# DESIGN AND ASSESSMENT OF TRANSPORTATION SYSTEMS WITH THE SUSTAINABILITY PERSPECTIVE

(ULAŞIM SİSTEMLERİNİN SÜRDÜRÜLEBİLİRLİK BAKIŞ AÇISIYLA TASARIMI VE DEĞERLENDİRİLMESİ)

by

**Orhan İlker Kolak, M.S.**

Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

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**ABSTRACT**

In the last few decades, the adverse effects of the considerable increase in the urban population have attracted a lot of attention to the concept of sustainable development and have led many researchers and policy-makers to work on this area. Depletion of natural resources, overcrowded urban areas, the effects of pollution on human health and natural environment, economical concerns plagued modern societies. Various definitions are proposed for sustainability, but its main objective is to maintain industrial and technological development without exhausting resources while ensuring livable environments for human kind for today as well as future generations. Urban transport systems, which cause negative externalities such as congestion, high energy consumption and air pollution, play a vital role for sustainability when designed appropriately.

In this thesis, the design and evaluation of sustainable transportation systems are investigated with two perspectives: macro or country wide scope and micro or urban wide scope. For the macro perspective, we define proper quantitative indicators to evaluate the sustainability of a country transport system and categorize them into three sustainability dimensions: economical, environmental and social. The relative importance of the indicators are identified with the aid of field experts and quantified by using MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique). Statistics about the studied sustainability indicators are collected from several available databases for selected 21 European countries and the data is normalized by again using MACBETH. Finally, the mentioned countries transport systems are rated by using two different multi-criteria decision making methods, namely TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) and Choquet integral. The former technique assumes decision criteria independence while the later one assumes the contrary. In the sustainability evaluation of systems, identifying uncompromised solutions is essential and thus the assumption of criteria dependence has an important role for the decision making. We successfully show

that using Choquet integral method favors uncompromised solutions compared to TOPSIS and helps to determine dimensions for improvements.

The micro perspective involves the modification of existing road networks so as to achieve sustainability at the urban level. In this context, mainly two different mathematical models are developed. In the former model, the minimization of air pollution is investigated within a deterministic environment. The second model is based on stochastic user equilibrium and is developed with a multi-objective perspective so as to consider sustainability dimensions concurrently. Both models are bilevel programming models which involve traffic authority decisions at the upper level and network user decisions at the lower level. In this study, only flow management strategies such as toll pricing and capacity enhancement are considered at the upper level. The first single objective model is solved by a commercial solver while a meta-heuristic is adapted to solve the second multi-objective model. Finally, we analyze the results obtained by solving numerical instances and identify which strategy is effective to achieve sustainability under different scenarios.

Transportation networks are crucial to support urban living but they also produce some undesired results for the society and the environment. Obviously not sufficient alone but the sustainability of transport networks will eventually contribute to the sustainable development of future generations. It is expected that the approaches presented in this thesis will contribute to the livability of the world in the future.

## RÉSUMÉ

Au cours des dernières décennies, les effets négatifs de l'augmentation considérable de la population urbaine ont attiré de nombreux chercheurs et de décideurs à travailler sur à la notion du développement durable. L'épuisement des ressources naturelles, les villes surpeuplées, les effets de la pollution sur la santé humaine et l'environnement et les dépressions économiques sont devenus des préoccupations prioritaires pour les sociétés modernes. Plusieurs définitions sont proposées pour la durabilité, mais l'objectif principal est de maintenir le développement industriel et technologique sans épuiser les ressources tout en assurant un environnement vivable pour l'espèce humaine aujourd'hui et dans la future. Systèmes de transport urbain, qui causent des externalités négatives comme la congestion, la forte consommation d'énergie et la pollution de l'air, jouent un rôle vital pour la durabilité lorsqu'ils sont bien conçus.

Dans cette thèse, la conception et l'évaluation des systèmes de transport durables sont étudiées par deux perspectives: échelle macro ou du pays et échelle micro ou urbaine. Sous la macro perspective, nous définissons des indicateurs quantitatifs appropriés pour évaluer la durabilité d'un système de transport d'un pays et les regroupons en trois catégories: économique, environnemental et social. Les importances relatives des indicateurs sont identifiées à l'aide des experts du domaine et sont quantifiée en utilisant MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique). Les statistiques sur les indicateurs de durabilité étudiées sont collectées à partir de plusieurs bases de données disponibles pour 21 pays européens et les données sont normalisées encore en utilisant MACBETH. Enfin, les systèmes de transport des pays mentionnés sont évalués à l'aide de deux différentes méthodes de décision à multicritères, à savoir TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) et l'intégrale de Choquet. La première technique suppose l'indépendance des critères de décision tandis que la deuxième suppose le contraire. Dans l'évaluation de la

durabilité des systèmes, l'identification de solutions sans compromis est essentielle et donc l'hypothèse de la dépendance des critères a un rôle important pour la prise de décision. Nous montrons que l'utilisation de l'intégral de Choquet privilégie les solutions sans compromis par rapport à TOPSIS et aide de déterminer les dimensions à améliorer.

Le micro perspective implique la modification des réseaux routiers existants afin d'assurer la durabilité au niveau urbain. Dans ce contexte, principalement deux différentes modèles mathématiques sont élaborées. Dans le premier modèle, la minimisation de la pollution de l'air est étudiée dans un environnement déterministe. Le deuxième modèle est basé sur l'équilibre de l'utilisateur stochastique et développé avec une perspective multiobjectif afin de tenir en compte plusieurs dimensions de la durabilité simultanément. Les deux modèles sont des modèles de programmation mathématique à deux niveaux, ce qui implique que les décisions des autorités du réseau sont considérées au premier niveau, et celles des utilisateurs du réseau au deuxième niveau. Dans cette étude, seulement les stratégies de gestion des flux comme la tarification de péage et l'augmentation des capacités routières sont considérées au premier niveau. Le premier modèle mono objectif est résolu par un solveur commercial tandis qu'une méta-heuristique est adapté pour résoudre le deuxième modèle multiobjectif. Enfin, nous analysons les résultats obtenus en résolvant des cas numériques et identifions quelle stratégie est efficace pour atteindre la durabilité dans différents scénarios.

Les réseaux de transport sont essentiels pour supporter la vie urbaine, mais ils produisent également des résultats indésirables pour la société et l'environnement. Bien qu'elle ne soit pas suffisant tout seul, la durabilité des réseaux de transport va enfin contribuer au développement durable pour les prochaines générations. On envisage que les approches présentées dans cette thèse contribueront à l'augmentation de la qualité de vie dans le monde du future.

**ÖZET**

Son elli yılda, kentsel nüfusta görülen belirgin artışın olumsuz etkileri, sürdürülebilir gelişmeye olan ilginin önemli oranda artmasına neden olmuştur ve birçok araştırmacı ve karar vericiyi bu alanda çalışmaya yöneltmiştir. Doğal kaynakların tükenmesi, kentlerin aşırı kalabalıklaşması, kirliliğin insan sağlığı ve çevre üzerindeki etkisi ve iktisadi hayattaki sıkıntılar, çağdaş toplumlar için artan bir endişe kaynağı haline gelmiştir. Sürdürülebilirlik hakkında çeşitli tanımlar önerilmiştir, fakat buradaki temel amaç, hem bugünkü ve gelecek nesiller için yaşanabilir bir çevreyi mümkün kılmak, hem de aynı zamanda kaynakları tüketmeden sınai ve teknolojik ilerlemeyi sağlamaktır. Kentsel ulaşım sistemleri trafik sıkışıklığı, yüksek enerji tüketimi ve hava kirliliği gibi olumsuz sonuçlara neden olmakla birlikte uygun tasarlandıklarında sürdürülebilirliği sağlamada önemli bir rol oynarlar.

