696	3,109	36,850	2,872
ZEYTİNBURNU	1,057	2,419	9,669	20,601	59,826	3,087	17,216	6,568	1,456	9,338	1,272	537	7,935	1,797	7,374	53,887	6,790	26,484	4,055	9,212
ADALAR	441	212	655	650	1,041	464	1,063	1,385	221	1,138	319	321	570	234	709	4,428	492	500	481	1,133
ATAŞEHİR	1,349	472	1,898	1,516	2,111	1,435	2,685	5,044	633	3,508	825	721	1,306	701	1,938	9,621	1,189	1,598	2,134	2,762
BEYKOZ	1,884	748	3,217	2,561	3,371	2,256	4,481	10,841	976	5,389	1,243	953	2,335	1,093	3,561	13,547	2,460	2,368	4,214	4,471
ÇEKMEKÖY	748	256	1,019	812	1,136	774	1,405	2,480	344	1,750	456	411	703	381	1,008	5,004	644	813	1,075	1,520
KADIKÖY	1,980	750	2,916	2,355	3,317	2,111	4,142	7,810	954	5,308	1,252	1,097	2,056	1,069	3,003	14,467	1,885	2,446	3,277	4,177
KARTAL	1,825	600	2,311	1,860	2,542	1,851	3,167	5,387	832	4,080	1,089	1,024	1,544	904	2,205	12,041	1,317	1,947	2,353	3,535
MALTEPE	2,927	1,028	3,880	3,374	4,463	3,127	5,620	10,941	1,414	6,963	1,837	1,662	2,796	1,486	3,992	20,639	2,449	3,193	4,099	6,206
PENDİK	2,073	668	2,558	2,065	2,810	2,082	3,490	5,842	936	4,495	1,226	1,175	1,701	1,010	2,409	13,498	1,424	2,159	2,559	3,964
SANCAKTEPE	705	232	931	731	1,007	729	1,267	2,197	322	1,648	420	382	618	355	895	4,694	544	772	983	1,381
SULTANBEYLİ	1,069	344	1,352	1,077	1,495	1,080	1,861	3,128	479	2,404	630	592	904	522	1,296	7,079	775	1,138	1,388	2,057
ŞİLE	426	163	538	506	681	428	784	1,367	210	816	286	287	423	214	550	2,754	375	398	483	962
TUZLA	546	191	700	550	797	516	926	1,355	244	1,090	333	331	472	277	650	3,317	427	552	649	1,054
ÜMRANİYE	2,625	945	3,795	3,141	4,135	2,932	5,347	11,082	1,293	6,727	1,659	1,398	2,683	1,396	3,928	18,563	2,485	3,029	4,316	5,701
ÜSKÜDAR	2,424	901	3,657	2,919	4,042	2,680	5,210	10,550	1,175	6,944	1,516	1,280	2,554	1,310	3,808	18,262	2,339	3,108	4,376	5,133
GEBZE	1,691	540	2,046	1,582	2,288	1,591	2,711	3,903	726	3,375	984	993	1,340	813	1,864	10,354	1,150	1,688	1,928	3,097

