SUSTAINABLE STOCHASTIC TRAFFIC ASSIGNMENT WITH MULTIPLE OBJECTIVES AND USER CLASSES

(BİRDEN FAZLA AMAÇ VE KULLANICI SINIFI İLE SÜRDÜRÜLEBİLİR RASTLANTISAL TRAFİK ATAMASI)

by

Çağla DOĞRU, B.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

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Supervisor : Assoc. Prof. Dr. Orhan FEYZİOĞLU

Committee Members: Asst. Prof. Dr. S. Şebnem AHİSKA

Asst. Prof. Dr. Nilay NOYAN

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Çağla DOĞRU

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BPR	:Bureau of Public Roads
CO	:Carbon Monoxide
CO_2	:Carbon Dioxide
DTA	:Dynamic Traffic Assignment
DUE	:Deterministic User Equilibrium
FBTP	:First Best Toll Pricing
MOEA	:Multi-Objective Evolutionary Algorithm
MSA	:Method of Successive Averages
NCP	:Nonlinear Complementarity Problem
NDP	:Network Design Problem
NOTP	:No Toll Pricing
NO_x	:Oxides of Nitrogen
NSGA-II	:Non-Dominated Sorting Genetic Algorithm
OD	:Origin-Destination
PM	:Particulate Matter
SBTP	:Second Best Toll Pricing
SO	:System Optimum
SO-DTA	:System Optimum Dynamic Traffic Assignment
SRA	:Self-Regulated Averaging
SSO	:Stochastic Social Optimum
SUE	:Stochastic User Equilibrium
UC	:User Class
UE	:User Equilibrium
UE-DTA	:User Equilibrium Dynamic Traffic Assignment
VI	:Variational Inequality
VOC	: Volatile Organic Compounds

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Abstract

As the global warming has become a major concern, the sustainability of transportation is an actual and crucial issue. Within this context, defining criteria in relation with the transportation sustainability and by using these criteria, measuring the performance of the transportation systems and increasing their efficiency is an active research area. In this study, we introduce some social, environmental and economic criteria to evaluate the sustainability of a solution developed for the traffic assignment stage of the urban transportation planning: accessibility to the network centers, equity in the accessibility to the centers, number of road accidents, carbon dioxide and noise emissions due to the transportation vehicles, and affordability of transportation for the individuals. Then, we develop a bilevel mathematical model to assign the traffic flow in a sustainable way by paying attention to these criteria. The lower level of our bilevel model includes the stochastic user equilibrium, and concepts such as multinomial logit choice and multiple user classes are considered at this equilibrium model. Our main aim is to identify each user class optimum toll pricing scheme at the upper level of the bilevel model while taking into account social, environmental and economic objectives. As multiple objectives exist at the upper level and these objectives are in conflict, we try to generate the Pareto optimum solution set. To achieve this, we use the Non-Dominated Sorting Genetic Algorithm which has a proven performance record for solving multiobjective optimization problems. At each iteration of the genetic algorithm, the stochastic user equilibrium problem is to be solved for each individual (toll pricing vector) of the current population. Consequently, we use the Self-Regulated Averages Method which enables to solve large size problems efficiently by concentrating on the network links instead of the network paths. Finally, we solve some well-known transportation network planning problems from the literature by using the developed solution method and elaborate on the obtained results.

Résumé

Comme le réchauffement planétaire est devenu une inquiétude majeure, la durabilité des transports pose un problème actuel et essentiel. Dans ce contexte, définir des critères en relation avec la durabilité des transports, et en utilisant ces critères, mesurer la performance des systèmes de transport et améliorer leurs efficacités est un domaine active de recherche. Dans ce travail, on introduit des critères sociaux, environnementaux et économiques pour évaluer la durabilité d'une solution développée pendant l'étape d'affectation de trafic de la planification des transports urbains: accessibilité des centres du réseau, équité dans l'accessibilité des centres, nombre des accidents routiers, carbone dioxyde et sons émis par les véhicules de transport, et abordabilité des couts de transport. Alors, on développe un modèle mathématique à deux niveaux pour affecter le flux de trafic de façon durable en faisant particulièrement attention à ces critères. Le second niveau de notre modèle inclut l'équilibre stochastique de l'utilisateur, et divers notions comme le choit logit multinomial ou multiple classes d'utilisateurs sont considères pour ce modèle d'équilibre. Notre but essentiel est d'identifier les prix des péages optimaux pour chaque classe d'utilisateur au premier niveau du modèle bi-niveau en tenant compte des objectifs sociaux, environnementaux et économiques. Comme plusieurs objectives existent au premier niveau et que ces objectives sont contradictoires, on essaie de trouver l'ensemble des solutions Pareto optimales. Pour achever celle-ci, on utilise l'Algorithme Génétique du Classement en Strates de Pareto qui a une performance reconnue envers la résolution des problèmes d'optimisation multiobjectif. A chaque itération de l'algorithme génétique, le problème d'équilibre stochastique de l'utilisateur doit être résolu pour chaque membre (vecteur de prix des péages) de la population actuelle. En conséquence, on utilise le Méthode des Moyennes Autorégulées qui permet de résoudre efficacement les problèmes en grande taille en se concentrant sur les liens du réseau au lieu les chemins du réseau. Enfin, on résout quelques problèmes étudiés dans la littérature à propos de la planification des

réseaux de transport en utilisant la méthode de résolution proposée et détaille les résultats obtenues.

Özet

Ulaşımda sürdürülebilirlik, özellikle küresel ısınmanın ciddi bir problem haline gelmiş olmasından dolayı güncel ve önemli bir konudur. Bu kapsamda, ulaşımda sürdürülebilirliğe ilişkin ölçütler tanımlamak ve bunlardan faydalanarak ulaşım sistemlerinin performansını ölçmek ve verimliliklerini arttırmak büyüyen bir çalışma alanıdır. Bu çalışmada, kent içi ulaşım planlamasının trafik ataması aşaması için geliştirilen bir çözümün sürdürülebilirliğini değerlendirebilmek için bazı sosyal, çevresel ve ekonomik ölçütler ortaya konmuştur: ağdaki merkezlere erişilebilirlik, merkezlerin erişilebilirliğinde eşitlik, oluşan yol kazası sayısı, ulaşım araçlarının karbondioksit salınımı ve yaydıkları gürültü, bireylerin taşıma maliyetlerini bütçelerinden karşılayabilirlikleri. Ölçütler yardımıyla sürdürülebilir bir trafik ataması yapabilmek için iki seviyeli bir matematiksel model geliştirilmiştir. İki seviyeli modelin alt seviyesinde rastlantısal kullanıcı dengesi, bu denge modelinde de çok terimli logit seçim ve gelir seviyelerine göre kullanıcı sınıfları dikkate alınmıştır. İki seviyeli modelin üst seviyesinde ise sosyal, çevresel ve ekonomik amaçlar göz önünde bulundurularak her bir kullanıcı sınıfı için eniyi geçiş ücretleri belirlenmeye çalışılmıştır. Üst seviyede birden fazla amaç bulunmasından ve bu amaçların birbirleri ile çelişmesinden dolayı Pareto eniyi çözümler kümesi elde edilmeye çalışılmıştır. Bunun için çok amaçlı eniyileme problemlerinin çözümünde etkinliği gösterilmiş Baskın-Olmayan Sınıflandırmalı Genetik Algoritma kullanılmıştır. Genetik algoritmanın herbir iterasyonunda nesli oluşturan her birey (geçiş ücreti vektörü) için alt seviyeyi oluşturan rastlantısal kullanıcı dengesi probleminin çözülmesi gereklidir. Bunu etkili biçimde gerçekleştirebilmek içinse ağdaki yollar yerine bağlantıları göz önünde bulunduran ve bu sayede büyük çaplı problemlerin çözülmesine imkan veren Öz-Düzenlemeli Ortalamalar Yöntemi kullanılmıştır. Çalışmanın sonunda yazında iyi bilinen bazı ulaşım ağlarının verileri kullanılarak oluşturulan matematiksel modeller geliştirilen yöntemle çözülmüş ve elde edilen sonuçlar kapsamlı bir şekilde ele alınmıştır.

1. INTRODUCTION

As an important dimension of urban sustainability, transportation has significant and long lasting social, environmental, and economic impacts. Accordingly, there are some attempts that are related to the urban transportation within the framework of sustainable development. Some studies apply sustainable transportation indicators to compare sustainability among different world cities (Haghshenas & Vaziri, 2012). Kennedy et al. (2005) state that we require some pillars such as "effective governance of land use and transportation", "fair, efficient, stable funding", "strategic infrastructure investments", and "attention to neighborhood design" in order to succeed sustainable urban transportation in the cities.

The main characteristics of sustainable transportation are safety, comfort, affordability, efficiency in energy consumption and reduction/elimination of the environmental pollution. Carbon emissions into the atmosphere cause environmental pollution such that it decreases quality of life (Yazid et al., 2011). With some regulations and restrictions, we can reduce carbon emission, and thus environmental pollution. Besides, if we balance the transportation costs between the social classes, transportation can become more affordable. In addition to these, if safety measures are taken and traffic is adequately managed, the number of road accidents can be reduced. Accomplishing all of these goals within the scope of sustainable transportation will evidently improve the quality of life. With the consideration of these, we can easily say that sustainable transportation is a substantial issue for the life quality.

Transportation has a crucial aspect which is the social dimension of transportation. This dimension includes concepts such as accessibility and equity. In order to have sustainable transportation, we have to give more importance to these concepts. In a transportation network, users should reach the centers easily, namely the centers must have an effective accessibility. In addition to this, it is desired for the users to have equal conditions and rights to reach these centers. Another considerable aspect is economic dimension of transportation which consists of affordability concept. The travelers should afford to use transportation systems. The allocated budget by users to transportation should be enough to use these systems.

The speed of life in the 2lst century continues to increase substantially, and as a result of this, it can be said that mobility is now one of the most significant features of the societies. This means more and more cars, and unfortunately, more and more pollution (Muntwyler & Koch, 2002). This pollution can be air or noise pollution. If we can build sustainable transportation systems, we can reduce these pollutions. Consequently, if we reduce these pollutions, there will not be any requirement to decrease mobility.

In order to assure the sustainability of transportation, there are some studies in the literature which are related to traffic assignment models. These models can be examined in two categories: Deterministic User Equilibrium (DUE) and Stochastic User Equilibrium (SUE). In DUE model, users have perfect information about the traffic network such that they know the travel times of all the routes on the network (Wardrop, 1952b). In this model, users aim to minimize time/cost associated with their route choices (Lee et al., 2010). It is difficult to implement this idea to real network problems, because it is impossible to know all the routes' travel times rigorously. The other model for traffic assignments is SUE model. In this model, the travel time of paths is perceived by the users and it is a random variable. The users determine their respective shortest paths through multiple candidate paths between the origin-destination (OD) pair. Although these two models are in contrast, their purposes are the same. Both of them aim to investigate effective and efficient methods which assign the traffic flow on the transportation network properly (Lee et al., 2010).

For solving the SUE model, there are some algorithms in the literature. One of them is that Self-Regulated Averaging (SRA) method. This method is an improved version of a well-known algorithm which is Method of Successive Averages (MSA) (Liu et al., 2009). SRA method can be used to assign the traffic flow onto the network links adequately with the integration of Bell's second algorithm to this method. Bell's second algorithm is used for solving logit-based stochastic network loading problems (Lee et al., 2010).

The thesis is organized as follows. Chapter 2 gives an extensive literature survey about sustainability of transportation systems. It also describes traffic assignment problems such as DUE and SUE in details. Chapter 3 presents the developed sustainable traffic assignment model with SUE. The model is explained with bi-level programming and multiple user classes concepts. Moreover, the objectives that are included in this model such as social, environmental, and economic objectives are clarified in this chapter. Chapter 4 provides the solution method for the problem and gives the obtained results. Finally, chapter 5 concludes the study and gives future directions for this study.

2. LITERATURE SURVEY

2.1. OVERVIEW OF SUSTAINABILITY

Sustainable development has emerged as an important concept with global priority during the last decades. It indicates a big challenge for the societies in the world, therefore it needs new analytical tools to deal with this challenge (Gudmundsson & Hojer, 1996). It has the potential to affect future government policies and identify new business models for the countries in the world. Moreover, sustainable development is seen as a significant research area by the researchers, because it has a rich potential for academic research to give some studies related to this area for the future (Ilbery & Maye, 2005). It has become the catchword in the international discussions and several approaches to sustainability assessment have been created (Becker, 1997).

Sustainability indicators and composite index are gaining much more significance and becoming increasingly recognized as a strong tool for policy making and public communication in obtaining information for countries. Furthermore, they provide information on corporate performance in some fields such as social, environmental, economic, and technological improvement. These indicators also simplify, quantify, analyze, and communicate the complicated information for conceptualizing phenomena and emphasizing the trends. In the literature, there are some attempts and studies exist on these indicators for sustainable development (Singh et al., 2012). In a one study, it is explained that indicators can help package complex information into a usable form for the public policy (Shields et al., 2002). They are needed to determine progress toward sustainability goals. In this study, it is also explained that the sustainability paradigm is suitable to be applied to the complicated, urgent, and interconnected problems. The reason of this is that it has several features which are "comprehensive and inclusive", "simple in concept and feasible", "value-based", and "an approach that needs consistency among policy areas".

Sustainable development has become a considerable principle for all governments in the world (Bond & Saunders, 2011). It is studied in an international report which is "Brundtland Report" (World Commission on Environment and Development, 1987) which is a culmination of public attention being directed among public concerns over poorly planned resource usage. This report has gained popularity with the contribution of some reports which are developed by the "Club of Rome" (Meadows et al., 1972) and "Rachel Carson's Silent Spring" (Carson, 1963). Brundtland Report includes a definition for sustainable development which is: "*Development which meets the needs of current generations without compromising the ability of future generations to meet their needs.*"

The main international political driver which is the "Rio Earth Summit, 1992" sets out a series of action points for accomplishing sustainability (Bell & Morse, 2008). After that time, the governments in the world have constituted their own policies about sustainability development such that the European Union has recently modernized its sustainable development strategy (CEU, 2006). Moreover, the United Kingdom (HM Government, 2005) and Western Australia (GWA, 2003) have also renewed their own strategies on sustainable development. In the context of high level political commitment to the principle of sustainable development, sustainability assessment has become more common as a decision-making tool aimed to estimate the sustainability effects of proposed actions (policies, plans, projects, and programmes) (Pope et al., 2004). The general definition of sustainability assessment is given as follows (Bond & Saunders, 2011): "*A process which directs decision-making towards sustainability.*"

The categorization of sustainability assessment tools within the broader objective of the understanding of sustainability assessment can be lifted from the environmental-focused region to an extensive interpretation of sustainability. The tools can be categorized as indicators/indices, product-related assessment, and integrated assessment tools. Besides these, the tools are classified by their spatial focus and the level of nature-society system unification. These tools are essential to accomplish the objectives of the current understanding of sustainability assessment (Ness et al., 2007).

In order to avoid social instability, environmental depletion, and economic decline in the city regions which can be urban or rural agglomerations, a multidimensional sustainability assessment tool is required to address these problems in the regions (Nijkamp & Vreeker, 2000; Wiek & Binder, 2005). This tool should include three dimensions which are systemic dimension, normative dimension, and procedural dimension (Figure 2.1).