Bu tezde, ulaşım sistemlerinin sürdürülebilir biçimde tasarlanması ve sürdürülebilirliklerinin değerlendirilmesi, iki bakış açısından incelenmiştir: makro veya ülke ölçeğinde, ve mikro veya kentsel ölçekte. Makro bakış açısı kapsamında, bir ülkenin ulaşım sisteminin sürdürülebilirliğini değerlendirmek için uygun nicel göstergeler tanımlanmıştır ve bunlar sürdürülebilirliğin üç temel boyutu altında sınıflandırılmıştır: iktisadi, çevresel ve toplumsal. Göstergelerin göreceli önem dereceleri, alanının uzmanları yardımı ile belirlenmiş ve MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique) yöntemi ile nicelenmiştir. Uygulama olarak 21 Avrupa ülkesi ele alınmış ve bu ülkeler için incelenen sürdürülebilirlik göstergeleri ile ilgili istatistikler mevcut veri tabanlarından toplanarak yine MACBETH ile normalleştirilmiştir. Son olarak, bahsi geçen ülkelerin ulaşım sistemleri TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) ve Choquet integral çok ölçütlü karar verme yöntemleri yardımıyla değerlendirilmiştir. İlk yöntemde karar ölçütlerinin birbirlerinden bağımsız olduğu, ikicisinde ise bunun aksi varsayılmaktadır. Sistemlerin sürdürülebilirliklerinin değerlendirilmesinde tavizsiz

çözümlerin belirlenmesi esastır ve bu bağlamda, ölçütler arasındaki bağımlılık dikkate alınmalıdır. Choquet integral yönteminin tavizsiz çözümleri öne çıkarmada TOPSIS'e göre daha başarılı olduğu ve iyileştirilmeye ihtiyaç duyulan boyutları belirlemede yardımcı olduğu gösterilmiş.

Mikro bakış açısı, kentsel ölçekte sürdürülebilirliği sağlamak için mevcut yolların düzenlenmesini ele almaktadır. Bu bağlamda, iki temel matematiksel model geliştirilmiştir. İlk modelde, hava kirliliğinin en azaltılması gerekirci bir ortamda ele alınmıştır. İkinci model ise, çok amaçlı bir bakış açısıyla birden fazla sürdürülebilirlik boyutunu eşzamanlı ele alarak ve stokastik kullanıcı dengesini temel alarak geliştirilmiştir. Her ikisi de, üst seviyede trafik düzenleyicisinin, alt seviyede ise trafik ağı kullanıcılarının kararlarını kapsayacak şekilde iki seviyeli programlama modeli olarak kurulmuştur. Bu çalışmada üst seviyede sadece geçiş ücretlendirmesi ve yol kapasite artırımı gibi akış yönetimi stratejileri ele alınmıştır. İlk model bir ticari çözücü yardımıyla, ikinci çok amaçlı model ise uyarlanan bir meta-sezgisel ile çözülmüştür. Son olarak, sayısal örnekler çözülerek elde edilen sonuçlar incelenmiş ve farklı senaryolarda hangi stratejinin daha etkili olduğu belirlenmiştir.

Ulaşım sistemleri kentsel yaşam için çok önemlidir fakat toplum ve çevre için bazı istenmeyen sonuçlara da neden olmaktadır. Elbette, tek başına yetersiz olsa da, taşıma ağlarının sürdürülebilir olması gelecek nesillerin sürdürülebilir gelişimine katkı sağlayacaktır. Bu tezde ortaya konan yaklaşımların, dünyanın gelecekte daha yaşanabilir olmasına katkıda bulunması beklenmektedir.

# 1 INTRODUCTION

In the last few decades, the adverse effects of the considerable increase in the urban population have attracted a lot of attention to the concept of sustainable development and have led many researchers and policy-makers to work on this area. Urban transport systems, which cause negative externalities such as congestion, high energy consumption and air pollution, play a vital role in maintaining sustainability when designed appropriately. In the literature, there are many definitions for a sustainable transport system. In a very simple way, we may say that a transport system is sustainable if it responds to the mobility needs while preserving the nature, supporting the social equity and the economic development in the present as well as in the future. Our main focus is not on sustaining the transport system but on guaranteeing that the associated system outputs support the sustainable development of the society in terms of its environmental, economic, and social dimensions.

The dimensions of sustainability and its relation with the urban transportation can be summarized as follows (Litman, 2005b).

**Table 1.1**: Sustainability dimensions and impacts

| Economic | Social | Environmental |
|---|---|---|
| -Traffic congestion | -Equity/Fairness | -Air pollution |
| -Infrastructure costs | -Impacts on mobility disadvantaged | -Climate change |
| -Consumer costs | | -Noise and water pollution |
| -Mobility barriers | -Human health impacts | -Habitat loss |
| -Accident damages | -Community cohesion | -Hydrogen impacts |
| -Depletion of non-renewable resources | -Community livability | -Depletion of non-renewable resources |
| | -Aesthetics | |

Sustainability is generally evaluated using various *indicators*, which are specific variables suitable for quantification (measurement). Such indicators are useful for establishing baselines, identifying trends, predicting problems, assessing options, setting performance targets, and evaluating a particular jurisdiction or organization. Which indicators are selected can significantly influence the analysis results. A particular policy may seem beneficial and desirable when evaluated using one set of indicators but harmful and undesirable when evaluated using others. It is therefore important for every stakeholder involved in sustainable transportation planning to understand the assumptions and perspectives used to select and define sustainable transportation indicators (Litman, 2005b).

Sustainability requires limiting the resource consumption to satisfy the ecological constraints (such as limiting land use to protect habitat and fossil fuel use to minimize climate change), so the sustainable development requires maximizing the efficiency with which wealth provides social welfare (Litman, 2006). Similarly, sustainable transportation requires that we maximize the amount of happiness produced per unit of mobility (Litman, 2005b).

Sustainability is sometimes defined narrowly, focusing on a few specific problems such as resource depletion and pollution, but is increasingly defined broadly to include other issues. Narrowly defined sustainability can overlook connections between issues and opportunities for integral solutions. A comprehensive analysis helps to identify strategies that achieve multiple objectives and are truly optimal (Litman, 2008b). For example, a comprehensive analysis allows planners to identify the congestion reduction strategies that also help to achieve equity and environmental objectives, or at least avoid those that are socially and environmentally harmful. These integrated solutions can be considered the most sustainable (Litman, 2005b).

If sustainable transportation is defined only in terms of resource depletion and climate change risks, more efficient and alternative fuel vehicles may be considered the best solutions. But these strategies fail to achieve other objectives such as congestion reduction, facility cost savings, safety or improved mobility for non-drivers; in fact, by reducing vehicle operating costs, it tends to stimulate more driving which increases these problems (Litman & Rickert, 2005). When these additional impacts are considered, other policies are considered more sustainable. Described differently, when defined narrowly, sustainable planning is a specialized activity, but when defined more broadly it can be integrated with other planning activities (Nicolas et al., 2003).

Policies that are crucial in achieving sustainable goals and objectives for urban transportation systems can be implemented at several stages, one of which is the traffic assignment. The traffic assignment is the last step in the traditional four-step transportation planning process, following trip generation, trip distribution, and mode choice. Traditionally, urban traffic volumes are assigned in order to minimize the travel times of the users, however, this economic goal is insufficient by itself. Thus, the goal of this project is to integrate sustainability dimensions into the optimization models for urban transport system planning and to provide decision support for the development of sustainable transport policies.

In this thesis, first a sustainability evaluation model is developed. By sustainability evaluation model we refer to a framework which involves the selection of sustainability objectives, policies to achieve those objectives, and the performance criteria to measure the policies' outcomes. Then, we describe how to incorporate those selected and quantified measures into optimization model. Bilevel programming models involving several sustainability performance measures, deterministic or stochastic user equilibriums, deterministic or elastic demand, and more than one policies, are constructed. Finally, solution methods are developed and implemented, and computational studies are performed.

The main contributions of this thesis are summarized below:

- There are many studies in the literature on sustainable transportation but they have some missing and contradicting points. Our objective is to develop an integrated evaluation model which involves *economic*, *social* and *environmental* dimensions to rate the sustainability of the countries' transportation systems. This model can also be used as a reference model by other researchers working on sustainable transportation.

- In order to evaluate the sustainability of a traffic network, relevant indicators are needed. We collect readily available data to construct a model for evaluating and comparing the sustainability of the existing traffic networks.

- Sustainability in the area of transportation can be achieved in several ways, for example producing more resource efficient vehicles. In this thesis, we will focus on the traffic planning especially on the traffic assignment.

- We first develop several bi-level optimization models where traffic authority's (sustainability related) objectives and constraints are reflected in the upper-level and network users' objectives and constraints are reflected in the lower level. These bi-level models can be reference models for other researchers.
- We focus on solution methods. We analyze the proposed models theoretically, and use exact or heuristic solution methods accordingly.
- We implement these models and solution methods and solve several illustrative numerical examples. We provide managerial insights according to the results.

This thesis is structured as follows. In chapter 2, an extensive literature survey on sustainable transportation is presented. In chapter 3, a multi-criteria evaluation framework using sustainability indicators for existing traffic systems is introduced. In chapter 4, a single objective bi-level sustainable traffic assignment model using deterministic user equilibrium is developed. In chapter 5, a multi-objective bi-level sustainable traffic assignment model using stochastic user equilibrium is developed. In chapter 6, the findings of this thesis are summarized and future perspectives are provided.