	SARIYER	SİLİVRİ	SULTANGAZİ	ŞİŞLİ	ZEYTİNBURNU	ADALAR	ATAŞEHİR	BEYKOZ	ÇEKMEKÖY	KADIKÖY	KARTAL	MALTEPE	PENDİK	SANCAKTEPE	SULTANBEYLİ	ŞİLE	TUZLA	ÜMRANİYE	ÜSKÜDAR	GEBZE
ARNAVUTKÖY	1,950	2,979	4,289	7,803	3,406	175	338	901	220	3,184	310	428	360	136	136	294	320	907	857	607
AVCILAR	1,124	3,366	1,731	6,065	6,212	127	327	824	194	2,513	286	410	325	120	126	223	260	844	796	472
BAĞCILAR	4,221	2,952	10,112	19,845	17,448	258	930	2,575	503	5,169	709	1,062	763	321	311	409	628	2,436	2,159	1,037
BAHÇELİEVLER	3,769	3,163	5,571	18,837	25,215	269	801	2,157	460	5,150	644	933	712	294	280	433	625	2,121	1,949	1,056
BAKIRKÖY	964	987	1,539	5,670	17,611	71	379	837	186	2,062	292	471	317	108	135	157	195	861	967	409
BAŞAKŞEHİR	853	1,692	2,119	3,961	2,882	87	245	637	139	1,671	203	301	226	85	91	146	175	627	556	317
BAYRAMPAŞA	3,558	2,516	9,130	18,619	12,960	392	912	2,437	522	8,962	775	1,172	868	304	359	679	587	2,287	2,559	1,341
BEŞİKTAŞ	8,863	501	1,779	56,484	3,187	148	1,841	5,731	645	6,583	971	1,842	919	394	462	267	481	4,109	5,514	963
BEYLİKDÜZÜ	597	2,329	922	2,696	2,314	65	200	471	114	1,349	174	258	197	68	78	127	141	489	445	279
BEYOĞLU	2,675	446	2,580	79,382	5,236	83	921	2,085	332	3,731	537	982	530	205	254	171	281	1,952	2,844	589
BÜYÜKÇEKMECE	1,176	13,058	1,587	5,476	3,879	132	302	780	186	2,464	270	385	309	114	120	226	250	789	723	474
ÇATALCA	780	5,344	835	3,177	1,826	82	183	445	116	1,653	171	247	200	67	78	167	155	452	447	357
ESENLER	4,272	2,586	9,602	23,133	19,985	287	852	2,469	482	5,776	667	974	723	310	291	428	621	2,307	2,266	1,031
ESENYURT	1,318	4,349	2,194	6,910	5,375	138	362	938	214	2,522	307	432	348	137	132	232	303	958	820	499
EYÜP	5,926	1,171	14,126	31,989	8,577	214	974	3,036	476	4,858	664	1,067	675	300	300	304	496	2,549	2,573	848
FATİH	3,642	1,223	4,660	31,952	51,573	141	1,745	3,532	676	7,078	1,117	2,015	1,142	388	534	397	555	3,581	4,839	1,310
GAZİOSMANPAŞA	10,309	2,514	64,734	45,069	16,090	441	1,644	5,279	864	8,734	1,175	1,826	1,205	551	528	589	956	4,468	4,075	1,620
GÜNGÖREN	2,580	1,951	3,309	16,591	27,709	235	608	1,586	347	5,095	500	738	554	214	223	360	443	1,578	1,890	833
KAĞITHANE	14,409	836	5,335	106,137	6,557	226	1,531	5,991	659	6,091	874	1,493	838	425	394	299	613	4,046	4,242	943
KÜÇÜKÇEKMECE	5,663	8,313	8,081	27,402	25,015	623	1,374	3,693	844	11,649	1,214	1,728	1,377	520	539	1,012	1,120	3,650	3,408	2,102
SARIYER	365,500	1,696	3,348	32,972	6,654	442	1,621	5,613	844	8,696	1,152	1,780	1,204	535	513	645	966	4,370	3,718	1,634
SİLİVRİ	945	126,799	1,111	4,354	2,712	114	246	605	155	2,193	227	322	266	93	101	215	216	627	589	434
SULTANGAZİ	4,192	1,319	442,244	18,923	6,755	202	830	2,593	425	3,932	582	897	602	276	256	284	490	2,239	1,814	761
ŞİŞLİ	6,931	575	2,685	503,844	4,203	124	1,464	3,714	533	5,597	833	1,533	817	324	394	259	435	3,173	4,358	893
ZEYTİNBURNU	1,457	829	2,086	12,180	328,625	102	481	1,173	231	2,782	350	564	370	139	160	176	244	1,152	1,436	467
ADALAR	463	393	326	2,233	1,055	12,187	584	627	294	5,975	693	1,204	673	186	223	351	432	1,112	1,415	1,034
ATAŞEHİR	1,454	929	961	8,624	3,164	1,568	316,374	5,154	7,915	78,461	12,136	39,495	8,278	10,251	5,938	1,445	5,903	63,367	35,233	7,761
BEYKOZ	3,742	1,272	1,766	14,648	4,365	888	7,225	299,603	4,217	21,298	3,632	6,477	3,292	2,182	1,779	1,292	2,499	24,691	18,803	4,278
ÇEKMEKÖY	776	525	527	4,348	1,630	554	6,816	3,987	108,121	12,192	4,890	5,503	4,017	12,853	4,044	1,766	2,838	19,443	6,513	3,834
KADIKÖY	2,307	1,410	1,455	13,080	4,784	3,050	49,045	7,099	6,429	857,674	14,249	57,054	9,594	5,949	4,779	1,952	6,578	43,116	80,232	9,369
KARTAL	1,597	1,281	1,163	10,047	4,036	1,803	8,861	3,741	5,433	26,812	443,681	50,797	61,671	12,098	10,274	2,191	18,038	14,153	8,609	15,587
MALTEPE	3,472	2,085	2,024	17,941	6,520	4,169	29,492	6,691	6,261	78,013	46,324	426,072	22,535	7,388	6,355	2,894	13,444	25,737	22,954	17,818
PENDİK	1,729	1,458	1,284	11,099	4,525	1,638	6,499	3,705	4,970	22,800	55,947	20,420	584,966	7,247	20,769	2,618	54,811	12,126	7,235	32,312
SANCAKTEPE	641	486	466	4,037	1,570	525	8,907	2,400	19,906	11,157	13,261	13,907	7,368	146,136	17,085	1,216	4,427	19,109	4,762	4,835
SULTANBEYLİ	909	744	679	5,890	2,353	738	6,340	2,552	5,561	12,999	14,974	9,815	24,247	16,868	268,431	1,665	12,243	10,660	4,844	11,996
ŞİLE	543	344	312	2,261	820	213	602	938	1,200	3,886	712	835	830	448	470	40,451	674	1,434	1,212	1,708
TUZLA	469	409	371	2,656	1,131	447	1,636	1,087	1,274	6,695	5,970	3,919	24,265	1,284	2,762	893	144,276	3,087	2,136	28,935
ÜMRANİYE	3,533	1,805	1,965	17,375	5,975	2,048	51,037	14,004	22,199	64,867	12,292	24,748	9,697	14,422	6,647	2,540	7,526	532,661	55,301	11,489
ÜSKÜDAR	2,911	1,666	1,789	17,176	6,023	1,978	27,034	12,866	6,626	121,449	7,981	17,910	6,612	4,418	3,407	1,924	5,316	84,973	670,145	7,649
GEBZE	1,200	1,222	1,047	8,114	3,539	1,009	3,321	2,598	2,406	14,622	7,298	5,620	16,579	2,152	3,471	2,295	34,875	6,998	4,650	595,972

[14] This data is obtained from Center of Transportation Coordination (UKOME) of IBB.

Biographical Sketch

Büşra Buran was born August 13, 1988 in Kocaeli, Turkey. She finished her high school education in Kocaeli Anatolian High School. In 2010, she earned her B.Sc. in Industrial Engineering from Yıldız Technical University, Istanbul. At the same year, she joined the M.Sc. Program in Industrial Engineering of Galatasaray University. She is currently working as a consultant on Istanbul BRT (bus rapid transit) in Transportation Planning Department of IETT for almost two years.