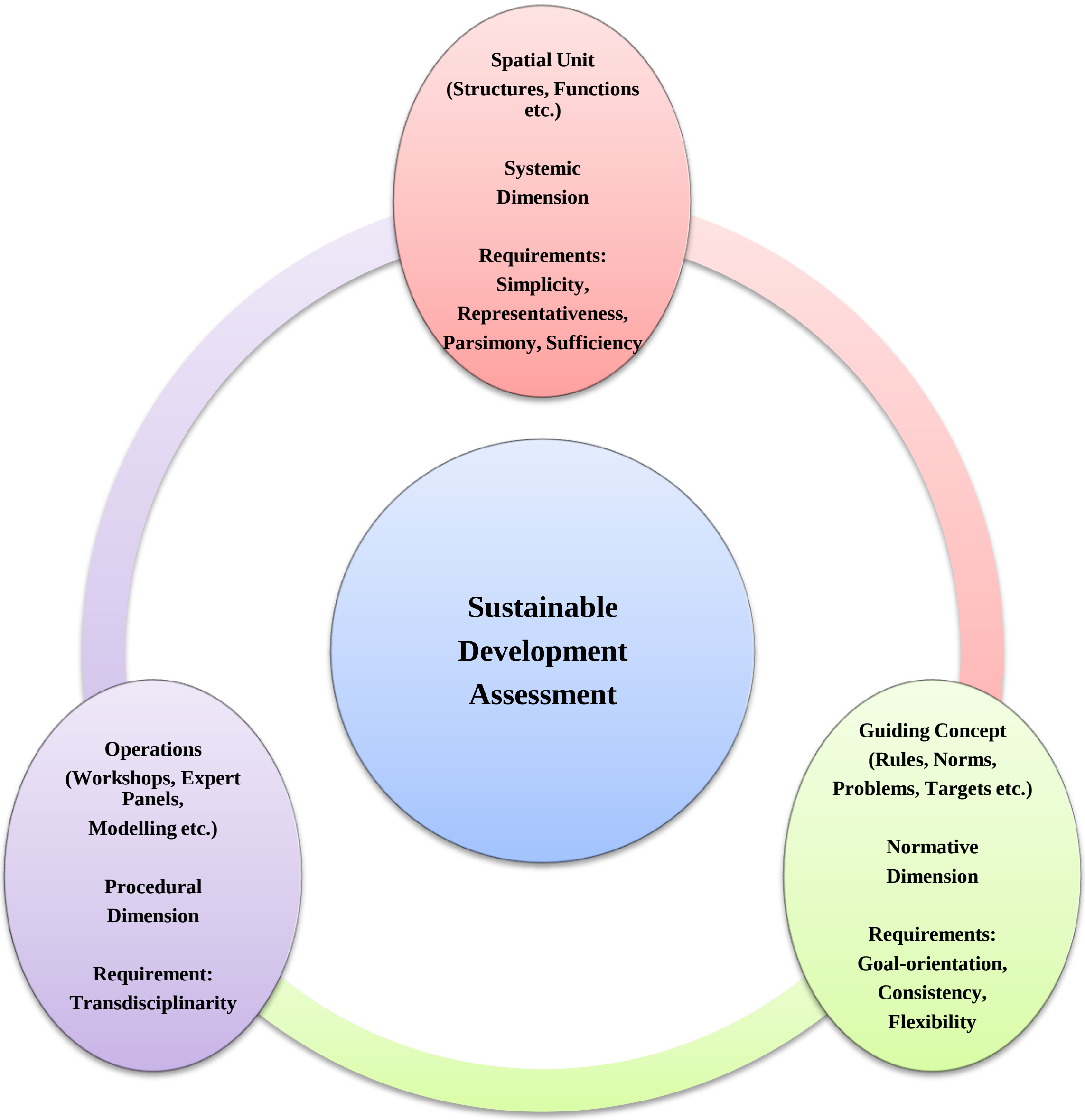

Figure 2.1 Requirements for assessing the sustainability of city regions by including systemic, normative, and procedural aspects

The systemic dimension of the sustainable development assessment tool includes a target-related model of the system to be assessed. Furthermore, the normative dimension involves a normative guiding concept which is operationalized in specific targets. And the last one which is the procedural dimension includes a convenient procedure to integrate the relevant stakeholders and to bridge systemic and normative aspects of the assessment tool (Wiek & Binder, 2005).

In order to solve the problems within the systemic dimension, the indicators can be used to describe and monitor the system to be assessed (United Nations, 1992). The system has to represented with as much simplicity as possible (parsimony) and as much complexity as necessary (sufficiency). The indicators have to demonstrate the main structures, processes, and functions of the social, ecological, and economic fields of the city region referring to the problems and targets which are identified in the normative dimension of the sustainable development assessment tool (problem and target-oriented representativeness).

The main problem for the normative dimension is that how the widely accepted concept of sustainable development can be applied to city regions (Finco & Nijkamp, 2001). For solving this problem, precise targets from the general concept of sustainability should be derived to match the particular problems of the city region (problem and goal orientation). Besides these, the targets have to be consistent internally and also they must allow the decision-makers to be flexible for getting measures.

The final dimension is the procedural dimension which gives better results than other dimensions if it is designed as a transdisciplinary approach (Ravetz, 1999; Thompson Klein et al., 2001). This approach includes stakeholders with different viewpoints, obligations, skills, and resources in the transition process of the city region. Moreover, this approach provides a framework to integrate the assessment tool to the perceptive, cognitive, and discursive skills of the stakeholders. In addition to all of these, in order to support socially consistent and scientifically founded decisions, the assessment tool can be adapted to the preferences and values of the stakeholders.

2.2. SUSTAINABILITY FOR TRANSPORTATION SYSTEMS

Every transportation system plays a major role for the sustainability of the planet. The transportation systems must be sustained in order to continue to afford to all people access to the social, environmental, and economic opportunities which are necessary for the quality of life. While great developments have been made to many transportation systems in the world, there are also a lot of problems in the sustainability of these systems (Richardson, 2005). Transportation problems are among the most pressing urban development problems, related to social, environmental, and economic concerns in many cities, and often a core constraint for urban development in general (Fedra, 2004). In the literature, there are some studies which find solutions to these problems with some models, approaches, methodologies, and algorithms for the sustainability of transportation systems.

The problems for the sustainability of transportation have become global issues. Many countries in the world are trying to find solutions for these problems. Some governments are using holistic approaches for addressing these problems in the context of globalization issues. All planning aspects and reporting relating to transportation systems have to be based on social, environmental, cultural, and economic impact areas to solve the problems effectively and provide the sustainability of these systems (Henning et al., 2011). Some of the primary attempts for achieving more sustainable transportation systems contain "controlling car use", "improving the uptake of public transport", and "increasing the opportunities for walking and cycling" (Bertolini & Le Clercq, 2003; Hensher & Stanley, 2003; Wolfram, 2004).

In the literature, there is an effective and efficient approach, for solving the challenges of transportation systems, which is the multi-criteria decision making approach. In order to select sustainable transportation systems, this approach is suitable to be used under partial or incomplete information (uncertainty). In this approach, fuzzy TOPSIS can be used for sustainability assessment and selecting the best alternative among all the transportation systems. This approach includes three steps. In the first step, the criterion for sustainability assessment of transportation systems is identified properly. Furthermore, in the second step, experts give linguistic ratings to the potential alternatives with respect to the selected criterion. Finally, in the third step, sensitivity analysis is used to determine the effect of criterion weights on the decision making process (Awasthi et al., 2011). Multi-criteria decision making approach is a consistent and comprehensive approach and planning methodology for the analysis of urban transportation systems' problems. With the contribution of this approach, we can generate and design strategies for obtaining sustainable transportation in sustainable cities. This approach consists of socioeconomic, environmental, and technological concepts which include the development, integration, and demonstration of tools and methodologies to improve the assessment of sustainability (Fedra, 2004).

Urban transportation systems are complicated systems which are influenced by social, economical, and environmental factors. Some conventional transportation modelling approaches are inappropriate to evaluate the systems' efficiency and performance. In the literature, there is a modern approach which is a system dynamics model of urban transportation system based on the cause-and-effect analysis and feedback loop structures. This modelling approach includes 7 sub-models which are population, economic development, number of vehicles, environmental influence, travel demand, transport supply, and traffic congestion. In this model, the effects of different policy scenarios on urban development and transportation systems can be analyzed to assess the sustainability of transportation systems (Jifeng et al., 2008).

The another approach in the literature for assessing the sustainability of transportation systems is the sustainability footprint model which is used in analyzing the impacts of transportation systems on regional sustainable development. This model is also used to assess the contributions of transportation systems to the quality of life of communities while taking account their impacts on the natural and social environment. Besides these, this model provides a basis for developing a planning concept, namely sustainability footprint management which is similar to the carbon emissions trading concept. In addition to all of these, it can be said that adopting this model for the sustainability of transportation systems has implications on research, policy, and practice (Amekudzi et al., 2009).

Sustainable transportation is a significant aspect of sustainable development. It considers all kinds of transport that minimize carbon dioxide emissions, fuel consumption, and pollutants. Besides this, it consists of at least four aspects which are "high level of accessibility (shorter travel distance or duration)", "environmentally efficient transport modes (use of renewable energy and low emissions)", "public transportation", and "social equity" (Nicolas et al., 2003). Many studies have demonstrated that urban growth management in land development has important effects on sustainable transportation (Figure 2.2). According to the researchers, urban sprawl on the urban fringe increases long-distance travel demand and the travelled vehicle kilometers (Camagni et al., 2002). Some studies have explained that how the compact land development attributes such as high density, high level of jobs-housing balance, and compact physical pattern increases residents' accessibility to services and facilities while decreases the travel distance and the number of trips with private vehicles (Cervero, 1995; Levinson & Kumar, 1997; Schwanen et al., 2004; Zhao, 2010).

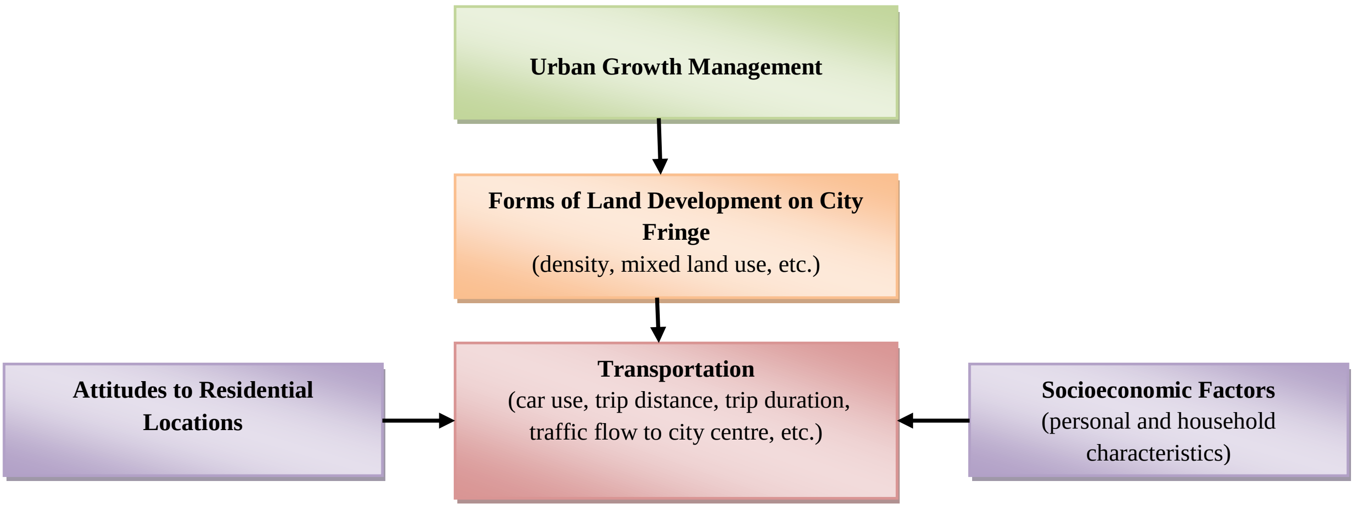

Figure 2.2 The relationship between urban growth management, forms of land development and transportation

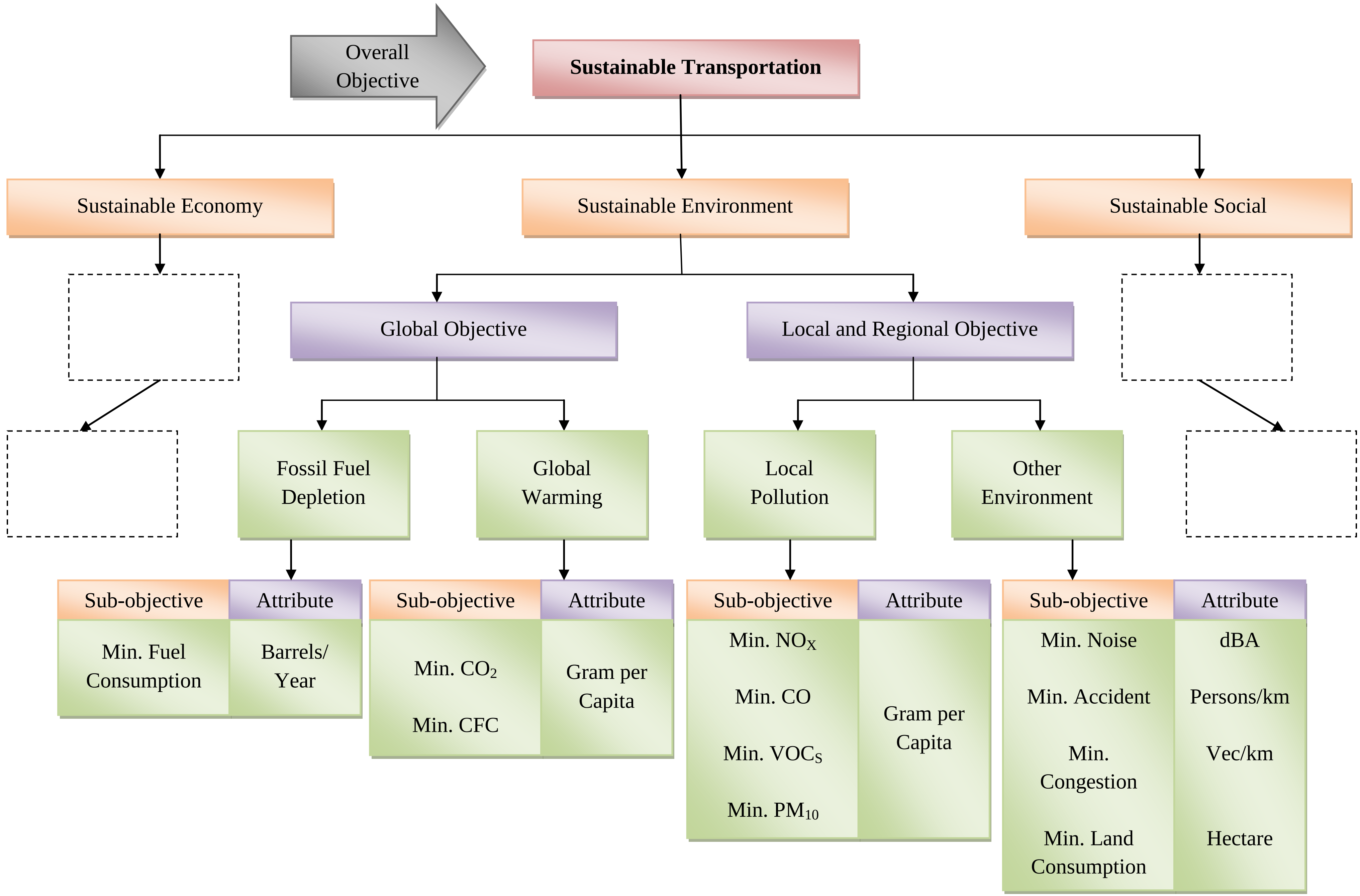

Figure 2.3 Hierarchical diagram for sustainable transportation

The above Figure 2.3 represents the hierarchical diagram for sustainable transportation. It begins with a global objective of sustainable transportation, after that it expands to sub-objectives and attributes. In order to achieve sustainability of transportation, we have to give more importance to "social equity", "environmental sustainability", and "economic efficiency" as shown in the diagram. In this diagram, only sustainable environment effects on sustainable transportation are explained in detailed. Environmental sustainability is analyzed with two objectives which are "global objective" and "local and regional objective" (Black et al., 2002). Global objective includes two sub-objectives which are "fossil fuel depletion" and "global warming" objectives. If we want to achieve fossil fuel depletion objective, we have to minimize fuel consumption in barrels per year. Moreover, if we would like to decrease global warming, we should reduce CO_2 and CFC emissions in grams per capita. The other objective is local and regional objective which also consists of two sub-objectives that are "local pollution" and "other environment". If the local pollution is wanted to reduce by local authorities, NO_X, CO, VOC_S, and PM_{10} emissions have to be minimized in grams per capita. The second sub-objective for local and regional objective includes noise minimization in dBA, accident minimization in persons per km, congestion minimization in vehicles per km, and land consumption minimization in hectare. In this study (Black et al., 2002), emphasis is only on environmental sustainability, however we can assess sustainability of transportation by incorporating social equity and economic efficiency issues to environmental sustainability in other studies.