# 2 LITERATURE SURVEY

## 2.1 Urban Transportation Planning

Within the rational planning framework, transportation forecasts have traditionally followed the sequential four-step model illustrated in Figure 2.1 or urban transportation planning procedure which was first implemented on mainframe computers in the 1950s at the Chicago Area Transportation Study (CATS) (Black, 1990; Ortuzar & Willumsen, 2001). The outputs of one step serve as the inputs of the next step. *Trip generation* determines the frequency of origins or destinations of trips in each zone by trip purpose, as a function of land uses and household demographics, and other socio-economic factors. *Trip distribution* matches origin and destination (O–D) pairs, and determines number of trips between each O–D pair. *Mode Choice*, computes the proportion of trips between each origin and destination that use a particular transportation mode. *Traffic assignment* allocates trips between O–D pairs to roads and determines flow quantity on each route and link. Mathematical traffic assignment models are widely used as they provide reasonably accurate results. This model is also criticized due to its inherent weakness, such as lack of a single unifying rationale that would explain or legitimize all aspects of demand jointly (Zhou et al., 2009a).

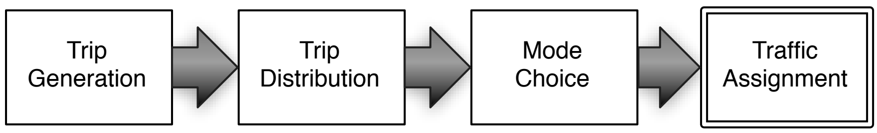



**Figure 2.1**: The sequential four step model

The first step of the sequential four-step model is trip generation, widely used for prediction of travel demands. Trip generation estimates the number of trips to work, education, entertainment etc. but does not deal with the flows between points within the network (Meyer, 1974). Hensher (1976) studies the shopping trips, while Barber (1995) states that work trips are the most common purpose of trips.

There are mainly two approaches to trip generation: aggregate trip generation and disaggregate trip generation (Cubukcu, 2001). In aggregate model, data is collected at geographic level (neighborhoods, cities etc.), linear regression and categorical analysis techniques are widely used in these models (FHWA, 1975; Hobbs, 1979; Koppelman & Pas, 1984; Bruton, 1986; Sheppard, 1995). In disaggregate models, data is collected at individual or household level, discrete choice models are used in these models (Vickerman & Barmby, 1984, 1985).

The second step in the sequential four step model is trip distribution. This stage matches trip maker origins and destinations estimated by trip generation models to develop the “trip tables”. A trip table is a matrix that displays the number of trips going from each origin to each destination. The most well known models of trip distribution are gravity model and entropy maximization model (Abdel-Aal, 2014).

The gravity model is originally generated from an analogy with Newton gravitation law. Isard (1956) first introduced gravity model to trip distribution. To estimate the parameters of gravitational models the statistical principle of maximum likelihood is frequently used (Evans, 1971; Sen, 1986; Sen & Matuszewski, 1991; Gonçalves & Ulyssea Neto, 1993; Gonçalves & de Cursi, 2001). Other statistics are also used such as the squared errors (Diplock & Openshaw, 1996) or the phi-normalized statistic (Smith & Hutchinson, 1981).

Murchland (1966) fromulated the entropy maximization model and showed its equivalence to the gravity model. Wilson (1967) explained the trip distribution behaviors using the entropy maximization model. Wilson (1970) formulated various entropy maximization models. In order to overcome the oversimplification caused by the use of linear cost per unit flow, a quadratic cost constraint is introduces as a better approximation (Tomlin, 1971). Fang & Tsao (1995) give some properties and an efficient algorithm about the quadratic cost constraint entropy maximization model. Additionally many other models on entropy maximization model are proposed (Potts & Oliver, 1972; Hallefjord & Jörnsten, 1984; Willumsen, 1990).

The third step in the sequential four step model is the mode choice where the modes are usually route cars and public transit. Mode choice analysis serves to determine the mode of transport that will be used (Warner, 1962; Garling et al., 1994; Ortuzar & Willumsen, 2001). The first traffic assignment model with elastic demand was proposed by Beckmann et al. (1956). In elastic demand models, the number of trips between an origin and destination pair is not fixed but variable. In these models, users that do not use traffic network are usually supposed to use alternative modes of transport (Sheffi, 1985). Trip distribution and mode choice models are also combined in later studies using negative exponential deterrence function in order to model the elastic demand (Florian et al., 1975; Evans, 1976). Florian (1977) and Florian & Nguyen (1978) consider the modal split where two modes are either independent or interdependent. Location choice and travel choice are also incorporated into the mode choice models (Boyce et al., 1983, 1988). A combined model incorporating all four sequential steps is also proposed that utilize the logit model to define the mode split (Safwat & Magnanti, 1988). Oppenheim (1995) propose the multinomial logit model in hierarchical structure assuming each traveler is a customer of urban trips. Several researchers proposed combined models with multiple user classes (Lam & Huang, 1992; Boyce & Bar-Gera, 2001, 2004; Wong et al., 2004).

Previously presented mode choice models are formulated as convex optimization programs under the assumption that travel costs are separable and symmetric. But, this assumption may not be always realistic. Smith (1982), Heydecker (1983), Meneguzzer (1995), Mahmassani & Mouskos (1988) consider non separable link costs for modeling interaction delay with asymmetric interactions. Mahmassani & Mouskos (1988), Wu & Lam (2006) consider asymmetric interactions between cars and truck. Gabriel (1997), Lo & Chen (2000), Chen et al. (2001) consider non-additive route cost structures. To be able to model asymmetric interactions, various combined travel demand models are formulated as variational inequality problems (de Cea & Fernandez, 2001; Florian et al., 2002; García & Marín, 2005; Hasan & Dashti, 2007). Vrtic et al. (2007) present the EVA algorithm – model from the German terms for production (Erzeugung), distribution (Verteilung) and mode choice (Aufteilung) – that unifies first three steps. Zhou et al. (2009b) propose alternative formulations for a combined travel demand model that integrates trip generation, trip distribution, model split, and traffic assignment.

The final step in the sequential four steps model is the traffic assignment. This step is presented in details in the next section as it constitutes an importatnt part of this thesis and thus deserves spectial attention.

## 2.2 Traffic Assignment and User Equilibrium

The amount of travel taking place at a given moment on any street, intersection, or transit line in an urban area is the result of many individuals' decisions. These decisions depend, in part, on how congested the transportation system is and where the congested points are. Congestion at any point of the transportation system, however, depends on the amount of travel through that point. The notion of equilibrium in the analysis of urban transportation networks stems from the dependence of the link travel times on the link flows (Sheffi, 1985).

The determination of the flows on each of these paths requires solving a demand/performance equilibrium problem. The demand for travel, is rooted in motorists' behavior and is not defined for each link separately. Instead, it specifies how motorists choose among the alternative paths (routes) connecting each origin-destination (O–D) pair. No link, path, or origin-destination pair can be analyzed in isolation. It is reasonable to assume that every motorist will try to minimize his or her own travel time when traveling from an origin to a destination. A steady state is reached only when *no traveler can improve his travel time by unilaterally changing his routes.* This is the characterization of the *User Equilibrium* (UE) condition (Sheffi, 1985).

Since individual motorists can be expected to behave independently, the UE situation ensures that at this point there is no force that tends to move the flows out of the equilibrium situation. Consequently, this point will be stable and, in fact, a true equilibrium (Sheffi, 1985).

**Wardrop's first principle:** Wardrop (1952) states: *the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route.* Each user non-cooperatively seeks to minimize his/her time of transportation. The traffic flows that satisfy this principle are usually referred to as UE flows, since each user chooses the route that is the best.

**Wardrop's second principle:** Wardrop (1952) states: *at equilibrium the average journey time is minimum.* This implies that each user behaves cooperatively in choosing his own route to ensure the most efficient use of the system. Traffic flows satisfying Wardrop's second principle are generally deemed "System Optimal" (SO).

### 2.2.1 Traffic Assignment Optimization Models

As an optimization model, Traffic Assignment Problem (TAP) is generally modeled in two ways:

- In static traffic assignment problems, average demand on rush hours gains importance (Sheffi, 1985; Patriksson, 1994; Florian & Hearn, 1995).

- In dynamic traffic assignment problems, demand variation and route selection and/or time of departure of travelers must be taken into account (Peeta & Ziliaskopoulos, 2001; Boyce et al., 2005).

The objective of a transportation system administrator is to configure system parameters in order to obtain optimum system equilibrium (OSE) in terms of performance. In simplest sense, this can be defined as minimizing users' total travel time. However, transportation system users are personal decision makers who choose their own route for their trip. Consequently, the transportation system administrator can not control the users behavior on route selection but can affect that by configuring traffic management and control sub-systems. Under the assumption that the users always select their routes considering their travel costs or times, UE principle is frequently used to describe the users route selection behavior, and can be represented by a nonlinear optimization problem (Patriksson, 1994; Sheffi, 1985). In TAP, UE can be handled in two ways:

- If it is assumed that users have complete knowledge on all roads and their conditions in the transportation network, and that traffic flows do not change over time, *the Deterministic User Equilibrium* (DUE) condition is sufficient to explain users' behavior. The mathematical expression of Kuhn-Tucker conditions convenient with Wardrop (Wardrop, 1952) UE principle is first given by Beckmann et al. (1956) and is widely used ever since.

- In *Stochastic User Equilibrium* (SUE) models, it is assumed that users may have different perceptions of the travel time, and accordingly, route selection is made according to the perceived travel time instead of actual travel time. In the literature, SUE is modeled in many ways. Multivariate Probit model is first proposed by Daganzo & Sheffi (1977) and is later developed by Sheffi & Powel (1982) and Yai et al. (1977). Multinominal Logit model is first proposed by Luce (1956). Although it is proved theoretically to be insufficient for modeling route selection (Daganzo & Sheffi, 1977; Ben-Akiva & Lerman, 1985), it is widely used in many applications. Other models are proposed to correct flaws of Multinomial Logit model to some extent such as C-Logit (Cascetta et al., 1996), Implicit Availability/Perception Logit (Cascetta & Papola, 1998), Path-Size Logit (Benedek & Rilett, 1998), Cross-Nested Logit (Vovsha, 1997), Paired Combinatorial Logit (Chu, 1989), Kernel (Mixed) Logit (McFadden & Train, 2000).

Within the scope of TAP, travel quantities between O–D pairs, which are simply referred to as travel demand, can be handled in three ways:

- If it is assumed that the travel demand for an O–D pair do not change, this is a *Fixed Demand* (FD) (Beckmann et al., 1956; Dafermos & Sparrow, 1971).

- A more realistic way is to define travel quantity as a function of the minimum travel time between an O–D pair. This kind of demand is known as *Elastic Demand* (ED) (Beckmann et al., 1956; Gartner, 1980; LeBlanc & Farhangian, 1981; Yang, 1997).

- In problems with *Stochastic Demand* (SD), variation of demand in short and long terms is taken into account. There may be many causes for the transportation demand variation: a) unexpected events, b) political and socio-economical changes, c) ambiguities in demand model, d) difficulties in quantifying performance criteria, e) differentiation among decision makers choices. Long term variation is modeled under the assumption of the existence of specific demand scenarios or that demand fit multivariate normal distribution (Nagae & Akamatsu, 2005; Atamturk & Zhang, 2007; Ukkusuri & Mathew, 2007; Gardner et al., 2008). Short term or day-by-day variation on the other hand, is modeled generally, under the assumption that demand fit a specific continuous or discrete distribution (Dafermos & Sparrow, 1971; Gartner, 1980; LeBlanc & Farhangian, 1981; Asakura & Kashiwadani, 1991; Yang, 1997; Bell et al., 1999; McFadden & Train, 2000; Clark & Watling, 2005; Nagae & Akamatsu, 2005; Atamturk & Zhang, 2007; Ukkusuri & Mathew, 2007; Gardner et al., 2008; Unnikrishnan, 2008). Naturally, expected travel time is considered instead of perceived travel time while modeling UE.

To illustrate, we provide the basic model of DUE-FD problem in (2.1a)-(2.1e) (Dirkse & Ferris, 1997).

$$
\begin{aligned}
\text{minimize} \quad & \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} t_{ij}(y)\,\mathrm{d}y && && (2.1\text{a})\\
\text{subject to} \quad & \sum_{j:(i,j)\in\mathcal{A}} x_{ij}^s - \sum_{j:(j,i)\in\mathcal{A}} x_{ji}^s = d_i^s,\ i \in \mathcal{N}, s \in \mathcal{D}, && && (2.1\text{b})\\
& \sum_{s\in\mathcal{D}} x_{ij}^s = f_{ij}, && (i,j) \in \mathcal{A}, && (2.1\text{c})\\
& x_{ij}^s \geq 0, && (i,j) \in \mathcal{A}, s \in \mathcal{D}, && (2.1\text{d})\\
& d_i^s \geq 0, && i \in \mathcal{N}, s \in \mathcal{D}. && (2.1\text{e})
\end{aligned}
$$

Here, $\mathcal{N}$ is the set of nodes, $\mathcal{D}$ is the set of destination nodes and $\mathcal{A}$ is the set of arcs in the traffic network. $x_{ij}^s$ is the flow on link $(i,j) \in \mathcal{A}$ to the destination $s \in \mathcal{D}$, $f_{ij}$ is total link flow on link $(i,j) \in \mathcal{A}$ and $d_i^s$ is the demand at node $i \in \mathcal{N}$ with destination $s \in \mathcal{D}$. $t_{ij}(\cdot)$ is a monotonically non-decreasing function that represents the relationship between the flow and travel time on link $(i,j)$, as the flow on a link increases, the travel time of each vehicle on that link increases too.

Here the set of constraints (2.1b) is for the flow conservation and constraints (2.1c) link the total flow on an arc to the flows resulting from individual destination points. Constraints (2.1d) and (2.1e) ensure that the link flows and travel demands are nonnegative.

### 2.2.2 Traffic Assignment Strategies

As the traffic users choose their own paths from their origins to their destinations, it is usually not possible to directly identify these paths. Meanwhile, there are strategies that will help traffic authorities to influence the decisions of the traffic users increasing heir paths. This is possible thanks to the UE models that allow to predict the behaviors of traffic users in different situations. The following traffic management methods and control sub-systems are widely studied for TAP.

#### 2.2.2.1 Network Design

Changing the physical characteristic of a traffic network is the most adressed technique to manage the flow and also to respond the changing conditions over time. Doing this alteration with minimum cost leads to network design (ND) problem.

Inclusion of new links to a traffic network is a widely used approach to improve a traffic network. This type of problems are named as Discrete Network Design Problems (DNDP). These models deal with the determination of new links to be added to the network. Chen & Alfa (1991b) present a two-phase branch and bound based algorithm to solve Discrete Stochastic Network Design Problem (SNDP) with fixed demand. At the first phase of their algorithm, they obtain the initial logit user equilibrium with the method of successive average. Then at the second phase, they use the branch and bound method for selecting the links to include in the network. The upper level objective aims to minimize the total network travel time.

Continuous Network Design Problems (CNDP) are also proposed which involve capacity enhancement of present links. Davis (1994) proposes two algorithms for capacity enhancement to find an exact local solution of the continuous logit-based SNDP with fixed demand. The developed model is non-convex and is formulated such that the optimal capacity increases of the existing road segments are identified while the total network travel time is minimized. The first algorithm use the generalized reduced gradient algorithm, and the second is based on the sequential quadratic programming. Both approaches are illustrated using Sioux Falls Network. Lim et al. (2005) present a CNDP model with capacity enhancement strategy. The problem is formulated as a bi-level program, in which the upper level represents the designer's decisions and the lower level the travelers' responses. The authors use logit based route choice model. They propose a local search algorithm and apply the algorithm to two example networks to test and briefly compare the results. Capacity enhancement may not always be feasible, so Wu et al. (2009) present a traffic assignment model with reversible lanes. Some of the users are assumed to possess advanced traveler information systems (ATIS) and thus to have perfect knowledge about the network. The rest of the travelers choose their way to their destination according to the travel time they perceive. The authors develop a bi-level optimization model where the upper level consists of lane reversing decisions and the lower level consists of SUE with ATIS. The chaotic optimization algorithm is applied to solve the problem and several illustrative examples with and without ATIS are provided. Sumalee et al. (2009) investigate the capacity reliability in their paper. They present design model for transport network capacity under demand variability. They use stochastic demand where the demand follows normal distribution. Travelers make their path choices according to the probit model. Since the demand is stochastic, the flows on transport links are also stochastic. The objective is to determine the probability that the link flows are less than the link capacities. This probability also determines the reliability of the link capacity. The network capacity reliability is calculated using link capacity reliabilities. A model to determine network capacity enhancements in order to increase capacity reliability is proposed.