2.3. TRAFFIC ASSIGNMENT PROBLEMS

2.3.1. User Equilibrium and System Optimum

The User Equilibrium (UE), which is defined by Wardrop's first principle, assumes that each user has complete and precise information about all available routes. The underlying assumption is that all users who are taking a trip between an Origin-Destination (OD) pair have the same travel time which is less than or equal to the travel time on any unutilized path (Wardrop, 1952b). Furthermore, Wardrop's second principle states that at equilibrium point the average journey time is minimum. This means that each user behaves cooperatively when choosing his or her own route to ensure the most efficient use of the whole system. This principle corresponds to the "System Optimum" (SO) traffic assignment (Wardrop, 1952a; Yıldırım & Hearn, 2005).

Every traveler tries to minimize his or her own travel time when travelling from origin to destination. This situation does not mean that all the travelers between each OD pair have to be assigned to a single path. The travel time on each link changes with the flow, and thus the travel time on some of the network paths changes when the link flows change. We can obtain a stable condition when *no traveler tries to improve his or her travel time by unilaterally changing routes.* This is the feature of the UE condition. Although every traveler can be expected to behave independently, the UE condition ensures that at this point there is not any force which tends to take the flows out of the equilibrium situation. It can be said that this point will be stable and this situation is a true equilibrium (Sheffi, 1985).

According to the UE definition, travelers have full information about the routes such that they know the travel time on each possible path. They always make correct decisions when they choose their routes on the traffic network. Moreover, this condition assumes that all the travelers demonstrate the same behaviors in their route choice decisions (Sheffi, 1985).

In the literature, there are several attempts for modeling users' selection of their routes in congested networks. There are two choices for users which are SO and UE models to select their routes (Helbing et al., 2005). The UE model assumes that the users have perfect information of travel costs of the routes and they choose the best routes with this knowledge. This situation is explained with the Wardrop's first principle as given above. This principle is derived from non-cooperative mixed-strategy Nash equilibrium in game theory (Wardrop, 1952a; Bell & Cassir, 2002). UE model is a significant classical traffic assignment model (Sheffi, 1985). In equilibrium, the routes, which carry positive flows, have the same travel costs. However, UE model has scarce resources such as street and road capacity. This is a disadvantage for UE models (Helbing et al., 2005).

The other model is the classical Wardrop SO traffic assignment model. This model assumes that all users can cooperate with each other for minimizing the overall system-wide travel costs (Sheffi, 1985). The model has a disadvantage such that it is not applicable for real life situations. However, this model gives good and efficient solutions if the transportation network is controlled successfully with the route inducement (Moreno-Quintero, 2006). Route inducement is accomplished by traffic lights and adaptive routing such that if signal timings are re-optimized and alternative paths are re-defined, the traffic flow can be conducted successfully in order to obtain good solutions for traffic flows and travel times (Poli & Monteiro, 2005).

In the both UE and SO traffic assignment models, the travel times are generally assumed to be deterministic. The SO models usually explain the travel costs considering deterministic travel time functions (Prashker & Bekhor, 2000). These times vary for each trip and also for each day, because the traffic flows on the network are not stable. These travel times are usually obtained from the classical formulas which have been developed over the past 40 years. The most popular formula is the Bureau of Public Roads (BPR) formula which was developed using the data from the Highway Capacity Manual in 1964 (Bureau of Public Roads, 1964). There is also another formula, for acquiring travel times in the UE or SO models, which is based on an approximation to the time-dependent models (Cruz et al., 2010).

2.3.2. Dynamic User Equilibrium and System Optimum Models

Dynamic UE aims to estimate future dynamic traffic states in a short-term fashion. It assumes that the users follow certain reasonable behavioral alternatives. Dynamic UE is based on the Dynamic Traffic Assignment (DTA) which has been studied extensively over the past decades. In order to model dynamic UE, Variational Inequality (VI) and Nonlinear Complementarity Problem (NCP) can be used (Ran & Boyce, 1996; Peeta & Ziliaskopoulos, 2001; Facchinei & Pang, 2003; Friesz et al., 2010). The first DTA model depends on system optimality and it is formulated with discrete travel times (Merchant & Nemhauser, 1978a; Merchant & Nemhauser, 1978b). After that, the model has been formulated by using continuous travel times (Friesz et al., 1989; Friesz et al., 1993; Smith, 1993; Heydecker & Addison, 1996; Ran & Boyce, 1996; Ban et al., 2012). The major characterization of DTA is that it takes into account the time dimension. This feature gives important advantages to DTA in examining congested road networks so that it is able to be understood how the congestion emerges and dissipates over the time period. Due to the importance of the DTA, there are many significant attempts to develop and solve dynamic UE models (Han & Heydecker, 2006).

Another DTA model is the System Optimum Dynamic Traffic Assignment (SO-DTA) model. This model is the most well-studied model among the other DTA models. The SO-DTA models have more well-defined objective functions such as total system cost minimization or total system time minimization functions than User Equilibrium Dynamic Traffic Assignment (UE-DTA) models which investigates dynamic extensions of the Wardrop equilibrium (Mahmassani & Herman, 1984; Friesz et al., 1993; Smith, 1993; Ran & Boyce, 1996). SO-DTA models are used in many implementations in transportation planning and operations. Moreover, the solution of SO-DTA models are used to assess the benefits of investment decisions, traffic management policies, and operational strategies (May & Milne, 2000; Waller, 2000; Munoz & Laval, 2006; Karoonsoontawong & Waller, 2009; Shen & Zhang, 2009; Nie, 2011a).

2.3.3. Deterministic User Equilibrium

Deterministic User Equilibrium (DUE) model is one of the network equilibrium models. In this model, users investigate the best paths in order to minimize their individual travel times. The travel times on all paths which are actually used between any OD pair on the network are equal to or less than the other travel times that would be experienced by a single vehicle on any of the unused paths (Wardrop, 1952b). In DUE model, users have perfect information about all the paths on the network. In this model, the users usually consider directed experienced costs such as travel times when travelling on the network. They have the knowledge of travel times of all the paths. This model is generally used for congested urban transportation networks. Moreover, it gives realistic and reasonable results for the users.

DUE can be modelled as a classical optimization problem. User-optimized flow patterns are obtained by solving the optimization model. The notations of the DUE model are given in the Table 2.1 as follows:

Table 2.1 Notations in the DUE model

x_a	flow of the vehicles on link a
t_a	travel time on link a
T_{ij}	the number of trips from origin i to destination j
f_k	flow of the vehicles on path k
K_{ij}	all the paths from origin i to destination j
L	all the links on the paths from origins to destinations
δ_{ak}	1 if link a is on path k, 0 otherwise

The mathematical model of the DUE problem is given as follows:

$$\text{minimize} \quad \sum_a x_a t_a(x_a) \tag{2.1}$$

$$\text{subject to} \quad \sum_{k \in K_{ij}} f_k = T_{ij} \qquad \forall i, j \tag{2.2}$$

$$x_a = \sum_{k \in K} \delta_{ak} f_k \qquad \forall a \in L \tag{2.3}$$

$$f_k \geq \ 0 \qquad \forall k \in K \tag{2.4}$$

In this model, we aim to minimize the total travel time on the network. Total travel time is obtained by multiplying the travel time on a link for one user with the flow on a link. Travel time is a function of the link flow, namely travel time is dependent on link flow. For instance, if the link flow increases, the traveled time for one user on the network also increases. This model includes some constraints. The flow on all the paths between an OD pair should be equal to the number of trips between this pair. Moreover, the flow on a link must be equal to the flow on all the paths which use this link. In addition to these, the flow on a path must be equal to or more than zero.

In this DUE model, the traffic is firstly assigned to the least travel time paths after solving the problem. However, after the first assignment, the travel times of these paths increase due to the demand to these paths. If this situation occurs, we again have to assign the traffic to new least travel time paths. Frank-Wolfe algorithm can be an appropriate algorithm in order to solve this model and obtain optimal re-assignments (Frank & Wolfe, 1956; Ortúzar & Willumsen, 1994). With this algorithm, we reach to the optimal solutions in a short time period, because the algorithm converges with a small number of iterations even in large urban transportation networks (Taplin, 2000).

2.3.4. Stochastic User Equilibrium

Stochastic User Equilibrium (SUE) models are contrast with DUE models, because users have not perfect knowledge of travel times/costs of the routes. These models are based on a hypothesis such that users can make systematic errors in the perception of travel times/costs of the routes on the network. In these models, systematic errors of the perception can be given with probability density functions. SUE models should be preferred when the transportation network is not congested or unlikely to be congested. Moreover, these models can be used when the routes of the network is not only chosen according to travel times/costs information by the users. When the users are choosing their routes, they have to consider the other information about the network in these models (Florian & Hearn, 2008).

To formulate the SUE model, it is significant to determine the probability of paths on the network. The path probability is given by pr_k.

$$pr_k = pr_k(Z_i) \quad k \in K_i \;\; i \in I \tag{2.5}$$

- pr_k : probability that an individual chosen from the population g_i will choose path $k \in K_i$
- Z_i : vector of perceived travel times of all paths k for an OD pair i
- g_i : user population between an OD pair i
- K_i : all paths between an OD pair i
- I : set of OD pairs on the network

The perceived travel time on link *a* is given by the probability density function which is presented below:

$$z_a \sim D(s_a, \theta s_a) \tag{2.6}$$

- z_a : perceived travel time on link *a*
- s_a : actual travel time on link *a*
- θs_a : actual travel time variance
- θ : constant

The probability of choosing path *k* can be given by a formulation where chosen path is perceived to be the shortest path by the users. The formulation is given as follows:

$$pr_k = Pr\left[z_k = min_{k^1 \in K_i}(z_{k^1})\right] \tag{2.7}$$

In addition to these, the path flow h_k also satisfies the below formulation of probability with the user population g_i.

$$pr_k = \frac{h_k}{g_i} \quad i \in I \quad k \in K_i \tag{2.8}$$

- h_k : flow on path k

The SUE model can be solved as an optimization problem (Evans, 1976). Objective function of the model is represented as follows:

$$\min_v \left(\sum_{i \in I} g_i E \left\{ \min_{k \in K_i} [z_k \mid s_k(v)] \right\} \right) + \sum_{a \in A} v_a s_a(v_a) - \sum_{a \in A} \int_0^{v_a} s_a(x)dx \qquad (2.9)$$

- z_k : perceived travel time on path *k*
- s_k : actual travel time on path *k*
- v_a : flow on link *a*
- A : all links on the network

This model only has non-negativity constraints. Although the objective function is not convex, there is only one stationary point. Moreover, objective function is strictly convex in the flow variables in the neighborhood of the stationary point. Therefore, it can be said that the resulting link flows are unique.

Path probabilities of the network can also be given by a logit function. This function is given below:

$$pr_k = \frac{exp[-\theta s_k(v)]}{\sum_{k^1 \in K_i} exp[-\theta s_{k^1}(v)]} \quad k \in K_i \text{ , } i \in I \qquad (2.10)$$

When the path probabilities are given by a logit function as above, the model of SUE problem is represented as follows:

$$\min_h \left(\sum_{i \in I} \sum_{k \in K_i} h_k \ln(h_k) \right) + \theta \sum_{a \in A} \int_0^{v_a} s_a(x)dx \qquad (2.11)$$

In addition to the objective function which is given above, this model also has flow conservation and non-negativity constraints which are below:

$$\sum_{k \in K_i} h_k = g_i \quad i \in I \ , \ h_k \geq \ 0 \ , \ k \in K \tag{2.12}$$

$$v_a = \sum_{k \in K} \delta_{ak} h_k \quad a \in A \tag{2.13}$$

- δ_{ak} : 1 if link a is on path k, 0 otherwise
- K : all paths on the network

2.4. SOME STUDIES FROM THE LITERATURE

In the literature, there are studies which are related to this study. Some of them are explained as follows:

Lam et al. (1999) explain a SUE assignment model for congested transit networks with a solution algorithm. In this study, a mathematical programming problem is formulated for this model. The model gives information on how passengers will choose their optimal routes. Moreover, it predicts the total passenger travel cost on congested transit networks. Bell (1995) developed an algorithm which solves SUE road traffic assignment problem with queues and explicit capacity constraints. This algorithm can be adapted for solving the mathematical programming problem which is developed for SUE assignment model for congested transit networks. Numerical examples are also given to illustrate this proposed model at the end of this study.

Prashker & Bekhor (2000) present traffic assignment models which are classified according to the behavioral assumption that governs route choice in their study. The focus of this study is on the relationship between “SUE” and “deterministic SO” traffic assignments. The flow pattern which is acquired from the SO solution serves as a yardstick for comparison with the flow patterns obtained from the UE and SUE solutions. In this study, mathematical formulations for “UE”, “SUE”, and “SO” are given for comparison in detailed. Moreover, numerical examples are also given extensively. With these examples, the study investigates whether the SUE is closer than the DUE to the SO.

Rudinger et al. (2004) explain the work of the European Union network Sustainable Transport in Europe and Links and Liaisons to America (STELLA). They study social and behavioral aspects of sustainable transport from a transatlantic perspective. Moreover, they examine STELLA network in detailed. They take into account society, behavior of the society such as mobility behavior, and sustainable transportation for the development of this network. In addition to these, they agree to deepen to multi-level models for designing sustainable transportation of the network.

Steg & Gifford (2005) explain sustainable transportation concept and its relation to the quality of life. They consider the continuing increase in the use and density of automobiles in relation to the transportation sustainability and quality of life. According to the social dilemma perspective, this trend is a result of an unfortunate preference for short term gains by car users at the cost of long term loses to the society. Furthermore, they assess some approaches for measuring quality of life by taking account sustainable transportation.

Kennedy et al. (2005) argue that the process of achieving sustainable transportation. This requires some appropriate pillars which are “effective governance of land use and transportation”, “fair, efficient, stable funding”, “strategic infrastructure investments”, and “attention to neighborhood design”. In this study, an effective body for integrated land-use transportation planning is established properly. A fair, efficient, stable funding mechanism is also explained. Furthermore, making strategic investments in major infrastructure is clarified. Consequently, support of investments through local design is expressed thoroughly. In this study, all of these are carried out for obtaining sustainable transportation successfully.

Maher et al. (2005) explain Stochastic Social Optimum (SSO) which relates to the SUE in the same way as the SO relates to the UE in a deterministic environment. At the SSO, users' total perceived travel costs are tried to minimize. For SSO, it is possible to use probit or logit traffic assignment models. The SSO solution can be acquired with an algorithm which can also be used for SUE. The difference is that marginal social costs are taken into consideration at the SSO whereas at the SUE standard costs are used.

Ho et al. (2006) consider a city with several facilities competing for multiple user classes that are distributed continuously over space. The road network is relatively dense and is considered as a continuum in the city region. A logit-type demand distribution function is specified for modeling the probabilistic choice behavior of destinations for the multiple user classes. For all of these, a continuous UE problem can be formulated as a mathematical program. Effective solution algorithms are preferred to use to obtain good results from this mathematical program. In order to illustrate the proposed UE model with multiple user classes within a continuum network, appropriate numerical examples have to be used.

Shouhua et al. (2007) examine combination of the benefit-cost of the traffic flow guidance system and the random users' equilibrium under the action of the traffic flow guidance system. Some travelers in the network can choose their paths according to both the guidance information and their experience with the application of the traffic flow guidance system. Road network SUE model based on the bi-level programming can be explained under the action of the traffic flow guidance system. Upper level programming problem can be given as SO of the road network. However, lower level programming problem can be given as SUE. In order to solve the bi-level programming problems, heuristic algorithms are usually applied.

Chen et al. (2009) analyze three stochastic Network Design Problem (NDP) models for designing transportation networks with demand uncertainty. First model is formulated as the expected value model, the second model is formulated as the chance constrained model, and the third model is designed as the dependent chance model. Stochastic bi-level mathematical program can be used for all of these three models. For solving these stochastic NDP models, traffic assignment algorithm, genetic algorithm, or Monte-Carlo simulations can be used. To illustrate and compare expected value model, chance constrained model, dependent chance model and solution algorithms which are traffic assignment algorithm, genetic algorithm, Monte-Carlo simulations, some numerical experiments should be done.

Lim (2010) considers multiple user class daily stochastic assignment model. In this model, there is more than one class of users and a class may be defined on the basis of the vehicle type, driver's cost functions, and the sections of the network available. The used solution algorithm for this model is based on the method of Vuren & Watling (1991), which was originally proposed by Vliet et al. (1986) for solving the multi-class UE assignment problem, and the MSA for stochastic network loading with a probit model. In order to evaluate this model and solution algorithm, network examples can be used.

Guo & Yang (2010) investigate Pareto-improving congestion pricing and revenue refunding schemes in general transportation networks that make every road user better as compared with the situation without congestion pricing. A multi-class user model with fixed OD demands can be adopted by considering user heterogeneity in value of time. Firstly, the preliminaries on multi-class user model have to be provided, after that existence of Pareto-improving congestion pricing and revenue refunding schemes can be explained.

Rosa & Maher (2010) study on "multiple user classes SUE" and "SUE with elastic demand" formulations. Besides these, they also have formulations for "multiple user classes SUE elastic demand problem". In addition to, they suggest some algorithms for solving these formulations effectively and efficiently.

Nie (2011b) examines stochastic performance model thoroughly. Moreover, the formulation and properties of the percentile UE problem for multiple user classes are given in this study. Gradient projection algorithm can be used to solve the percentile UE model. In addition to these, flow dependent stochasticity is clarified properly in the study. In order to solve the UE problem, the application of the same algorithm as the standard traffic assignment problem can also be used for this problem. To illustrate all of these, it is possible to use some numerical experiments.

Haghshenas & Vaziri (2012) examine some attempts which have been made to develop sustainable transport indicators. In this study, various world cities are ranked according to urban sustainable transport composite index. For this study, the database is generated from UITP databank. In this study, nine sustainable transportation indicators are created. Three indicators are used for social impacts, three indicators are used for environmental impacts, and the other three indicators are used for economic impacts. Taking into account these indicators, a composite index is developed. Eventually, various world cities are compared for their transportation sustainability using this composite index.

Table 2.2 Illustration of the relevant studies from the literature

Investigated Studies	Sustainable Transportation	Stochastic User Equilibrium	Multiple User Classes	Bi-level Programming	Multiple Objectives
Lam et al. (1999)		✓			
Prashker and Bekhor (2000)		✓			✓
Rudinger et al. (2004)	✓			✓	
Steg and Gifford (2005)	✓				
Kennedy et al. (2005)	✓				
Maher et al. (2005)		✓			
Ho et al. (2006)			✓		
Shouhua et al. (2007)		✓		✓	
Chen et al. (2009)		✓		✓	
Lim (2010)		✓	✓		
Guo and Yang (2010)			✓		
Rosa and Maher (2010)		✓	✓	✓	
Nie (2011)		✓	✓		
Haghshenas and Vaziri (2012)	✓				✓

2.5. SIGNIFICANCE OF DEVELOPED TRAFFIC ASSIGNMENT MODEL

Many studies from the literature have been examined related to this work. Some of these studies are represented in Table 2.2 above. After that, it has been decided that how this study will be constituted.

In this study, a sustainable traffic assignment model with SUE and multiple user classes is developed. This model is built with bi-level programming. At the upper level of the model, multiple objectives which are social, environmental, and economic objectives are integrated. At the lower level of the model, SUE assignment with multinomial logit discrete choice and multiple user classes is included.

"Sustainable transportation", "bi-level programming", "multiple objectives", "SUE", and "multiple user classes" concepts have been used in the examined studies from the literature. These concepts have been usually integrated to the studies as single or dual combinations of them as shown in Table 2.2. On the other hand, in this work, all of these concepts are integrated to the study different from the other studies. Used concepts in this study are given with their lower concepts in the following Figure 2.4.

In the investigated studies, it has been seen that SUE concept is usually used with only one user class and one objective. However, in this study, the SUE concept is integrated with multiple user classes and multiple objectives different from the other examined studies.

Another difference of this study from the other studies is that the objectives consist of some significant concepts. Social objective includes accessibility, equity and road accidents concepts, environmental objective contains emission and noise concepts, and economic objective comprises affordability concept.

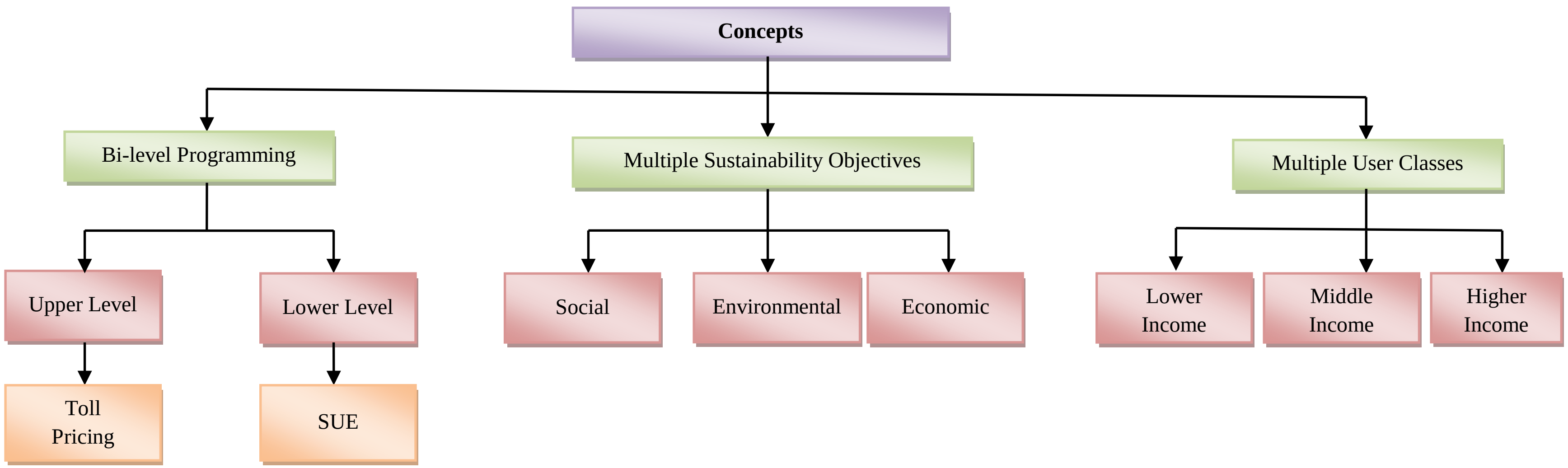

Figure 2.4 Used concepts in the sustainable traffic assignment model

3. SUSTAINABLE TRAFFIC ASSIGNMENT WITH SUE

Sustainable traffic assignment with SUE is aimed to achieve in this study. In order to carry out this aim, a model is developed. This model is created with bi-level programming, multiple user classes, and multiple objectives. In this model, bi-level programming has two levels which are upper and lower levels of the model. Moreover, this model has three type user classes which have different income levels. In addition to these, three different types of objective, which are social, environmental, and economic objectives, are used in this model. Social objective consists of accessibility, equity and road accidents, environmental objective includes emission and noise, and economic objective is formed with affordability sustainability concept.

3.1. BI-LEVEL PROGRAMMING

Bi-level programming problems were first formulated in a monograph on market economy by H.V. Stackelberg in 1934. Stackelberg games bi-level programming problems have been taken into account in economic game theory over the past years. These game theory problems are particular types of bi-level programming problems. Bi-level programming has begun to use in optimization problems in the seventies of the 20^{th} century. After that time, a comprehensive research has begun to develop these problems in both theory and implementation. Some engineers, economists, and mathematicians have studied in order to make some developments on this topic. They have given some papers related to this subject over the years and now the other studies are being performed by researchers to improve bi-level programming. As a result of this, the given studies are increasing in this field (Dempe, 2002).

Bi-level programming is a suitable tool in order to model non-cooperative decision processes. Bi-level programming problems can be considered as game theory problems.

In game theory problems, while one player is trying to optimize his or her own situation, he or she has to consider the other player's independent reaction to this situation, because the other player will also try to optimize his or her own situation. It can be said that these two players are opposite with each other (Saati & Memariani, 2004). In bi-level programming problems, there are two objectives which are conflicting with each other as players in game theory problems. For instance, one objective minimizes the problem; the other one is trying to maximize it.

Bi-level programming optimization problems have a hierarchic structure. They have two levels which upper and lower levels. In each level, an objective function is solved. In the upper level, main objective function of the problem is solved. In addition to this, in the lower level, the second objective function as a part of the constraints is solved.

Bi-level programming problems can be considered in two different areas which are given below:

- Economics
- Engineering and Natural Sciences
- Mathematics

From the economics point of view, the lower level of the bi-level programming model explains the right of subaltern parts of large economic units. In this model, the overall purpose considering both the upper level and the lower level of the model is to find and select best decisions for economic units. On the other hand, in engineering and natural sciences, the lower level of the model is used to find an appropriate model for the nature. Considering all of these, it can be said that the upper level of the model is used to reach to the main purpose of the problem. However, in order to reach this aim, the lower level also has to be taken account to obtain effective and efficient results for the problem. According to the mathematics, the bi-level programming problems are difficult and complicated problems. They are NP-hard problems. Moreover, to formulate them is also a difficult process, it requires higher efforts. When they convert into one level optimization problems (general optimization problems), the regularity conditions cannot be satisfied at any feasible point therefore it is not possible to find feasible or optimal solutions (Dempe, 2002).

3.1.1. Bi-level Optimization Program

Bi-level optimization programs are extended version of general (one level) optimization programs. In general programs, there is only one objective function and constraints. On the other hand, in bi-level programs, there can be two objective functions which work opposite to each other. These programs also have some constraints. The second objective function of the program is considered as a constraint of the overall bi-level program.

Bi-level program is based on some basic mathematical programs which are general mathematical program and multiple objective program. Before examining bi-level program, it is necessary to understand these programs. This general mathematical program and multiple objective program are represented as follows (Fricke, 2003):

General Mathematical Program:

$$\min_{x} \quad f(x) \tag{3.1}$$

$$\text{s.t.} \quad Ax \geq b \tag{3.2}$$

$$x \geq 0 \tag{3.3}$$

General mathematical program is a basic optimization program. The other developed optimization programs are extended versions of this program. Most practical mathematical programming models which are used in operational research include either minimizing cost or maximizing profit (Williams, 2002). The above mathematical program is a minimization program which aims to minimize the cost. This program has also some constraints as given above. One of these constraints is non-negativity constraint which is $x \geq 0$. It means that in this program, the variable x must be equal to or greater than zero.

Multiple Objective Program:

$$\min_{x} \quad f(x) \tag{3.4}$$

$$\min_{x} \quad g(x) \tag{3.5}$$

$$\text{s.t.} \quad Ax \geq b \tag{3.6}$$

$$x \geq 0 \tag{3.7}$$

Multiple objective program is similar to the general mathematical program. The only difference is that this program has more than one objective function. In the general mathematical program, there is only one objective function.

Bi-level Program:

$$\min_{x} f(x, y) \tag{3.8}$$

$$\text{s.t.} \quad A(x, y) \leq b \tag{3.9}$$

$$\min_{y} g(x, y) \tag{3.10}$$

$$\text{s.t.} \quad C(x, y) \leq d \tag{3.11}$$

$$x, y \geq 0 \tag{3.12}$$

Bi-level program is an advanced version of multiple objective program. In this model, there is more than one objective function. In the above bi-level model, there are two objective functions. The first objective function which is $\min_x f(x,y)$ is the main objective function of the above model. The second objective function of the model which is $\min_y g(x,y)$ is considered as a constraint of the overall model. These objective functions are conflicting with each other. In addition to these, this model includes some other constraints which are $A(x,y) \leq b$ and $C(x,y) \leq d$. This model also has non-negativity constraint which is $x, y \geq 0$. It means that the variables x and y must be equal to or greater than zero in this model. After solving this model, Pareto optimal solutions can be acquired.

Bi-level programming models have some properties which are given below:

- In these programming models, there is not any guarantee that they will have a solution.
- They order the decisions according to the importance levels.
- The solutions of these models sometimes do not satisfy Pareto optimality.
- These models can be implemented to the non-convex optimization problems.
- All the functions of these models must be continuous and bounded.
- These programming models can have a number of possible reformulations in order to find the solution effectively and easily.
- It is possible to use these models in particular applications.

3.2. MULTIPLE USER CLASSES

In traffic assignment models, only one user class is usually used. However, in this study, sustainable traffic assignment is aimed to achieve with multiple user classes different from the other studies. There are three types of user classes in the developed model. These users are classified into classes according to their income levels. The first class is lower income group, the second class is middle income group, and the third class is higher income group as Figure 3.1.

Figure 3.1 Lower-Middle-Higher income groups

3.2.1. General Explanation of Multiple User Classes

Using the multiple user classes concept in general SUE models corresponds to market segmentation. In order to obtain multiple user classes, a heterogeneous population of users is separated into some groups. With this separation, each user group has homogenous characteristics. Each group is referred as a class. After the separation, each class of the population can be modeled in SUE. In SUE traffic assignment models, this classes generation is useful to consider the users' different properties and perceptions for the transportation networks. For instance, some vehicles can have some equipments such as route guidance devices. Furthermore, the users can have different perceptions for the "values of time" and "willingness to pay". In addition to these, it is possible to use multiple user classes concept for taking into account restrictions to the circulation of some vehicle categories (Rosa & Maher, 2010).

In the SUE traffic assignment models, one class of user may be determined according to the vehicle type, drivers' cost functions, or available sections of the transportation network (Lim, 2010). For example, lower income users have cheaper cars, however higher income users usually have expensive cars. It means that these two different groups of users have different perceptions and expectations in the transportation network, therefore they should be divided into different user classes.

3.2.2. Integration of Multiple User Classes Concept

It is possible to integrate multiple user classes concept into different kind of studies. Some examples are given below that how it is integrated and in which studies it is integrated.

- Multiple user classes concept can be included in the model of time-dependent travel choice problems of the road networks. In this model, the users are categorized according to their trip purposes and their decision making processes on travel. In this model, time is a significant criterion in travelling for all type of user classes (Lam et al., 2006).

- Combined distribution and assignment models can use multiple user classes concept. These models are constituted for continuum traffic equilibrium problems. In these models, the users are separated into some classes with respect to their choice behavior of facilities (destinations) within the transportation network. The purpose with these models is to acquire a continuum UE condition for multiple user classes in the network (Ho et al., 2006).

- Multiple user classes notion can be used Pareto-improving congestion pricing and revenue refunding schemes general transportation network models. In these models, a population of users with heterogeneity is divided into homogenous groups with regard to their value of time importance levels. In these network models, the users become better after fixing congestion pricing to the roads as compared with the state without congestion pricing (Guo & Yang, 2010).

- Congestion pricing is an effective and efficient way to decrease network wide travel costs. Methodologies can be developed for toll design on the transportation network. These methodologies have to give information on which links of the network will have tolls and how much the tolls will be charged. These methodologies can include multiple user groups which are classified according to their income levels (Chen & Bernstein, 2004).

3.3. SUSTAINABILITY OBJECTIVES

In this study, three sustainability objectives, which social, environmental, and economic objectives, are used in the bi-level traffic assignment model with SUE and multiple user classes. It can be said that multiple objectives are used in this model. Social objective includes accessibility, equity and road accidents concepts, environmental objective consists of emission and noise concepts, and economic objective involves affordability concept. In this study, a transportation network is examined and this network is tried to become sustainable with the developed model. In order to acquire sustainability on the network, zones (centers) must be accessible that the users can reach them easily. Moreover, accessibility of the zones must be distributed equally between each others. The other social concept is road accidents. In this model, the road accidents are tried to minimize on the transportation network. The environmental concepts which are emission and noise generated by vehicles are also tried to minimize to obtain the sustainability of the network. In addition to these, the users must have affordability to use the transportation systems effectively and easily.