#### 2.2.2.2 Toll pricing

Although ND is a useful approach, it is not always feasible or cost effective. Recently, electronic tolling systems allowed the widening of application areas. As an alternative to ND, toll pricing (TP) is considered in the literature (Rouwendal & Verhoef, 2006). The first-best toll pricing involves pricing all links in a traffic network, but in practice it is difficult to implement. The second-best toll pricing on the other hand involves pricing a subset of links in the traffic network (Labbe et al., 1998; Brotcorne et al., 2001; Patriksson & Rockafellar, 2002; Lawphongpanich & Hearn, 2004). Fumero et al. (1999) investigate optimal link tolls on a network with logit-based SUE. They develop a mathematical model with an objective to minimize total network travel time. They do not provide a solution algorithm for large scale problems but present an illustrative example with a small unsophisticated network. Chen et al. (2004) consider multi-user classes in their paper and present a bi-level toll-design problem with logit-based SUE-FD. Their upper level model objective is to minimize total travel time. They consider multiple user classes (cars, trucks, etc.). They transform the bi-level model to single level to solve the problem. They assume that only a subset of links can be tolled. They propose two methods to solve the problem. The first method is the feasible direction method which is basically applicable to almost all nonlinear programming problems. The drawback of this model is that it can provide a saddle point instead of a local optimum. The second method is the interior point algorithm which approximates the constrained optimization problem with unconstrained problems. They apply the methods to Sioux Falls Network considering cars and trucks as different user types. They choose arbitrarily a subset of links to toll, and define different tolling values for both user types. Maher et al. (2005) present a model to identify the Stochastic System Optimum (SSO) solution. In their model, users are assigned to the paths such that the total network travel time is minimized. As the users are not necessarily allocated to the paths with their minimum perceived travel time, SSO flows are obtained. Then, comparing SSO flows with SUE flows, they obtain the marginal social cost (MSC) toll set. They conclude that by applying MSC toll set to the network, the SUE flows match the SSO flows. They point out that this solution is not unique so they construct another model to find the toll set that minimize total revenue while ensuring SSO flows. Stewart (2007) investigates optimum link tolls to minimize total perceived travel time in a network with logit-based SUE. Desired traffic flow is obtained by calculating SSO in which traffic flow is directed to minimize the total perceived travel time. It is possible to obtain this solution by applying marginal social cost price but this solution is not unique and high toll values and revenue are not desirable. The author suggests minimizing total toll revenue while conserving SSO. A local search algorithm is proposed to solve the problem and several examples with different number of tolled links are presented. Toll revenues and total perceived travel times for different number of tolled links are compared.

#### 2.2.2.3 Signalization, turning delays and turn restrictions

Other approaches like signalization, turning delays and turn restrictions are also considered to improve a traffic network (Cantarella et al., 1991b; Cipriani & Gori, 2000; Taale & van Zuylend H. J., 2001). Ceylan & Bell (2004a,b) present a traffic signal timing optimization model with logit-based SUE-FD. The objective is to minimize the system performance index which is defined as the sum of a weighted linear combination of the delay and the number of stops per unit time for all traffic streams. They present two numerical examples to illustrate their model and solve them with Genetic Algorithm (GA). In a later study, Ceylan & Bell (2005), extend their work by studying the effects of increasing travel demand between origin destination pairs by 10% and 20% and they compare the results with previous studies. Cascetta et al. (2006) present models and algorithms to optimize signal settings on networks with logit-based SUE. They adopt two approaches in their study: local and global signal optimization. In the local signal optimization, they consider signal settings independently and optimize each of them separately. In the global signal optimization, they consider all signal settings simultaneously. In both cases, they aim to minimize the total travel time on the traffic network. They utilize the method of successive averages to find the optimal solution. In the local signal optimization approach, the optimal solution is easily found as the problem is shown to be convex. In the global signal optimization however, only a local optimum is guaranteed. The methods and algorithms are applied to two different networks and results of local and global signal optimization are compared. Sun et al. (2006) present a bi-level programming formulation for dynamic traffic signal optimization and propose a meta-heuristic approach to solve the problem. Logit-based SUE traffic network with fixed demand is assumed in this formulation. Unlike previous studies where travel demand is static, in this study dynamic travel demand is considered. In this approach, travel demand varies thorough the day and as a result, traffic signals are configured accordingly. To solve the problem, they apply two different versions of genetic algorithm: elitist GA and micro-GA. They present an illustrative example and compare both methods. Near optimal solutions are found and the use of different starting points is advised to find closer results to global optimum.

Zhu et al. (2009) propose a reliability-based SUE model to investigate the effects of turn delay uncertainties. In the proposed model, link travel times and turn delays are considered as correlated random variables with covariance relationships. The concept of effective travel time is adopted to model the route choice behavior for all users. A path based heuristic algorithm is adopted to solve the problem. Long et al. (2010) present a Turning Restriction Design Problem (TRDP) for urban road networks. In TRDP, the aim is aimed to determine a set of intersections where turning restrictions should be implemented. A bi-level programming model is proposed to formulate TRDP. The objective of the upper level problem is to minimize the total travel cost. The lower level problem is to depict travellers' route choice behavior based on logit SUE. A branch and bound method based on sensitivity analysis is proposed to find the optimal turning restriction strategy. A numerical example is provided and solved with different methods including the genetic algorithm and the solutions are compared.

#### 2.2.2.4 Frequency design and transportation fare optimization

In mass transportation and multi modal networks, frequency design and transportation fare optimization are also proposed. Uchida et al. (Uchida et al., 2006) develop a multi-modal transport network model considering various travel modes including railway, bus, auto, and walking. Travelers are assumed to choose their multi-modal routes so as to minimize their perceived disutilities of travel following the probit based SUE formulation. Factors influencing the disutility of a multi-modal route include actual travel times, discomfort on transit systems, expected waiting times, fares and constants specific to transport modes. A local search algorithm based on sensitivity analysis is proposed to solve the problem. Two instances of this general formulation are presented in the paper: the optimal frequency design problem for public transport services and the anti-freezing admixture dispersion problem. Yoo et al. (Yoo et al., 2010) present a methodology for modelling the transit frequency design problem with variable demand. The objective of transit operator is to maximize travel demand. The passengers try to minimize their perceived travel time. The problem is modeled as a bi-level optimization model where the upper level operator is formulated as a non-linear optimization model to maximize demand while considering fleet size and frequency constraints. The lower level user problem is formulated as a capacity constrained SUE-ED. While the lower level problem is solved by the extant iterative balancing method, the overall problem is solved by the iterative gradient projection method. An example is provided to illustrate the model and solution algorithm. Although the method converges to a local solution, it is indicated that an optimal solution cannot be guaranteed. Ren et al. (2009) propose a transit assignment model for assessing the effects of the integrated implementation of en-route transit information systems and time-varying transit pricing systems. There are two classes of passengers: equipped with an information system or not. It is assumed that unequipped passengers make their choices according to stochastic user equilibrium, and the equipped passengers make their choices according to deterministic user equilibrium. A bi-level program is formulated to investigate the passengers' departure time choice behavior, route choice behavior, transit network performance, and transit operator's revenue. The lower level is a multi-class stochastic dynamic transit assignment model. A GA based solution method is proposed to solve the problem. The combined system cost and operators benefits under varied transit conditions are investigated with numerical examples.

### 2.2.3 Solution Methods for Traffic Assignment Problems

TAP is widely formulated as a bilevel optimization problem to take into account user equilibrium while optimizing single or multiple objectives for the entire system (Migdalas, 1995; Colson et al., 2007). Multi-level optimization is closely related to the economic Stackelberg problem (Stackelberg, 1952) and is rather used to model asymmetric games where a "leader" (system administrator) makes decisions considering the reasonable response of the "followers" (network users). The basic property of bi-level models is the involvement of two mathematical models, one being part of the other's constraints. Regarding TAP; the objective and constraints concerning OSE, DUE or SUE generally constitute the lower level, and objective and constraints concerning traffic management and control constitute the higher level. Many bi-level optimization models are developed according to the management of flow in the network, user equilibrium, demand type and traffic management/control subsystem. However, bi-level transportation problems that are related to the equilibrium problem constitute a special category, and most of the methods developed to solve bi-level problems can not be applied directly (Chen, 1992; Vincente & Calamai, 1994). The main reason for that is the possible existence of many path flow solutions. Moreover, even if the lower level problem is convex, additional difficulties arise due to the fact that the network taken into account can be very large and may require a sparse data structure. Accordingly, the following solution methods are proposed to solve bi-level transportation problems:

- **Exact methods:** Developed for a very limited number of models (Marcotte, 1983).