Sustainability objectives of the developed bi-level traffic assignment model with SUE and multiple user classes are represented in Table 3.1 below:

Table 3.1 Sustainability objectives

Social Objectives	Environmental Objectives	Economic Objective
Accessibility	Emission	Affordability
Equity	Noise	
Road Accidents		

3.3.1. Accessibility

In order to acquire sustainable transportation, accessibility concept must be given more importance. In this work, the centers of the transportation network are tried to become accessible such that the users can arrive them effectively and easily. To achieve this purpose, a bi-level traffic assignment model is developed and this model is solved with an effective algorithm. Accessibility concept is placed in the social objective function at the upper level of the bi-level model.

It is possible to use accessibility concept in some specific scientific areas which are urban planning, transport planning, and geography areas. This concept plays a considerable role in policy making process. On the other hand, accessibility is sometimes defined poorly that as a result of this it is measured poorly and it is misunderstood at these times. Therefore, it is very important to define accessibility concept comprehensively. However, it is difficult and complicated to find an extensive definition for this concept (Geurs & Wee, 2004).

Accessibility research in transportation has been made since 1940s. Stewart defined the accessibility concept according to the trip potential in 1947 (Geurs & Eck, 2001). In this definition, transportation and land use systems are taken into account together and they are included in the accessibility. On the other hand, this definition has a disadvantage such that it cannot be implemented into the any practical case. This definition can be only used in theoretical applications. Furthermore, Wachs & Kumagai (1973) and Vickerman (1974) defined the accessibility concept in a different way. They defined the concept as “the number of opportunities that can be reached within a given travel time, distance, or generalized cost” (Jing & Xiwen, 2008).

Accessibility can be defined in different ways that some well-known definitions of it are given as follows:

- “The potential of opportunities for interaction” (Hansen, 1959)

- “The ease with which any land-use activity can be reached from a location using a particular transport system” (Dalvi & Martin, 1976)
- “The freedom of individuals to decide whether or not to participate in different activities” (Burns, 1979)
- “The benefits provided by a transportation/land-use system” (Ben-Akiva & Lerman, 1979)

In the literature, there are some studies which evaluate accessibility with different perspectives. The related study instances are given below:

- Location accessibility studies (e.g. Song, 1996; Handy & Niemeier, 1997)
- Individual accessibility studies (e.g. Pirie,1979; Kwan, 1998)
- The studies for economic benefits of accessibility (e.g. Koenig, 1980; Niemeier, 1997).

In location accessibility, a location (center) is reached by the users on the transportation network. On the other hand, in individual accessibility, a user reaches to the location. These two accessibility concepts essentially consider the same things, but with different perspectives. The main purpose for both of them is to acquire accessibility on the transportation networks. Accessibility concept is usually included in the social measures. When accessibility is obtained on a network, it provides a lot of social benefits for the transportation. In addition to this, it has also economic benefits that some studies evaluate these benefits of the accessibility.

Accessibility concept consists of some components which are important for both theoretical and practical measures of accessibility (Geurs & Wee, 2004). These components’ explanations and the figure of components (Figure 3.2) are given below.

Land-use component is related to the land-use system of transportation network. It includes the quality, amount, and spatial distribution opportunities which are supplied at destinations of the network. Moreover, it involves the demand for these opportunities at every origin of this network. In addition to these, it consists of the confrontation of supply and demand for these opportunities.

Transportation component reflects the transportation system. It is explained as the disutility for a user to cover the distance between each OD pair using a particular transportation mode. The confrontation between supply and demand causes this disutility. In this component, supply means that infrastructure supply of the transportation network. This supply infrastructure consists of its location and features such as number of lines, public transport timetables, travel costs, and maximum travel speed. The demand concept in this component includes passenger and freight travel.

Temporal component of the accessibility concept consists of the temporal constraints. These constraints include presence of the opportunities at different times of a day and the availability of time for users to attend major activities such as work and entertainment activities.

Individual component of the accessibility includes needs, abilities, and opportunities of the users. These features affect users' access levels to the transportation modes. The user's access level increases or decreases according to these features. Moreover, they influence spatially distributed opportunities and total aggregate accessibility consequence.

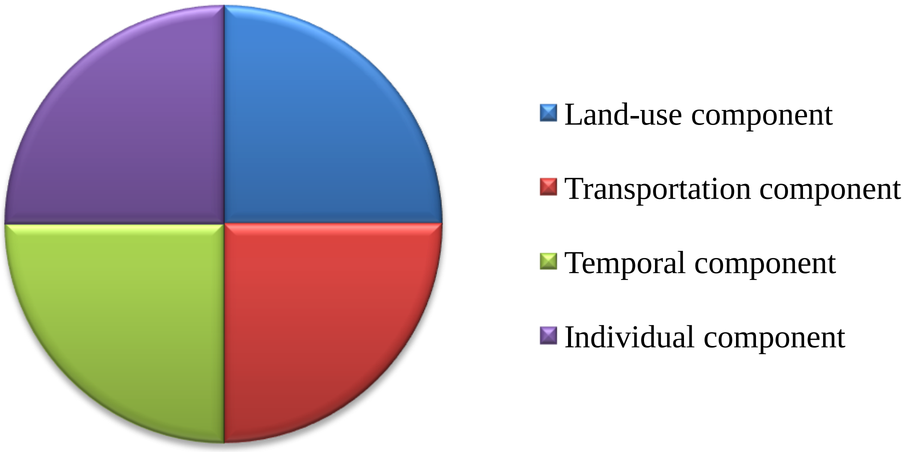

Figure 3.2 Components of accessibility

In this study, in order to measure accessibility of the centers (zones) on the transportation network, some formulations, which are taken from the literature (Santos et al. 2008), are needed to use. These taken formulations are modified according to the developed model of this study. These formulations are represented as follows with their originalities.

$$\max Z = w_A \times \frac{A - A_{\min}}{A_{\max} - A_{\min}} \tag{3.13}$$

In the formulation (3.13), the accessibility is tried to maximize. To achieve this purpose, the accessibility A is firstly calculated. Furthermore, maximum accessibility $A_{\max}$ and minimum accessibility $A_{\min}$ are calculated. After that, these accessibility calculations are scaled between 0 and 1 considering this formulation. Then, this scaled calculation is multiplied by w_A which is a weight attached to the accessibility.

The accessibility A in the formulation (3.13) is calculated as follows:

$$A = \sum_{j \in \mathcal{N}} P_j \times A_j(y) \tag{3.14}$$

In the formulation (3.14), N is referred as the set of centers on the network and *j* is any center which is included in this set. P_j is the population of center *j* and $A_j(y)$ is the accessibility of center *j*. Moreover, *y* is a matrix of binary variables which are shown by y_{lm}. In this matrix, *y* is equal to 1 if link *l* is on path *m,* otherwise it is equal to 0.

The term $A_j(y)$ in the formulation (3.14) is given explicitly with the following expression:

$$A_j(y) = \sum_{k \in N \setminus j} \frac{P_k}{C_{jk}(y)^{\beta}} \quad \forall j \in N \tag{3.15}$$

In the formulation (3.15), a center's accessibility is tried to calculate. In this formulation, k is any center on the network. P_k is the population of center k. Moreover, C_{jk} is generalized cost of travelling between center j and center k for the users. β is the impedance parameter. This calculation is performed for each center on the transportation network.

3.3.2. Equity

In this study, equity concept is set in the social objective function at the upper level of developed bi-level traffic assignment model. This concept is dependent on accessibility concept such that it is evaluated with accessibility concept. In the developed model, equal distribution of the accessibility to the centers of the transportation network is aimed. This aim is significant to reach the overall aim of this study which is "to achieve a sustainable traffic assignment".

The equity concept is explained as "the degree to which services or amenities are distributed in an equal way over different zones (centers)". These centers can be located on a transportation network. Furthermore, it is important to distribute the services over economic, political, and ethnic groups of the society equally. The overall purpose of the equity concept is to achieve equal distribution of the services with the correlation of observed socio-economic patterns of the society (Talen & Anselin, 1998). In the literature, some studies focus on this concept with the consideration of low income groups of the society (Werna, 1998; Gandy, 2002; Omer, 2006).

According to the urban transportation planning, equity concept can be taken into account from the utilitarianism perspective traditionally. It means that this concept focuses on some actions which have the potential to generate a net social benefit (McFadden & Hensher, 2001). In addition to this, equity concept is considered from the perspective of outcome equality such that the benefits and burdens have to be allocated equally (Chakraborty, 2006; Rodriguez & Morton, 2006; Aytur et al., 2008).

In order to acquire a sustainable traffic assignment in this study, it is needed to distribute the accessibility to the centers of transportation network equally. In order to carry out this distribution in this study, some equity formulations are required to use. These formulations are taken from the literature (Santos et al., 2008) and they are modified for developed bi-level traffic assignment model of this study. They are given below with their original forms:

$$\max Z = w_E \times \frac{E - E_0}{E_B - E_0} \tag{3.16}$$

In the formulation (3.16), the equity is tried to maximize. To carry out this purpose, firstly, the equity E is calculated. In addition to this, maximum equity E_B and minimum equity E_0 are also calculated. Then, these equity calculations are scaled between 0 and 1 considering this formulation. After these, this scaled calculation is multiplied by W_E which is a weight attached to the equity.

The equity *E* in the formulation (3.16) is calculated with the following formulation:

$$E = \eta(y) \tag{3.17}$$

In the formulation (3.17), η is an equity measure of the centers on the transportation network. Furthermore, *y* is a matrix of binary variables which are shown by y_{lm}. In this matrix, *y* is equal to 1 if link *l* is on path *m,* otherwise it is equal to 0.

The expression $\eta(y)$ in the formulation (3.17), which is referred as the equity measure, can be calculated with Gini coefficient or Theil index. The explanations of these calculation approaches are given below. In this study, to calculate equity measure in the developed model, Gini coefficient is preferred to use. The reason of this preference is that this coefficient is one of the most widely used effective measures (Santos et al., 2008).

Gini Coefficient:

Gini coefficient is used to measure inequality of the centers on the transportation network. It is one of the most widely used approaches to measure inequality. In a fully equitable area, all centers of the network have the same accessibility. This area is referred as the perfect area. However, in practice, it is difficult to have a perfect area. Therefore, Gini coefficient is necessary to measure and compare the actual situation with the perfect situation. It measures the relative difference between these two situations. The value of this measurement is found between 0 and 1. If the value is closer to 0, it is said that the actual situation is closer to the perfect situation. The formulation of this coefficient is represented below:

$$\eta(y) = \left(\sum_{j \in N} \sum_{k \in N} \mid A_j(y) - A_k(y) \mid \right) / 2n^2 \bar{A} \tag{3.18}$$

In the formulation (3.18), N is a set of centers of the transportation network that j and k are the centers which belong to this set. $A_j(y)$ and $A_k(y)$ is the accessibility of the centers j and k respectively. Furthermore, n is the number of centers which are included in the center set N. $\bar{A}$ is the average accessibility to the centers of the network.

Theil Index:

Theil index (Theil, 1967) is used in minimizing the inequalities. For instance, this index can be used to measure and minimize inequalities between different regions of a country. Furthermore, it can be used to measure and minimize inequalities between different centers on a transportation network. The formulation of this index is given as follows:

$$\eta(y) = \sum_{g \in G} \hat{A}_g \times T_g + \sum_{g \in G} \hat{A}_g \times ln\left(\frac{\bar{A}_g}{\bar{A}}\right) \tag{3.19}$$

where

$$\hat{A}_g = \frac{\sum_{j \in N_G} A_j}{\sum_{j \in N} A_j} = \frac{n_g \times \bar{A}_g}{n \times \bar{A}} \tag{3.19a}$$

$$T_g = \frac{1}{N} \sum_{j \in N} \left(\frac{A_j}{\bar{A}}\right) \times ln\left(\frac{A_j}{\bar{A}}\right) \tag{3.19b}$$

In the above formulations, G is a set of groups (regions), $\hat{A}_g$ is an accessibility weight of group g which is included in the set G ($g \in G$), T_g is Theil index of group g, $\bar{A}_g$ is average accessibility to the centers on the transportation network of group g, $\bar{A}$ is average accessibility to all centers of the network, N_g is a set of centers of group g, and n_g is the number of centers of group g.

In the formulation (3.19), Theil index of the group is defined. This formulation has two terms. In the first term, the inequality within every subgroup is considered. In the second term of this formulation, the inequality across the subgroups is taken into account. In the formulation (3.19a), the share of the accessibility to the centers of a group is explained. This formulation is only used when all centers are accessible. Furthermore, in the formulation (3.19b), Theil index of every group is determined. The terms $\hat{A}_g$ and T_g, which are explained in the formulations (3.19a) and (3.19b) respectively, are used to calculate Theil index of the group in the formulation (3.19). This index measures and compares the difference between the actual situation and the perfect situation as Gini coefficient. It takes values between 0 and 1. If the value is closer to zero, it means that the actual situation is closer to the perfect situation. However, this index does not have an appealing interpretation.

3.3.3. Road Accidents

In this study, road accidents concept is placed to the social objective function at the upper level of the developed bi-level traffic assignment model. In this model, road accidents on the traffic are tried to minimize. Minimization of the road accidents has a significant effect on the accomplishment of sustainable transportation in this study.

Road accidents on the transportation network occur because of the some fundamental reasons (Yannis et al., 2007). These reasons are presented as follows:

- Inappropriate behavior of the users on the road network
- Inadequate maintenance of the road network
- Deficiency of efficient and systematic enforcement
- Congestion on the road network

In this study, congestion on the transportation network is a reason of road accidents. It can be said that if the congestion level on a link of the network increases, this link is under the threat for the road accidents more than the other links. Therefore, the objective with developed model is to distribute the traffic on the network in a reasonable way in order to decrease the congestion on the network links. As a result of this, congestion dependent road accidents on the transportation network can be also reduced.

In the literature, there are some formulations to measure "road accident cost" on the traffic (Shepherd, 2008). The most appropriate one of them for the developed model is used in this study. In this used formulation, the accidents are proportional to speed with flow effect. This formulation is modified according to the model which has been developed in this work. Original forms of both used formulation and the other formulations are represented as follows:

$$A_F = 4.02 \tag{3.20}$$

In the formulation (3.20), $A_F = 4.02$ min is "fixed accident cost per average trip" such that this value is calculated with Tinch value (2.9 cents/km). This value means that for per kilometer, fixed accident cost is 2.9 cents. To obtain the accident cost per average trip, Tinch value is multiplied by average trip length in kilometer. After that, acquired value in cents is converted into the value in minutes.

$$A_{V1} = K_1 V \tag{3.21}$$

In the formulation (3.21), A_{V1} is "accident cost per average trip" calculated. In this formulation, V is average speed and K_1 is a constant. This constant is calculated with respect to average speed and average accident cost at the initial equilibrium point. According to this formulation, the accidents are proportional to speed.

$$A_{V1T} = K_2 T^{0.45} V \tag{3.22}$$

In the formulation (3.22), A_{V1T} is "accident cost per average trip" calculated. In this formulation, V is average speed, T is the number of trips per day, and K_2 is a constant. This constant is calculated with regard to average speed, initial trips per day, and average accident cost at the initial equilibrium point. According to this formulation, the accidents are proportional to speed with flow effect.

$$A_{V2} = K_3 V^2 \tag{3.23}$$

In the formulation (3.23), A_{V2} is “accident cost per average trip” calculated. In this formulation, V^2 is average speed squared and K_3 is a constant. This constant is calculated with respect to average speed and average accident cost at the initial equilibrium point. According to this formulation, the accidents are proportional to speed squared.

$$A_{V2T} = K_4 T^{0.45} V^2 \tag{3.24}$$

In the formulation (3.24), A_{V2T} is “accident cost per average trip” calculated. In this formulation, V^2 is average speed squared, T is the number of trips per day, and K_4 is a constant. This constant is calculated with regard to average speed, initial trips per day, and average accident cost at the initial equilibrium point. According to this formulation, the accidents are proportional to speed squared with flow effect.