• **Heuristic methods:** Very effective to solve large scale problems quickly even though most of them are not proved to converge theoretically. Approaches reducing the problem to single level (Poorzahedy & Turnquist, 1982; Marcotte, 1983; Marcotte & Marquie, 1992), brach-and-bound strategies (LeBlanc, 1975; Chen & Alfa, 1991a), linear approximation (LeBlanc & Boyce, 1986; Ben-Ayed et al., 1988), and iterative assignment (Friesz, 1985; Cantarella et al., 1991a; Marcotte & Marquie, 1992; Yang et al., 1992; Smith & van Vuren, 1993) are widely used methods.

• **Local search methods:** The objective of these methods is to find a stationary point that might be a local optimum for bilevel problems or its derivates. Methods relying to sensitivity analysis (Fiacco, 1983; Tobin, 1986; Tobin & Friezs, 1988; Yang, 1997; Chiou, 1999) and gap functions (Fisk, 1984; Chen, 1992; Davis, 1994) are the most commonly used.

• **Meta-heuristics:** The technological advances and the increase of computational power make those kind of methods fairly attractive. Simulated annealing (Friezs et al., 1992; García & Marín, 2002; Xu et al., 2009) and genetic algorithm (Yin, 2000; Ceylan & Bell, 2005; Lee et al., 2006) are the most widely used methods.

Multistage traffic planning process that is widely used in practice, does not contain a single method explaining all characteristics of the demand, and is highly criticized (Boyce, 2007). The approach proposed to eliminate this deficiency is to add a feedback mechanism. Even in this case, convergence is not guarantied. Consequently, many integrated models based on different behavioral assumptions (generally, related to stochastic utility theory) are proposed (Lundgren & Patriksson, 1998; Boyce & Bar-Gera, 2004; Zhou et al., 2009a). We must note that the integration of the models for trip generation, trip distribution and especially mode choice stages to the main TAP can be fairly important for the construction of sustainable transportation models. The expected contribution of those combined models to sustainability can be greater than the solution of TAP alone.

## 2.3 Sustainability and Sustainable Development

There exists various definitions of sustainability and sustainable development in the literature (Beatley 1995; FHWA 2011; Schilleman and Gough 2012; NARC 2012).

Traditionally sustainability is narrowly defined with environmental concerns but it should also include other issues as well such as social and economical issues. Some examples of sustainability definitions are:

- Sustainable development *"meets the needs of the present without compromising the ability of future generations to meet their own needs."* (WCED 1987)

- *"...sustainability is not about threat analysis; sustainability is about system analysis. Specifically, it is about environmental, economic, and social systems interact to their mutual advantage or disadvantage at various space-based scales of operation."* (TRB 1997)

- *"A sustainable community is one that is economically, environmentally, and socially healthy and resilient. It meets challenges through integrated solutions rather than through fragmented approaches that meet one of those goals at the expense of the others. And it takes a long-term perspective–one that's focused on both the present and the future, well beyond the next budget or election cycle."* (ISC 1997)

- Environmental Sustainable Transportation (EST) is: *Transportation that does not endanger public health or ecosystems and meets needs for access consistent with (a) use of renewable resources at below their rates of regeneration, and (b) use of non-renewable resources at below the rates of development of renewable substitutes.* (OECD 1998)

- *"Sustainability is equity and harmony extended into the future, a careful journey without an endpoint, a continuous striving for the harmonious co-evolution of environmental, economical and socio-cultural goals."* (Mega and Peterson 1998)

- *"The common aim [of sustainable development] must be to expand resources and improve the quality of life for as many people as heedless population growth forces upon the Earth, and do it with minimal prosthetic dependence."* (Wilson 1998)

- *"A sustainable transport system is one that is accessible, safe, environmentally-friendly, and affordable."* (ECMT 2004)

- Sustainability is *"the capacity for continuance into the long term future. Anything that can go on being done on an indefinite basis is sustainable. Anything that cannot go on being indefinitely is unsustainable."* (Center of Sustainability 2004)

Litman (2014) summarize sustainability goals in three dimensions: Economical, Social and Environmental (Table 2.1). A system should address all three dimensions to be sustainable.

**Table 2.1**: Sustainability goals (Litman 2014)

| Economic | Social | Environmental |
|---|---|---|
| - Economic Productivity<br>- Economic Development<br>- Resources efficiency<br>- Affordability<br>- Operational efficiency | - Equity / Fairness<br>- Human safety, security and health<br>- Community development<br>- Cultural heritage preservation | - Climate change prevention<br>- Air, noise and water pollution prevention<br>- Non-renavable resources conservation<br>- Openspace preservation<br>- Biodiversity preservation |

## 2.4 Sustainable Transportation

With the technological and industrial advancements, transportation plays an important role in modern societies. Consequently, transportation systems has an important impact on sustainability and sustainable development. It is then crucial to achieve sustainability for transportation networks. Comprehensive performance evaluation is an important component of sustainable transport planning (Strader 2012). Comprehensive sustainability helps to identify "win-win solutions", which are strategies that help to achieve multiple objectives (VTPI 2008). For example, comprehensive analysis allows planners to identify the congestion reduction strategies that also help to achieve equity and environmental objectives. These integrated solutions can be considered the most sustainable. Narrowly-defined sustainability planning is a specialized activity, but broader analysis allows it to be incorporated into all planning activities (Nicolas, Pochet and Poimbeouf 2003). A more comprehensive definition is due to CST (2005) which states that a sustainable transportation system is one that

- allows the basic access needs of individuals and societies to be met safely and in a manner consistent with human and ecosystem health, and with equity within and between generations.

• is affordable, operates efficiently, offers choice of transport mode, and supports a vibrant economy;

• limits emissions and waste within the planet's ability to absorb them, minimize consumption of non-renewable resources, limits consumption of renewable resources to the sustainable yield level, reuses and recycles its components, and minimizes the use of land and the production of noise;

### 2.4.1 Sustainable Transportation within a Country or Regional Scope

#### 2.4.1.1 Sustainability Dimensions

**Economic Dimension** *Economic development* refers to a community's progress toward economic objectives such as increased income, wealth, employment, productivity and social welfare. *Welfare* (as used by economists) refers to the total human wellbeing and happiness. Economic policies are generally intended to maximize welfare, although this is difficult to measure directly. Instead, monetary income, wealth and productivity (such as gross domestic product [GDP]) are often used as economic indicators. But these indicators can be criticized on several grounds (Litman, 2005b).

• They only measure material wealth that is traded in a market and so overlook other factors that contribute to wellbeing.

• These indicators give a positive value to destructive activities that reduce people's health and self-reliance, and therefore increase their use of market goods (medical services, purchased rather than home-grown or gathered foods and fuels).

• In the way as they are typically used, these indicators do not reflect the distribution of wealth (although they can be used to compare wealth between different groups).

People often have significant *nonmarket* wealth ignored by conventional economic indicators, such as clean air and water, health, public resources, self reliance skills, the ability to farm and gather food, and social networks that provide security, education, entertainment, and other services. Market activities that degrade these free and low-cost resources make people poorer, forcing them to earn and spend more money for commercial replacements. Conventional economic indicators treat these shifts as entirely positive. More accurate indicators account for both the losses and gains of such changes.

People also seldom recognize diminishing benefits, because their financial expectations increase as they become wealthier. As consumers become wealthier, an increasing portion of their expenditures reflect status (also called *prestige* or *positional*) goods. Although such expenditures provide perceived benefits to individuals, they provide little or no net benefit to the society since as one consumer displays more wealth, others must match it to maintain status. If you purchase a mansion, I feel obliged to purchase an equal size home, even if we both end up with larger houses than we really use. In this way, a large increase in productivity and income may provide little gain in social welfare, particularly if it is directed at already wealthy consumers.

Transportation activities reflect these patters. In accessible communities, people can reach most destinations using low-cost modes such as walking, bicycle and public transit, but increased automobile dependency tends to reduce the performance of these modes. Increased vehicle travel and associated costs may provide little economic benefits; Zheng et al. (2011) states that beyond an optimal level, increased automobile travel reduces economic productivity. It makes nonmotorized travel difficult and dangerous. Low-cost modes receive less consideration in planning and investments. More dispersed land use patterns result in more trips beyond walking and cycling distances. As private vehicles become common, other modes lose status and consumers must own more costly vehicles to maintain prestige. As a result, motor vehicle ownership and use may increase with little net gain in accessibility or social welfare (Litman, 2005b).

Transportation can leverage other economic impacts. Vehicle and fuel expenditures tend to provide less business activity and employment than most other consumer expenditures, since they are mostly imported and they are capital rather than labor intensive. Such expenditures are particularly burdensome to the economies of developing countries that import petroleum. The increasing motor vehicle ownership and use increase road and parking facility costs, reduce productivity due to congestion, and harm certain industries, particularly those that require clean environments such as tourism, agriculture and fisheries.