Formulation (3.22) is preferred to use for the developed bi-level traffic assignment model in this study. This formulation is set in the social objective function at upper level of the model. The formulation measures road accident cost on the transportation network and this cost is tried to minimize in the objective function of the model to reach the overall aim which is “to achieve a sustainable traffic assignment”.

3.3.4. Emission

Emission concept is placed in the environmental objective function at the upper level of the developed bi-level traffic assignment model in this study. Emission generated by the vehicles is tried to minimize with this model. Emission minimization has a significant contribution in order to achieve the sustainability in transportation in this work.

The power to move a motor vehicle is obtained with burning fuel in an engine. Pollution from the vehicles occurs with the by-products of this combustion process. Furthermore, Volatile Organic Compounds (VOC) escapes across fuel evaporation. When vehicle exhaust systems are improved, evaporative emission becomes a larger and significant component of total vehicle VOC emission (U.S. EPA, 1993).

There are two types of emission which are given and explained as follows:

- Exhaust emission
- Evaporative emission

Exhaust emission: In this type emission, the combustion process occurs with emissions of VOC, oxides of nitrogen (NO_x), particulate matter (PM), and carbon monoxide (CO). These emissions are released from the tailpipe while a vehicle is working.

Evaporative emission: In this type emission, VOC releases into the air through fuel evaporation. Evaporative losses are taken into account on hot days with efficient exhaust emission controls and gasoline formulations.

Emission generated from an individual vehicle is usually low. In crowded cities of the country, there are a lot of vehicles and as a result of this the emission level is higher, because emissions from lots of vehicles on the transportation network add up. This high level vehicle emission causes air pollution and this pollution affects the quality of life in a negative way such that it affects the people health badly (U.S. EPA, 1994).

In this study, a variable carbon dioxide (CO_2) emission formulation (Shepherd, 2008) is used to measure emitted CO_2 amount from the vehicles. This formulation is set in the environmental objective function at the upper level of the developed bi-level traffic assignment model. The emitted CO_2 amount is tried to minimize in this model. Used formulation is represented with its original form as follows:

$$g = 416.1 - 6.9808V + 0.0431V^2 \tag{3.25}$$

The formulation (3.25) is a speed-dependent formulation such that emitted CO_2 amount changes according to the vehicle speed. In this formulation, g is emitted CO_2 in g/vehicle-km such that it is emitted CO_2 amount in grams for per kilometer of a vehicle. V is average speed in km/h such that it is an average speed of a vehicle on the transportation network.

3.3.5. Noise

In this study, noise concept is established in the environmental objective function at the upper level of the developed bi-level traffic assignment model. In this model, the noise, which occurs because of the vehicles on the transportation network, is tried to minimize. Minimization of the noise is an important factor in order to accomplish the overall purpose of this study which is "a sustainable traffic assignment".

Noise is a ubiquitous environmental pollutant. Furthermore, it is a considerable public health issue. It causes the annoyance of people and decreases the quality of the environment significantly. In addition to all of these, higher noise has damaging effects on the people health such that it an important reason for reduction of the people cognition levels (Stansfeld et al., 2005).

Environmental noise, a particular type of noise, is a main resource of public complaints. This kind of noise causes socio-economic and physical effects on the society and it affects the human health in a negative way (Seong et al., 2011). Environmental noise with greater sound levels (greater than 55 dB(A)) leads to important annoyance in outdoor settlement places (Berglund et al., 1999). Traffic noise is an environmental noise which is a cause of numerous health problems (King & Davis, 2003; Murphy et al., 2009; Ko et al., 2011). These health problems are given below:

- Sleep disturbance

- High blood pressure
- Psycho-physiological symptoms

In this work, CoRTN equation (Steele, 2001) is used to measure the noise of vehicles on the road traffic. This equation is placed in the environmental objective function at the upper level of the developed model. The sound level of the traffic network is tried to minimize with this model. The original form of this used equation is demonstrated in the following expression:

$$L_{10} = 10log(q) + 33log(v + 40 + 500/v) + 10log(1 + 5p/v) + 0.3G - 27.6 \qquad (3.26)$$

The formulation (3.26) is a multiple variable traffic noise equation. In this formulation, q is the flow rate of vehicles on the road traffic network and v is the speed of the vehicles. In addition to these variables, the variable p and the variable G are used in this formulation. p is referred as the percentage of the heavy vehicles on the transportation network. G is the gradient which is assumed to equal 0.2 if the vehicles slow down up hill. Furthermore, this formulation includes a constant term which equals to 27.6.

3.3.6. Affordability

Affordability concept is significant in order to achieve the overall purpose of this study which is “a sustainable traffic assignment”. This concept is established in the economic objective function at the upper level of the developed bi-level traffic assignment model. The affordability of the users to the transportation is tried to increase with this developed traffic assignment model.

Affordability is the ability of people to purchase essential goods and services which are presented below (Litman, 2011):

- Housing
- Food
- Medical care
- Transportation

Affordability is also the situation such that the budget of household can buy essential necessities. There is an example situation that lower income households can purchase basic life requirements.

Transportation affordability is a kind of affordability such that people can buy access to essential goods and activities which are given as follows:

- Medical care
- Work
- Education
- Basic shopping
- Socializing

It can be said that lower and middle income households spend less than 20% of their total budgets for transportation activities. Moreover, they spend less than 45% for both transportation activities and housing.

When evaluating transportation affordability, some factors should be taken into account. These factors are given in the following list:

- Household incomes and budgets
- Individual needs and abilities
- Total economic impacts (indirect, external, and non-market costs and benefits)
- Transportation costs (all costs, not just fuel or transit fares)
- Transportation options (quantity and quality of affordable transportation modes)
- Affordability index (combined transport and housing costs)

- Land use patterns (the degree of accessibility)
- Impacts on accessibility rather than just mobility

Transportation inaffordability means that people cannot purchase access to basic goods and activities, therefore they have considerable problems in transportation. Transportation inaffordability restricts the opportunities of people and imposes the financial burdens to the people. Economically disadvantageous people usually face with these problems. Decrease of the transportation inaffordability provides significant economic and social benefits for economically disadvantageous people. As a result of this reduction, the financial burdens decline and disadvantageous people's opportunities increase.

Transportation inaffordability can be decreased by improving the quality and quantity of the affordable transportation options. Furthermore, it can be declined by improving the land use accessibility to decrease travel distances. These improvements also help succeed the other planning objectives which are "reduction of the road traffic congestion", "savings for road and parking facility costs", "improved health and safety", reduction of the pollution", and "conservation of the energy".

In this study, a special affordability formulation is used to measure affordability of the users to transportation. This formulation is placed in the economic objective function at the upper level of the developed bi-level traffic assignment model. The formulation is modified according to the developed model in this study. The original form of the formulation is represented as follows:

$$TC^l = \sum_{(r,s)\in K} \sum_{(i,j)\in A} x_{ij}^{rsl} \times c_{ij} \left(\sum_{l=1}^{M} \sum_{(r,s)\in K} x_{ij}^{rsl} \right) \ \forall l \in M \tag{3.27}$$

In the formulation (3.27), total cost on the transportation network for one user class is calculated. User classes are determined based on the income levels. In this formulation, there are M user classes and each of them is indicated as l. (r, s) is an OD pair which is included in the OD pairs set K. (i, j) is a link on the network which is within the links set A. Furthermore, x_{ij}^{rsl} is the flow of user class l on the link (i, j) of (r, s) OD pair. In addition to these, c_{ij} is the cost on the link (i, j) of a user.

In the above formulation, firstly $\left(\sum_{l=1}^{M} \sum_{(r,s)\in K} x_{ij}^{rsl}\right)$, which is the total flow on the link (i, j) according to both all user classes and all OD pairs on the transportation network, is calculated. c_{ij} is a function of this total flow. This function gives the cost of one user on the link (i, j) with respect to both all user classes and all OD pairs. After that, the term $c_{ij}\left(\sum_{l=1}^{M} \sum_{(r,s)\in K} x_{ij}^{rsl}\right)$ is multiplied by $\sum_{(r,s)\in K} \sum_{(i,j)\in A} x_{ij}^{rsl}$ for both all OD pairs and all links on the transportation network. As a result of all of these calculations, the total travel cost of the class $l \in M$ users on the network is acquired.

3.4. DEVELOPED BI-LEVEL TRAFFIC ASSIGNMENT MODEL

In this study, a traffic assignment model is developed with SUE and multiple user classes. Bi-level mathematical programming is used in this model. Bi-level programming is composed of the upper and lower levels. At the upper level of the model, there are three sustainability objectives which are social, environmental, and economic objectives. Social objective function consists of “accessibility”, “equity”, and “road accidents” concepts. Environmental objective function includes “emission” and “noise” concepts. Economic objective function contains “affordability” concept. These three objective functions are tried to optimize at the upper level. Furthermore, at this level, toll prices of the links on the traffic network are determined for each user class. In this model, users are separated into classes based on their income levels such as lower, middle, and higher income user classes. The lower level of the model consists of SUE with multinomial logit discrete choice and multiple user classes.

3.4.1. Notations of the Model

Used notations for the developed bi-level traffic assignment model are represented in the following Table 3.2.

Table 3.2 Notations of the developed bi-level traffic assignment model

$G(N, A)$	directed graph with N as the set of nodes and A as the set of links
$x_{a,u}$	flow of class $u \in U$ users on link $a \in A$
x_a	total flow on link $a \in A$
$t_a(x_a)$	flow-dependent travel cost for link $a \in A$
q_u^{rs}	trip demand of class $u \in U$ users for OD pair (r, s)
K^{rs}	set of paths for OD pair (r, s)
$f_{k,u}^{rs}$	path flow on path $k \in K^{rs}$
$c_{k,u}^{rs}$	path travel cost on path $k \in K^{rs}$

There is a relationship between path flow and trip demand. This relationship is described as $q_u^{rs} = \sum_k f_{k,u}^{rs}$ for class $u \in U$ users and OD pair (r, s). Furthermore, there is also a relationship between flow and total flow on link $a \in A$. This relationship is represented as $x_a = \sum_{u \in U} x_{a,u}$.

After representing the notations which are necessary for building the model, the developed bi-level traffic assignment model with SUE and multiple user classes is explained in detailed. Firstly, the upper level of the model is explained, after that the lower level is explained.

3.4.2. Upper Level of the Model

Sustainability objectives which are social, environmental, and economic objectives exist at the upper level of the model. Social objective function consists of "accessibility", "equity", and "road accidents" concepts. Environmental objective function includes "emission" and "noise" concepts. Economic objective function contains "affordability" concept. At this level, toll prices for the network links are identified in order to best serve sustainability objectives. The functional forms of these objectives are explained as follows:

Accessibility and Equity:

$$g^{AE}(x) = w_1 \frac{A^{max} - A}{A^{max} - A^{min}} + w_2 \frac{E - E^{min}}{E^{max} - E^{min}} \tag{3.28}$$

In this developed model, the minimum accessibility of all the nodes on the network is tried to maximize taking account user classes. With this way, the equity between the nodes is tried to acquire. In the formulation (3.28), total accessibility is calculated with the equation $A = \sum_s A_s(x)$ where A_s is the accessibility of node $s \in N$. The accessibility of node s is found by the equation $A_s = \sum_{r \in N \backslash s} q^{rs}/\bar{c}^{rs}$ where $q^{rs} = \sum_u q_u^{rs}$ and $\bar{c}^{rs}$ is the minimum actual travel cost for OD pair (r, s). Furthermore, the equity of the accessibility is calculated with the well-known Gini coefficient. This coefficient is formulated as $E = \left(\sum_{s \in N} \sum_{s' \in N} |A_s(x) - A_{s'}(x)|\right) / 2n^2 \bar{A}$ where n is the number of destinations on the network and $\bar{A}$ is the mean accessibility of these destinations. The equity value (Gini coefficient value) changes between the interval 0 and 1. If the value is near 0, it means that the accessibility of the perfect destination is close to the other destinations' accessibility on the network. However, the value is near 1, there is a large gap between the perfect destination and the other destinations' accessibility. Consequently, in this formulation, w_1 and w_2 are simple weights with $w_1, w_2 \in [0, 1]$ and $w_1 + w_2 = 1$.

Road Accidents:

$$g^{ACC}(x) = \frac{B - B^{min}}{B^{max} - B^{min}} \tag{3.29}$$

In this model, total number of accidents on the links are tried to minimize without considering user classes. In the formulation (3.29), the number of road accidents are calculated with the equation $B = \sum_{a \in A} KT^{0.45} v_a(x_a)$. In this equation, K is a constant, T is the number of trips per day, and $v_a(x_a)$ is the average speed (km/h) on the link a.

Vehicle Emission:

$$g^{EM}(x) = \frac{C - C^{min}}{C^{max} - C^{min}} \tag{3.30}$$

In this developed model, total emission amount on the links is tried to minimize without taking into account user classes. In the formulation (3.30), the total network emission (g) is acquired with the equation $C = \sum_{a \in A} e(v_a(x_a)) l_a x_a$. In this equation, $e(v_a(x_a))$ is the vehicle emission (g/km) and l_a is the length (km) of link a.

Vehicle Noise:

$$g^{NO}(x) = \frac{D - D^{min}}{D^{max} - D^{min}} \tag{3.31}$$

In this model, the maximum noise level on the links is aimed to minimize without considering user classes. In the formulation (3.31), the vehicle noise is measured with the equation $D = max_{a \in A} N_a(x_a, v_a(x_a))$. In this equation, N_a is the noise (dBA) which is generated by the vehicles when travelling on the link a. N_a is a function of the vehicle flow x_a and average vehicle speed $v_a(x_a)$.

Affordability:

$$g^{AFF}(x) = \frac{F - F^{min}}{F^{max} - F^{min}} \tag{3.32}$$

In the formulation (3.32), the affordability of users to transportation is calculated as follows:

$$TC^u = \frac{\sum_{(r,s)} \sum_{a \in A} x^{rs}_{a,u} \times c(\sum_{u=1}^{U} \sum_{(r,s)} x^{rs}_{a,u})}{\sum_{(r,s)} q^{rs}_u} \tag{3.33}$$

$$F = max_u \left\{ max \left(0, \frac{TC^u}{OG^u} - 0.2 \right) \right\} \tag{3.34}$$

In the formulation (3.33), $x^{rs}_{a,u}$ is the flow of user class $u \in U$ on link a between OD pair (r, s). Moreover, q^{rs}_u is the total demand of class $u \in U$ users between OD pair (r, s). In the formulation (3.34), OG^u is the allocated transportation budget for user class $u \in U$. In this formulation, 0.2 indicates 20% that users allocate 20 percent of their monthly budget for transportation expenses. In this model, the expense for transportation more than 20% of the monthly budget is tried to minimize taking into account user classes.

In the above formulations (3.28), (3.29), (3.30), (3.31), and (3.32), (A^{max}, A^{min}, E^{max}, E^{min}), (B^{max}, B^{min}), (C^{max}, C^{min}), (D^{max}, D^{min}), and (F^{max}, F^{min}) are calculated respectively with the standard genetic algorithm which is within Matlab program.

The social, environmental, and economic objectives are formulated based on the above definitions as follows:

$$\min g^{SOC} = w_{AE} \times g^{AE}(x) + w_{ACC} \times g^{ACC}(x) \tag{3.35}$$

$$\min g^{ENV} = w_{EM} \times g^{EM}(x) + w_{NO} \times g^{NO}(x) \tag{3.36}$$

$$\min g^{ECO} = w_{AFF} \times g^{AFF}(x) \tag{3.37}$$

In the formulations (3.35), (3.36), and (3.37), the social, environmental, and economic sustainability objective functions are aimed to minimize respectively. In these formulations, the weights w_{AE}, w_{ACC}, w_{EM}, w_{NO}, and w_{AFF} are determined according to the traffic authority priorities.

3.4.3. Lower Level of the Model

The lower level of the developed bi-level traffic assignment model consists of SUE assignment with multinomial logit discrete choice and multiple user classes which are lower-middle-higher income classes. The detailed explanation of SUE assignment in this model is given as follows:

In this assignment, $\Delta = (\ldots, \Delta^{rs}, \ldots) = (\delta_{ij})$ is defined as the link-path incidence matrix. In this matrix, if δ_{ij} is equal to 1, it is said that path j traverses link i. Otherwise, δ_{ij} is equal to 0. There is a relationship between link-flow and path-flow which is represented as $x = \Delta f$. Moreover, there is a relationship between link-cost and path-cost which is demonstrated with the expression $c = \Delta^T(t + \bar{t})$. In this expression, $\bar{t}$ is a toll price vector. In this SUE assignment, flow of the class $u \in U$ users on path k is given with the equation $f_{k,u}^{rs} = q_u^{rs} P_{k,u}^{rs}$. In this equation, $P_{k,u}^{rs}$ is the probability of choosing path k between OD pair (r, s) on the network for user class $u \in U$.

The random term of discrete route choice satisfies Gumbel distribution, therefore the route choice probability $P_{k,u}^{rs}$ can be represented as a multinomial logit with the following formulation:

$$P_{k,u}^{rs} = \frac{e^{-\theta_u c_{k,u}^{rs}}}{\sum_l e^{-\theta_u c_{l,u}^{rs}}} \tag{3.38}$$

In the formulation (3.38), $\theta > 0$ points out the familiarity degree of the class $u \in U$ users to the traffic conditions. If the users have more equipped cars, it can be said that they have larger θ. In this study, lower income user classes have smaller θ, however, higher income user classes have larger θ.

The unconstrained convex minimization model for SUE traffic assignment problem is represented in the following optimization model:

$$\min z(x) = -\sum_{rs}\sum_{u} q_u^{rs} S_u^{rs}[c^{rs}] + \sum_{a \in A} x_a t_a(x_a) - \sum_{a \in A} \int_0^{x_a} t_a(w)dw \tag{3.39}$$

where

$$S_u^{rs}[c_u^{rs}] = E\left[\min_{k \in K^{rs}}\left\{c_{k,u}^{rs}\right\}|c_u^{rs}\right] \tag{3.40}$$

$$P_{k,u}^{rs} = \frac{\partial S_u^{rs}(c_u^{rs})}{\partial c_{k,u}^{rs}} \tag{3.41}$$

In the formulations (3.40) and (3.41), the expected perceived travel cost for OD pair (r, s) and user class $u \in U$ is defined. This travel cost is related to the whole path set between OD pair (r, s).

4. SOLUTION ALGORITHMS AND NUMERICAL RESULTS

In this study, in order to solve the developed bi-level traffic assignment optimization model with SUE and multiple user classes, a well-known genetic algorithm which is Non-Dominated Sorting Genetic Algorithm (NSGA-II) is used. This algorithm is proven to be a very efficient algorithm for multi-objective problems (Li et al., 2010). At every iteration of this algorithm, SUE minimization model in the formulation (3.37) must be solved for each individual of the current solution population. In order to accomplish this, the Self-Regulated Averaging (SRA) algorithm (Liu et al., 2009) and the Bell's second algorithm for solving logit-based stochastic network loading problem (Lee et al., 2010) are used in this study. The detailed explanations of all these algorithms are provided in the following sections.

4.1. SELF-REGULATED AVERAGING (SRA) ALGORITHM

In this study, SUE minimization problem in the formulation (3.37) is solved with some set of equations. These equations must be solved simultaneously to obtain a result for the traffic assignment problem in this study. Furthermore, these equations are solved for each user class $u \in U$. The equations are given with the gradient as follows:

$$\nabla z(x_u) = \nabla_{x_u} t(x_u) \left[x_u - \sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u) \right] \ \forall u \in U \tag{4.1}$$

If the travel cost function is a separable function, $\nabla_{x_u} t(x_u)$ is a diagonal positive definite matrix. According to this characteristic of the function, the set of equations can be also represented as follows:

$$\nabla z(x_u) = 0 \Leftrightarrow x_u - \sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u) = 0 \quad \forall u \in U \tag{4.2}$$

In the formulation (4.2), $\sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u)$ can be equated with $y_u(x_u)$. It is demonstrated as $y_u(x_u) = \sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u)$. After that, the solution of the SUE minimization problem is obtained by solving $x_u - y_u(x_u) = 0$ for every user class $u \in U$ simultaneously. It can be shown that $y_u(x_u) - x_u$ has a descent direction. It is possible to solve the set of equations above iteratively with this property.

The SRA algorithm (Liu et al., 2009) exactly solves the set of equations which are represented in above formulations. The general description of the adapted SRA algorithm is given below:

I. Set $k = 1$, $\Gamma > 1$, $0 < \gamma < 1$, and the stop criteria $\epsilon > 0$.
Calculate initial points x^1 and $y^1 = F(x^1)$.
II. While $\|x^k - y^k\| \geq \epsilon$ do
if $\|x^k - y^k\| \geq \|x^{k-1} - y^{k-1}\|$
$\beta_k = \beta_{k-1} + \Gamma;$
else
$\beta_k = \beta_{k-1} + \gamma;$
end
$\alpha_k = 1/\beta_k;$
$x^{k+1} = x^k + \alpha_k(y^k - x^k);$
$y^{k+1} = F(x^{k+1});$
$k = k + 1;$
End.
III. Output: x^k

The SRA algorithm is based on the consideration that the step size must be larger to give a more aggressive search of the solution space while the current iteration's solutions converge, however, the step size must be smaller while the current iteration's solutions diverge. The step size series $\{\alpha_k\}$ in the SRA algorithm satisfies the conditions of $\sum_k \alpha_k = \infty$ and $\lim_{k\to\infty} \alpha_k = 0$. According to this property of the step size series, the SRA algorithm ensures the convergence for SUE minimization problems. In the SRA algorithm, $\{\alpha_k\}$ is a monotonically decreasing positive series. On the other hand, it maintains a more reasonable decreasing speed. Especially, when the iterations are close to the optimal solution, the step sizes decrease slowly to avoid the slow convergence speed (Liu et al., 2009).

In the SRA algorithm above, the operation $F(x)$ corresponds to the stochastic network loading. Bell's second algorithm is used for solving the logit-based stochastic transportation network loading problem (Lee et al., 2010) in this study. The detailed explanation of the Bell's second algorithm is given in the following section.

4.2. BELL'S SECOND ALGORITHM SOLVING LOGIT-BASED STOCHASTIC NETWORK LOADING PROBLEM

Bell's second algorithm for solving logit-based stochastic network loading problem (Lee et al., 2010) in this study is represented as follows:

Input: link travel cost pattern $\{t_{ij}, (i,j) \in L\}$ and OD demand $\{q_{od}, (o,d) \in C\}$
Output: origin-based link flow pattern $\{y^o_{ij}, (i,j) \in L, o \in C_o\}$

Step 0: (Initialization) Let the number of iterations $K = 1$ and define a $|N| \times |N|$ matrix, where $|N|$ is the number of nodes, $W^{(1)} = [w^{(1)}_{ij}]_{|N|\times|N|}$ with elements

$$\mathrm{w}^{(1)}_{ij} = \begin{cases} exp(-\theta t_{ij}), \text{ if there is link from node } i \text{ to node } j \\ \\ 0, \text{ otherwise} \end{cases} \tag{4.3}$$

Step 1: (Stop criterion) If $max_{i,j\in N}\{w^{(k)}_{ij}\} \leq \delta$, where δ is a very smaller positive tolerance, then go to Step 3. Otherwise, go to Step 2.

Step 2: (Matrix Updating) Define a matrix $W^{(K+1)} = [w_{ij}^{(K+1)}]_{|N|\times|N|}$ as follows:

$$W^{(K+1)} = W^{(K)} \times W^{(1)} \tag{4.4}$$

Let $K = K + 1$ and go to Step 1.

Step 3: (Origin-based link flow calculation)

1. Calculate the final weight matrix $W = [w_{ij}]_{|N|\times|N|}$ according to the formula

$$W = \sum_{K'=1}^{K} W^{(K')} \tag{4.5}$$

2. Calculate the origin-based link usage probabilities

$$p_{ij}^{od} = \frac{w_{oi} \times exp(-\theta t_{ij}) \times w_{jd}}{w_{od}} \quad \forall (i,j) \in L \quad \forall (o,d) \in C \tag{4.6}$$

3. Calculate the origin-based link flow pattern

$$y_{ij}^{o} = \sum_{d \in C(d)} q_{od} p_{ij}^{od} \quad \forall (i,j) \in L \quad \forall o \in C_o \tag{4.7}$$

In this algorithm, firstly, the matrix of $W^{(1)} = [w_{ij}^{(1)}]_{|N|\times|N|}$ is calculated in the step 0. If there is link from node i to node j on the network, the matrix element $w_{ij}^{(1)}$ takes the value of $\exp(-\theta t_{ij})$, otherwise it is equal to 0. In the step 1, stop criterion is controlled. In this step, If $\max_{i,j\in N}\{w_{ij}^{(k)}\} \leq \delta$, origin-based link flows are calculated in the step 3. Otherwise, the matrix is updated in the step 2 as $W^{(K+1)} = W^{(K)} \times W^{(1)}$, then the iteration is increased as $K = K + 1$ and the step 1 is returned. In the step 3, origin-based link flows on the traffic network are calculated. This step consists of three stages. In the first stage, the final weight matrix $W = [w_{ij}]_{|N|\times|N|}$ is calculated by adding the matrices of all the iterations. In the second stage, the origin-based link usage probabilities p_{ij}^{od} are calculated by using the final weight matrix W. In the third stage, the origin-based link flow patterns y_{ij}^{o} are calculated by using origin-based link usage probabilities p_{ij}^{od} and OD demand q_{od} of the users on the network.

4.3. NON-DOMINATED SORTING GENETIC ALGORITHM (NSGA-II)

There are several multi-objective evolutionary algorithms (MOEA) in the literature. In this study, NSGA-II algorithm is implemented among them because this algorithm is widely accepted as one of the best MOEA (Li et al., 2010).

NSGA-II algorithm has some characteristics such that “Non-Dominated Sorting” is one of the main characteristics of this algorithm. This characteristic is explained as “a vector $u = (u_1, u_2, \ldots, u_k)$ is said to dominate another vector which is $v = (v_1, v_2, \ldots, v_k)$, if and only if $u_i \leq v_i$ for all i and there exists i such that $u_i < v_i$” (Coello Coello et al., 2007). Moreover, another significant characteristic of this algorithm is “Crowding Distance”. It measures the density of an individual among all the other individuals in a specific rank (front).

In this study, the decision variables for the upper level of the bi-level traffic assignment model are the toll prices. Each solution is demonstrated by a vector of size $|\mathcal{A}'| \times |\mathcal{U}|$

where $\mathcal{A}'$ is the set of tolled links on the network. In this study, different toll prices are preferred to collect for each user class.

The general description of the adapted NSGA-II in this study is explained as follows (Bhattacharya & Bandyopadhyay, 2010):

I. Generate an initial population by randomly choosing toll prices between predetermined lower and upper bounds.

II. Assess all the objective functions. In order to accomplish this, first solve SUE model given toll prices for every individual of the population using SRA algorithm. After that, calculate the value of each objective function for every individual using optimal SUE flow patterns.

III. Assign the rank to every individual of the population on the basis of non-dominance.

IV. Classify the individuals of the population according to the assigned ranks.

V. Find the crowding distance for every individual of the population.

VI. Some tasks have to be carried out for each generation. These tasks are given below:

- Perform tournament selection to select the individuals from the population randomly.

- Produce offspring population by performing crossover and/or mutation on the basis of crossover and mutation probability.

- Generate intermediate population by integrating the population of parents and offsprings of the current generation.

- Accomplish non-dominated sorting on the intermediate population.

- Choose the individuals from the intermediate population based on the rank and crowding distance. The individuals in rank (front) are classified in the increasing order of the rank and added until the population size is reached. The final rank is included based on the individuals with the least crowding distance.

- Replace the individuals in the population.

4.4. ILLUSTRATIVE EXAMPLE

In order to demonstrate the efficiency of the used algorithms in this study, "Nine Node Network Example" (Hearn & Ramana, 1988) is employed.

Nine node network example has data similar to large-scale traffic assignment problems. This network has 18 links and all the links have cost functions with the same structure. The cost function is represented with the following formulation:

$$t_a(x_a) = T_a\left(1 + 0.15(x_a/b_a)^4\right) \tag{4.8}$$

In the formulation (4.8), T_a is the free flow travel time on link a, x_a is the total flow on link a, and b_a is the capacity of link a. In this network example, there are four OD pairs which are (1, 3), (1, 4), (2, 3), and (2, 4) OD pairs. Node 3 and node 4 are destinations of this network. The pair near the link a is (T_a, b_a). This network is represented in the following Figure 4.1:

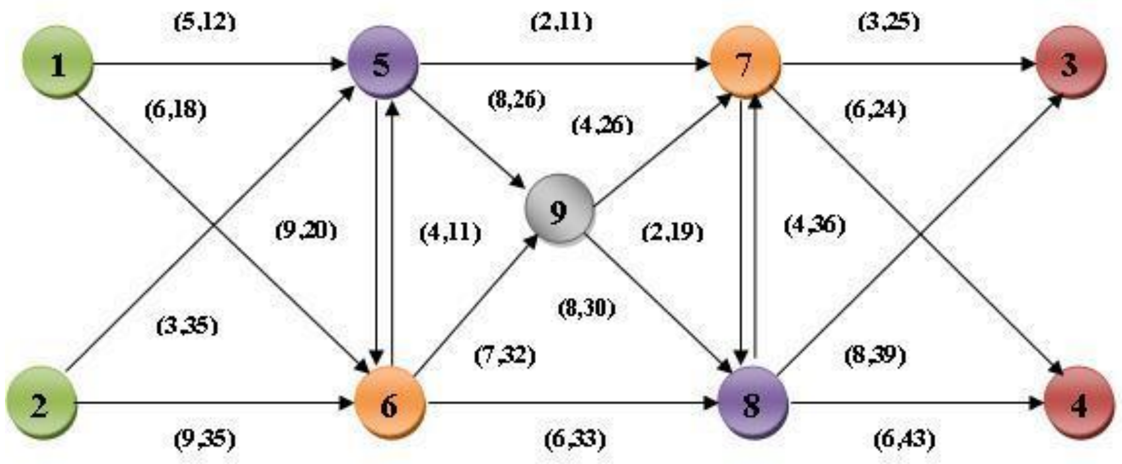

Figure 4.1 The nine node network

In this study, three types of user classes are investigated with $\theta_1 = 0.01$, $\theta_2 = 0.1$, and $\theta_3 = 0.5$. The type one users belong to the lower income class who have the least equipped cars. On the other hand, the type three users belong to the higher income class who have the most equipped cars. According to this, higher income user classes have bigger theta value, however lower income user classes have smaller theta value. The travel demands in this network with respect to the user classes are presented in the Table 4.1 below:

Table 4.1 Travel demands on the network

OD Pair	UC1	UC2	UC3
(1-3)	5	3	2
(1-4)	10	6	4
(2-3)	15	10	5
(2-4)	20	13	7

UCx = User Class x

In this nine node network example, some links of the network are tolled according to the user classes. These tolls are represented in the Table 4.2 and Table 4.3 as follows:

Table 4.2 Tolls of the links considering social and environmental objectives

OD Pair	UC1	UC2	UC3
(5-7)	7.2527	3.7066	11.1181
(6-8)	13.8963	9.5203	1.7323
(6-9)	11.0404	0.9305	6.6062
(7-8)	0.2960	0.0180	0.1299

UCx = User Class x

Table 4.3 Tolls of the links considering social and economic objectives

OD Pair	UC1	UC2	UC3
(5-7)	2.5701	13.7929	19.9955
(6-8)	2.4279	19.7465	18.9708
(6-9)	0.7719	3.0082	0.2515
(7-8)	0.1365	0.003	0.0537

UCx = User Class x

4.5. OBTAINED RESULTS AND DISCUSSIONS

In this study, MATLAB Program is used to obtain results from the used algorithms (SRA algorithm, Bell's second algorithm, and NSGA-II) for the bi-level traffic assignment problem. In the NSGA-II algorithm, firstly, a random binary vector is created for the crossover operator. After that, the genes are selected from both first and second parent and they are combined to generate a child. From the gene vector, 1 is selected from the first parent and 0 is selected from the second parent. Directions, which are adaptive with respect to the last successful or unsuccessful generation, are randomly created for the mutation operator. Then, a step length is chosen among each direction so that the linear constraints and bounds are satisfied. Consequently, the minimum and maximum toll prices which can be collected are set as 0 and 20 respectively within a toll vector. The toll prices are independent from the links and user classes selected.