Sustainable transportation economic indicators should reflect both benefits and costs of motor vehicle use, and the possibility that more motorized mobility reflects a reduction in overall accessibility and transportation diversity, rather than a net gain in social welfare. Increased mobility that provides little or negative net benefits to society can be considered to reduce sustainability, while policies that increase the net benefits from each unit of mobility can be considered to increase sustainability (Litman, 2005b). In Table 2.2, indicators relevant to economic dimension of sustainable transportation and their descriptions are provided (SUMMA, 2002; Litman, 2005b; GPI, 2008; Litman, 2014).

**Social Dimension** Transportation may have some social impacts on equity, human health, community livability (the quality of the local environment as experienced by people in an area) and community cohesion (the quality of interactions among people living in a community), and also on historic and cultural resources (such as historic sites and traditional community activities, and aesthetics (Litman, 2005b)).

Transportation equity can be evaluated by comparing transport options, service quality and impacts on different groups, particularly on economically, physically and socially disadvantaged people (FHWA & FTA, 2002; Caubel, 2004; Litman, 2005a). Transportation health impacts include accident injuries, pollution illness, and inadequate physical activity. Policies that increase non-motorized travel improve mobility for disadvantaged people and tend to support sustainable transportation. Community livability and cohesion (Litman, 2006) can be measured using surveys that evaluate impacts on the human environment, including interactions among neighbors, and how this affects property values and business activity. Historic and cultural resources can be evaluated using surveys which ascertain the value people place on them (Litman, 2005b). In Table 2.3, indicators relevant to economic dimension and their descriptions are provided (Anielski, 2001; EEA, 2000; SUMMA, 2002; Eads, 2003; Litman, 2005b; Jeon et al., 2008; GPI, 2008; Litman, 2014).

**Environmental Dimension** Environmental impacts include various types of air pollution (including gases that contribute to climate change), noise, water pollution, depletion of nonrenewable resources, landscape degradation (including pavement or damage to ecologically productive lands, habitat fragmentation, hydrological disruption due to pavement), head island effects (increase ambient temperature resulting from pavement), and wildlife deaths from collisions. Various methods can be used to measure these impacts and quantify their ecological and human costs (EEA, 2001; FHWA, 2004; Litman, 2004).

Of course there is considerable uncertainty about many of these costing methodologies and the resulting values. There are various ways of dealing with such uncertainty, including improved analysis methodologies, use of cost ranges rather than point values, and establishment of reference standards (such as acceptable levels of ambient air pollution and noise levels). Many existing environmental cost studies are incomplete, for example, many air pollution costs studies only include a portion of the types of harmful motor vehicle emissions, and many only consider human health impacts, ignoring ecological, agricultural and aesthetic damages (Litman, 2004). In Table 2.4, indicators relevant to economic dimension and their descriptions are provided (Anielski, 2001; EEA, 2000; SUMMA, 2002; Litman, 2005b; GPI, 2008; Jeon et al., 2008; Litman, 2014).

**Table 2.2**: Economic indicators of sustainable transportation (SUMMA, 2002; Litman, 2005b; GPI, 2008; Litman, 2014)

| Indicator | Description |
|---|---|
| Commute Time | Average door-to-door commute travel time. |
| Employment Accessibility | Job opportunities and Commercial services within 30 minutes travel time. |
| Vehicle Travel | Per capita motor vehicle-mileage, particularly in urban-peak conditions. |
| Mode split | Portion of travel made by non-automobile modes: walking, cycling, rideshare, public transit and telework. |
| Congestion delay | Per capita traffic congestion delay. |
| Travel costs | Portion of household expenditures devoted to transport. |
| Transport cost efficiency | Transportation costs as a portion of total economic activity, and per unit of GDP. |
| Facility costs | Per capita expenditures on roads, parking and traffic services. |
| Crash costs | Per capita monetary crash costs. |
| Mobility management | Implementation of mobility management programs to address problems and increase transport system efficiency. |
| Affordability | Portion of households expenditures devoted to transport. |
| Pricing reforms | Portion of transport costs that are efficiently priced. |
| Airplane power consumption | Fossil fueled, wind, solar or bio-generated power consumption. |

**Table 2.3**: Social indicators of sustainable transportation (Anielski, 2001; EEA, 2000; SUMMA, 2002; Eads, 2003; Litman, 2005b; Jeon et al., 2008; GPI, 2008; Litman, 2014)

| Indicator | Description |
|---|---|
| User rating | Overall satisfaction of transport systems by disadvantaged users. |
| Safety | Per capita crash disabilities and fatalities. |
| Fitness | Portion of population that walks and cycles sufficient for fitness and health (min. 15 min daily) |
| Community livability | Degree to which transport activities support community livability objectives (local environmental quality). |
| Affordability | Portion of budget spent on transport by lower income households. |
| Disabilities | Quality of transport facilities and services for disabled people. |
| Commuting time | Average door-to-door commute travel time. |
| Auto crashes | Per capita number of injuries or deaths. |
| Equity impacts | Fair distribution of costs and benefits among different groups in society. |
| Accessibility | The time required to reach basic services. |
| Mobility | Traffic speed and roadway level-of-service. |
| Community livability | Degree to which transport activities support community livability objectives. |
| Cultural preservation | Degree to which cultural and historic values are reflected and preserved in transport planning decisions. |
| Aircraft movements | Arrivals (hourly, monthly, yearly), Departures (hourly, monthly, yearly) |

**Table 2.4**: Environmental indicators of sustainable transportation (Anielski, 2001; EEA, 2000; SUMMA, 2002; Litman, 2005b; GPI, 2008; Jeon et al., 2008; Litman, 2014)

| Indicator | Description |
|---|---|
| Climate change emis. | Emissions of greenhouse gasses which contributes to global warming. Per capita fossil fuel consumption, and emissions of $CO_2$. |
| Other air pollution | Emissions of pollutants which affect harm and damage buildings. Per capita emissions of "conventional" air pollutants (CO, VOC, NOx, particulates, etc.). |
| Air pollution | Frequency of air pollution standard violations. |
| Noise pollution | Portion of population exposed to high levels of traffic noise. |
| Emis. to soil/ water | Emissions of pollutants to soil and water, wastewater from manufacture and maintenance, runoff from roads etc. |
| Resource efficiency | Non-renewable resource consumption in the production and use of vehicles and transport facilities. |
| Land use impacts | Daily individual consumption of public space for transport and parking. Space required for transport infrastructure. Per capita land devoted to transportation facilities. |
| Habitat protection | Preservation of high-quality wildlife habitat (wetlands, old-growth forests, etc.). |
| Habitat fragmentation | Average size of roadless wildlife preserves. |
| Ecological intrusion | Impacts of transport on flora and fauna. |
| Waste | Transport vehicle and infrastructure create large amounts of waste during their life cycle. |
| Airplane pollutant | NOx, CO2, N20, CO, NMVOC and PM10 (g) emissions of airplanes |
| Airplane noise | Day, evening and night LAeq (dB) and LA max (A-weighted long term average and peak sound levels |

#### 2.4.1.2 Evaluation of Sustainability of Transportation Networks

Considering the conflicting natures of indicators, developing an overall sustainability measure emerges as a difficult but the required task. Diverse indicators are proposed by many researchers but they are generally not studied in a unified manner. Nonetheless, several efforts have been made to provide economic, social and environmental indicators for practical implementations. In the context of the SUMMA project, the researchers identify eighteen outcomes related to the objectives and the goals that are mentioned in the definition of the sustainable transportation provided by the Council of EU (Ahvenharju et al., 2004). Related to those outcomes, sixty indicators are proposed and evaluated based on monetary values. The STPI project of the Canadian Center for Sustainable Transportation considers fourteen indicators based on the data extracted from the Canadian databases (Gilbert et al., 2002). Similarly, some indicators related to the environmental performance of transport systems of the European member countries are identified. Then, the annually collected data have been presented in the form of fact sheets and reports within the scope of the TERM project of the European Environment Agency (EEA, 2010). In another study, Black (2002) considers nine transport sustainability measures, among which the vehicle kilometer traveled is the most representative. Together with this indicator, the fuel consumption and the GDP are combined into a single sustainable transport and potential mobility index.