In this study, three different toll pricing schemes (plans) are investigated. These schemes are as follows:

- First Best Toll Pricing (FBTP)
- Second Best Toll Pricing (SBTP)
- No Toll Pricing (NOTP)

In the FBTP scheme, all the links on the network are tolled. It is difficult to be tolled all the links in practice. Therefore, in the SBTP scheme, only a subset of the links is tolled. In this study, under the SBTP plan, for the nine node network, only (5, 7), (6, 8), (6, 9), and (7, 8) links are tolled. Moreover, in the NOTP scheme, no links on the network are tolled. The result of the NOTP plan is obtained by a single execution of the SRA algorithm and the calculation of the upper level objective functions. For the nine node network, in the FBTP and SBTP schemes, the final results are pooled for 5 different runs of the NSGA-II. This algorithm is run for a population size 50 for the SBTP scheme and 100 for the FBTP scheme, tournament size 3, crossover rate 0.50, Pareto front population fraction 0.35, and maximum number of iterations 200. After that, the final Pareto front is acquired by removing dominated solutions from this pool. These results are represented in the Figure 4.2 and Figure 4.3 for nine node network.

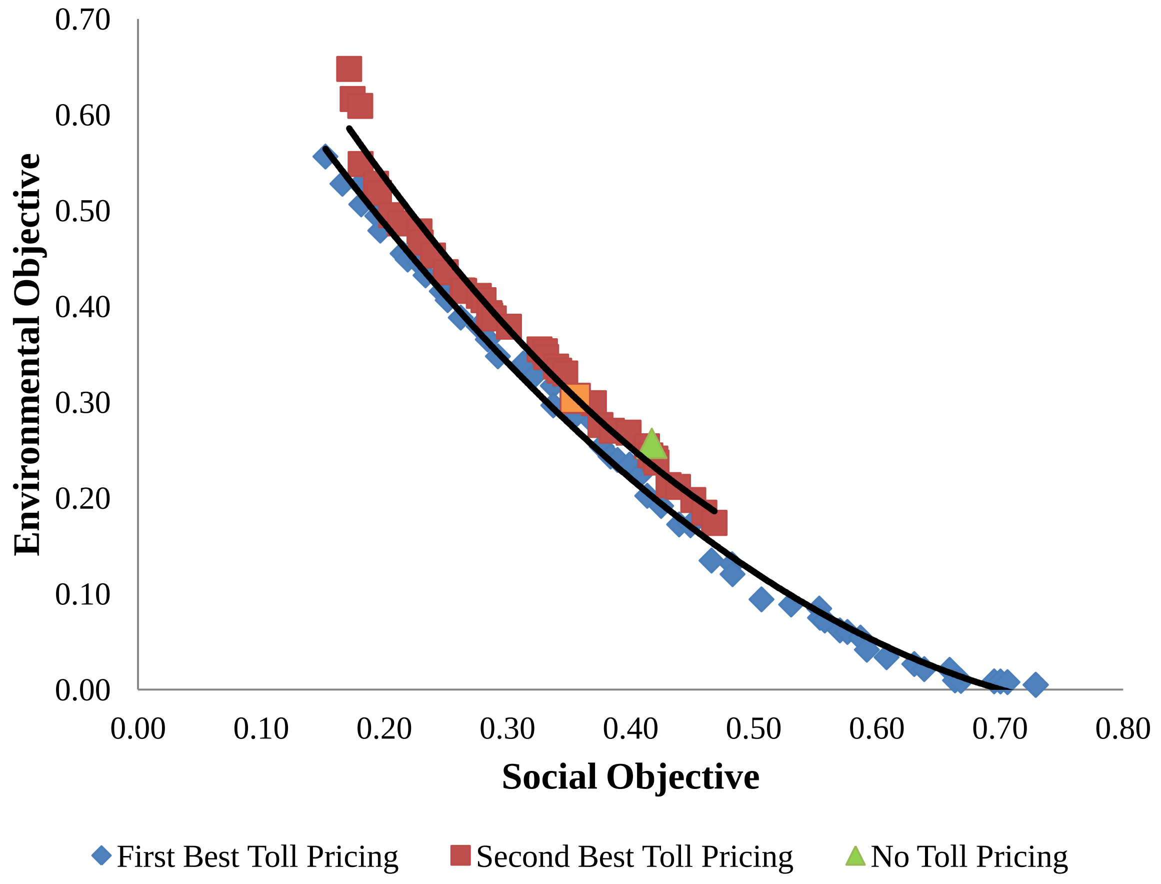

Figure 4.2 Pareto optimal solutions depicted in the social and environmental objective functions space for nine node network

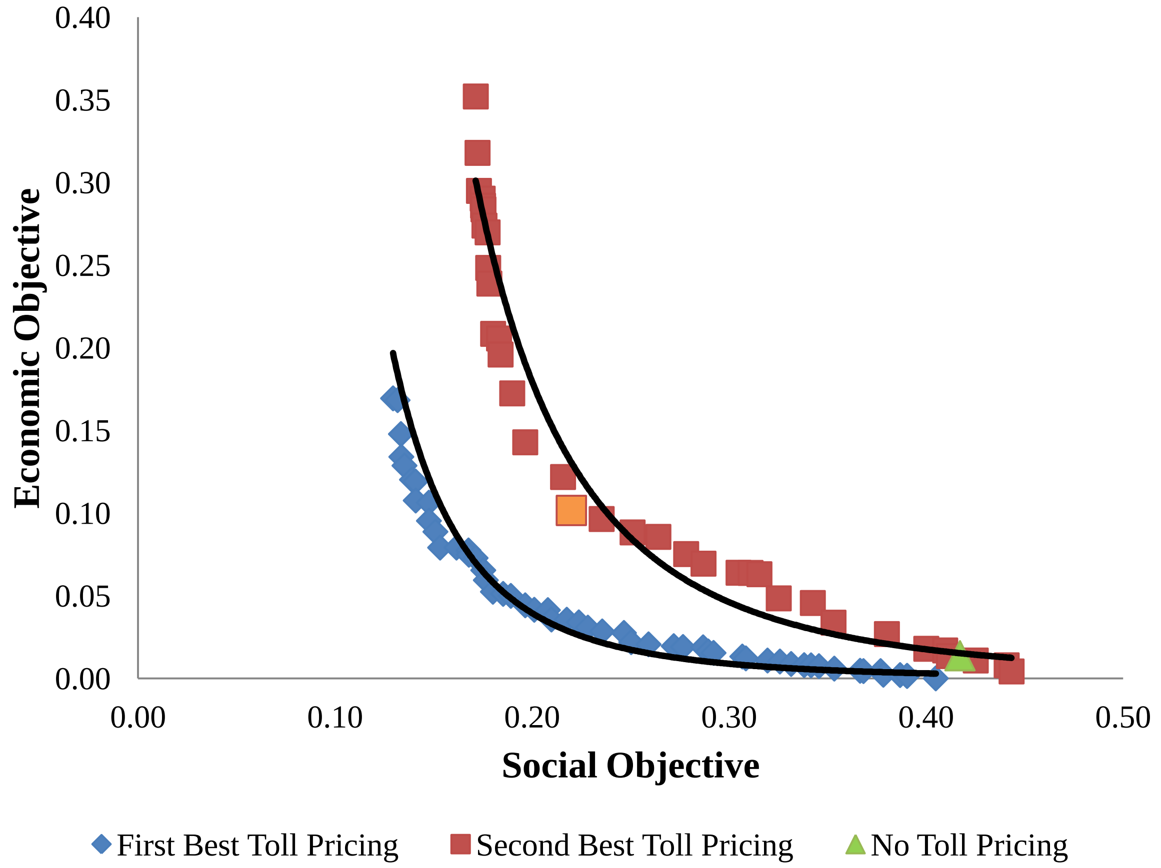

Figure 4.3 Pareto optimal solutions depicted in the social and economic objective functions space for nine node network

As shown above, social and environmental objectives are conflicting to each other. Moreover, social and economic objectives are conflicting to each other. On the other hand, environmental and economic objectives are non-conflicting, therefore they are not considered simultaneously in this study.

From these figures, it can be observed that the NOTP scheme is strictly dominated by all the FBTP and SBTP solutions. Furthermore, the FBTP scheme generates solutions which all strictly dominate the SBTP scheme solutions. The FBTP and SBTP plan solutions are much more diversified in the objective functions space, therefore they form much more interesting choices for the traffic authority. On the other hand, the inconvenience of these pricing schemes leads to an increase in the total travel time spent by the users on the transportation network (in the SO sense). When compared to the SO total travel time at the NOTP case, this increase resides in the interval 2.5%-5.5% for the nine node network for the SBTP solutions. Moreover, it resides in the interval 23%-28% for the FBTP solutions. Under the consideration of all of these, it can be said that the SBTP scheme is the most suitable policy for the sustainable traffic assignment.

The other insights can be acquired by examining link flows on the network. NOTP plan flows are only contrast to one of the Pareto optimal solutions of the SBTP plan for nine node network shown in Table 4.4 and Table 4.5. This selected solution distance to the origin at the objective functions space is minimal. This distance is calculated with assigning equal weights to used objective functions. The origin in the objective functions space corresponds to the ideal solution; however it is difficult to attain this solution. In this study, the closest Pareto optimal solution to the ideal solution is considered as sustainable solution. It can be indicated from Table 4.4 and Table 4.5 that flow of user class 3 is significantly altered with the optimum toll prices. On the other hand, this change is much more less for user class 2 and almost insignificant for user class 1. This implies that collecting tolls from the users are more familiar with the road conditions in order to achieve sustainability in traffic assignment.

Table 4.4 User flows on network links considering social and environmental objectives

	Second Best Tolling			No Tolling		
Links	**UC1**	**UC2**	**UC3**	**UC1**	**UC2**	**UC3**
(1-5)	5.7672	4.1477	2.0927	5.6113	3.8994	2.1086
(1-6)	9.1538	4.8050	3.8757	9.3097	5.0532	3.8598
(2-5)	10.3797	8.6039	2.6743	9.9396	7.2498	1.8112
(2-6)	24.4361	14.2750	9.2626	24.8762	15.6291	10.1257
(5-6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(5-7)	0.0967	0.1237	0.0461	0.0969	0.1348	0.1842
(5-9)	29.4268	17.0244	4.7408	28.0238	14.1284	3.7474
(6-5)	13.3766	4.3965	0.0199	12.5698	3.1140	0.0118
(6-8)	6.9167	4.6328	13.0707	7.5264	9.1121	13.3839
(6-9)	13.2966	10.0507	0.0477	14.0897	8.4563	0.5898
(7-3)	7.8459	0.5470	0.1214	8.1060	0.6548	0.136
(7-4)	11.3781	0.3579	0.0594	12.0703	0.5801	0.0905
(7-8)	2.6469	14.0044	3.1976	1.4153	11.2813	3.0235
(8-3)	12.0488	12.3846	6.8418	11.7887	12.2768	6.8271
(8-4)	18.4640	18.5421	10.8827	17.7718	18.3199	10.8516
(8-7)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(9-7)	21.7742	14.7856	3.3322	21.4946	12.3813	3.0658
(9-8)	20.9492	12.2895	1.4563	20.6189	10.2033	1.2714

UCx = User Class x

Table 4.5 User flows on network links considering social and economic objectives

	Second Best Tolling			No Tolling		
Links	**UC1**	**UC2**	**UC3**	**UC1**	**UC2**	**UC3**
(1-5)	5.7812	4.9802	3.2250	5.6113	3.8994	2.1086
(1-6)	9.1311	3.9671	2.7399	9.3097	5.0532	3.8598
(2-5)	9.8599	9.8653	7.8291	9.9396	7.2498	1.8112
(2-6)	24.9354	13.0002	4.1007	24.8762	15.6291	10.1257
(5-6)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(5-7)	0.1061	0.0753	0.0010	0.0969	0.1348	0.1842
(5-9)	28.2803	20.2045	11.2028	28.0238	14.1284	3.7474
(6-5)	12.7453	5.4343	0.1498	12.5698	3.1104	0.0118
(6-8)	7.3688	2.0085	0.0167	7.5264	9.1121	13.3839
(6-9)	13.9524	9.5246	6.6741	14.0897	8.4563	0.5898
(7-3)	7.7137	0.5239	0.1972	8.1060	0.6548	0.1360
(7-4)	10.8413	0.2696	0.0882	12.0703	0.5801	0.0905
(7-8)	3.0304	15.1792	11.3420	1.4153	11.2813	3.0235
(8-3)	12.1693	12.4001	6.7619	11.7887	12.2768	6.8271
(8-4)	18.9833	18.6193	10.8475	17.7718	18.3199	10.8516
(8-7)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(9-7)	21.4793	15.8974	11.6263	21.4946	12.3813	3.0658
(9-8)	20.7534	13.8317	6.2507	20.6189	10.2033	1.2714

UCx = User Class x

5. CONCLUSION AND FURTHER SUGGESTIONS

There exist some sustainability related measures in the literature to rate urban transportation systems. These measures are most of the time conflicting. Thus finding a single dominant solution which is the best performer regarding to all the objectives is not likely.

In this study, providing solutions which are sustainable for the traffic assignment under the consideration of social, environmental, and economic objectives is aimed. The social objectives include accessibility, equity and road accidents; the environmental objectives consist of vehicle emissions and vehicle noise concepts; and finally the economic objective contains affordability. A multi-objective bi-level traffic assignment model with SUE and multiple user classes is developed to identify the best class based toll pricing policy. The overall model is solved with the NSGA-II. During the course of this algorithm, the lower level model is solved many times by the means of SRA algorithm. It is necessary to load the traffic network with the Bell's second algorithm before operating the SRA algorithm. The efficiency of the developed bi-level traffic assignment model is demonstrated with an illustrative example which is a nine node network.

A descriptive analysis on the obtained results of the model is presented in this study. It is seen from the obtained Pareto optimal solutions at social-environmental objectives space and social-economic objectives space that the FBTP and SBTP schemes are better than the NOTP scheme. It means that collecting tolls from the users on the network links has a significant effect on leading the flow on the traffic network in an effective way. It can be deduced that the toll pricing policy is fair for all the user classes because each user class member pays toll according to his/her income level. The flow of high income user class is significantly changed with the optimum toll prices. However, this change is much less for middle income user class and almost insignificant for lower income user class.

This thesis has a potential of being a starting point for many future researches. The apparent ones can be only conceived here. As for instance, the number of social, environmental, and economic measures can be increased. In this work, two measures are used in the both social and environmental objective functions, and one measure is used in the economic objective function. Instead of only focusing on the car traffic assignment, the other stages of the transportation planning could be also incorporated into the traffic assignment model. These planning stages can be trip generation, trip distribution, and/or modal split. In this thesis, only peak hour demand of the users is considered. On the other hand, it is possible to take into account in-day and day-to-day traffic demand of the users. In addition to these developments, dynamic traffic assignment models can be used in the future studies for sustainable transportation.

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BIOGRAPHICAL SKETCH

Çağla Doğru was born in Istanbul on June 16. 1987. She received her high school education from Sehremini Anatolian High School. She obtained her Bachelor's degree in Industrial Engineering from Kadir Has University in 2009. She is currently a M.Sc. candidate in Industrial Engineering Department at Galatasaray University. Her research interests are urban transportation systems and sustainable engineering.

HONORS/AWARDS:

- Graduation Awards for Ranking Degree in Industrial Engineering Department as well as Faculty of Engineering. Kadir Has University. 2009.

    - Ranked 2nd among Industrial Engineering Department.
    - Ranked 4th among Faculty of Engineering.

- Bachelor's Degree with Honors in Industrial Engineering. Kadir Has University. 2009.

- Outstanding Achievement Scholarships for High GPA. Kadir Has University. 2005-2009.