Yevdokimov & Han (2004) use the genuine progress indicator as an aggregate sustainability criterion within a system dynamics approach to analyze the potential changes in the sustainability of the transport systems with respect to the policy variables. Rassafi & Vaziri (2005) construct composite indices from a selected set of economic, environmental and social indicators. Then the proposed composite indices are aggregated by the Concordance Analysis Technique to obtain comprehensive sustainability indices, which are used to rank, compare and classify the selected countries according to the sustainability level of their transport systems. Campos & Ramos (2005) propose the sustainable mobility index in urban areas that is a simple weighted linear combination of sustainability related transport and land-use indicators. The indicator weights are derived with a widely applied multi-criteria decision making (MCDM) method known as the analytic hierarchy process (AHP) (Saaty, 1980). Amekudzi et al. (2009) present a sustainability footprint framework that may be used in analyzing the impacts of transportation and other infrastructure systems on regional sustainable development. Bojković et al. (2010) introduce a MCDM outranking approach, namely the ELECTRE method for evaluating the transport sustainability at the macro level. Jeon et al. (2010) evaluate three transport and land-use scenarios at the urban level using the simple weighted average method in conjunction with composite sustainability indices and a range of performance measures.

Most of the studies mentioned above consider composite indices to evaluate the sustainability of the transport systems. We note that considering composite indices enables us to obtain a full comparison of alternate systems and we also prefer to focus on constructing a composite index from multiple indicators. Sustainability is based on the balanced development concept and therefore, the non-compromise alternatives are of special importance. To identify such preferred alternatives, it is crucial to consider the interaction between sustainability indicators. However, the proposed composite indices are based on the weighted average aggregation method, which ignores the interactions between sustainability indicators. In order to fill this gap in the literature, we propose a method that takes the indicator dependencies into account to identify the non-compromise alternatives.

### 2.4.2 Sustainable Transportation within an Urban Scope

To evaluation methods presented in previous section, here, we present studies that offer methods to improve a traffic network directly. To offer such improvements, first mathematical objectives and traffic flow models are proposed. Then, optimization methods are developed. The traffic assignment models are widely utilized in these studies to model the traffic networks. We present these studies in three main dimensions of sustainability.

#### 2.4.2.1 Objectives, Policies and Criteria

Transportation is an important social and economical activity causing the following undesirable consequences (Klein et al., 1993):

- air pollution
- accidents
- congestion
- depletion of petroleum and other natural resources
- social inequality
- noise pollution
- energy consumption
- pollution of soil and water sources

The increase rate of the motorized vehicles quantity is greater than the increase rate of human population on Earth which also causes an important problem (Haq, 1997). Planners and environmental experts predict that this orientation will cause the inability to meet economical, environmental and social needs of the present and future generations. The urge to find a solution to this problem has risen to the notion of sustainable transportation (Spaethling, 1996). Despite of many definitions (World Commission on Environment and Development, 1987; WBA, 1996; Transportation Research Board, 1997; Mega & Pedersen, 1998; Wilson, 1998; OECD, 1998; MOST, 1999; ECMT, 2004; CST, 2005) sustainable transportation consists of infrastructure investments and transportation policies serving many objectives covering economical development, environmentally-conscious management, and social justice. The objective is to achieve specific economical, social and environmental goals, while streamlining the usage of transportation system, and at the same time, not to decrease the ability of future generations to achieve the same goals. In parallel to the sustainable development concept, the following points are also desired to be improved and/or conserved (Litman, 1999):

- employment
- security
- efficiency
- accessibility
- livability
- mobility
- justice
- conservation of environment

Unfortunately the methods yielding those goals consistently and exhaustively are almost missing (Lindquist, 1998). Sustainable transportation is widely discussed but not much realized for urban transportation planning.

To achieve those goals, sustainable transportation policies have to be determined.

The actual dependence to fossil fuel and the desired levels of efficiency for transportation systems are most often in contradiction with environmental objectives and make the development of convenient policies for transportation sector rather difficult (Mason, 1994). According to World Bank's definition, a sustainable transportation policy reaches to balance not by hazard but by conscious decisions, and determines compromises and uses win-win political tools (WBA, 1996). Many researchers examined policies supporting sustainable transportation (Richardson et al., 1993; Deakin, 1993; Nijkamp, 1994; Sperling & Shaheen, 1995; ECO, 1995; Ewing, 1995). Those policies can be grouped as follows:

- **Pricing policies:** pricing transportation systems and services, reflecting social and environmental costs in order to assign resources optimally.

- **Technology policies:** technology contributes by making information accessible to users and reducing environmental destruction.

- **Non-motorized transportation policies:** Among the transportation modes, walking and cycling represent the positive contribution end and driving a car alone represents the negative contribution end. Thus, policies deterring the use of motorized vehicles are needed.

- **Regulatory and prohibitive policies:** some activities may have to be regulated or completely prohibited.

- **Traffic management policies:** traffic flow conditions can be improved by some traffic management methods, and improved flow contributes to sustainable transportation.

- **Education policies:** to achieve sustainability system, users of transport systems must change their existing behavior by choosing more efficient vehicles and driving their vehicles less aggressively.

- **Land usage and transportation policies:** it seems to be difficult to achieve sustainable transportation objectives without considering land usage and transportation policies together.

To obtain a sustainable transportation system those policies should be applied jointly (Transportation Research Board, 1997).

Another important issue encountered is the lack of consensus on a quantitative analysis of sustainable transportation content accepted by all parties, and it is ambiguous even qualitatively (Peake & Hope, 1994). Thus, performance criteria are needed to determine transportation policies that achieve the objectives associated with sustainability (Gardner & Carlsen, 1996; NSTC, 1998). Traditionally used criteria such as road service quality, average velocity and delay, parking convenience, accident per kilometer (Meyer, 1999; Homburger et al., 2007) focus primarily on motorized travel quality, and do not take into account secondary impacts. Moreover, most of the existing criteria are quantified based on aggregated data for a limited number of vehicles. However, many undesirable effects like vehicle emission are clearly non-linear, and such approximations cause severe errors (Zietesman & Rilett, 2001). Even more importantly, considering only average or aggregated information may lead to overlook many concepts contributing to sustainability.

With those points, the following principles are recommended for determining the transportation performance criteria: exactness, data quality, comparability, easily comprehensibility, accessibility, transparency, convenient cost, clear effect, convenience to determine objective (Hart, 1997; Marsden et al., 2006). In the literature and applications, there exist a considerable number of studies that contain hypotheses which sometimes overlap and sometimes contradict, on the subject of what should be the sustainability performance criteria (Anielski, 2001; Gilbert et al., 2002; EPA, 2003a; Gudmundsson, 2003; FHWA, 2004; Jeon & Amekudzi, 2005; Litman & Rickert, 2005; GPI, 2008; Hartgen et al., 2008; Jeon et al., 2008; Litman, 2008a; Zietesman et al., 2008; EEA, 2008).

#### 2.4.2.2 Multi-objective Sustainable Traffic Assignment Problem

**Economical Objectives** In the literature, economical objectives are usually toll revenue maximization and capacity investment minimization in urban transportation networks in the framework of road transportation. Revenue maximizing toll pricing dates back to previous centuries, with the implementation of tolling systems in the UK, USA and other countries (Levinson, 1998). Currently, high-ways are usually tolled and are viewed as a revenue source, but toll pricing is generally not optimized. Revenue maximizing toll optimization models are proposed in several articles (Yang et al., 2004; Roch et al., 2005; Chang & Hsueh, 2006; Meng & Wang, 2008). In network design problem, the investment cost is an important cost for the improvement of road capacities. This cost is also considered in the literature along with the toll pricing (Magnanti & Wong, 1984; Friesz, 1985; Ben-Ayed et al., 1988; Chiou, 2005; Dimitriou et al., 2007). Considering both toll pricing, capacity improvement and other traffic assignment strategies in the same framework, it becomes possible to improve economical benefits of the transportation network.

**Social Objectives** Social objectives cover mobility, accessibility, equity and safety needs of traffic network users. The most basic social objective is the minimization of total network travel time which is widely studied in the literature (Chen & Alfa, 1991b; Fumero et al., 1999; Chen et al., 2004; Maher et al., 2005; Long et al., 2010). Also, under stochastic user equilibrium, the minimization of *perceived* travel time is considered (Stewart, 2007). But travel time by itself is not sufficient in the framework of social dimension. More recent studies also consider the equity as a social objective. Equity can be measured in many ways, toll pricing discussed previously affects the poor more that the rich, so Wu et al. (2012) propose the equity in congestion pricing. On the other hand, users may not benefit the same from the road improvements in the context of spacial accessibility, so Delafontaine et al. (2011) propose the equity in accessibility. Another negative effect of urban transportation is the road accidents which are also considered a major social cost to the community (Shefer, 1994; Noland et al., 2008).

**Environmental Objectives** As urban transportation is mainly based on fossil fuels currently, environmental costs should also be considered in the framework of sustainable transportation (EEA, 2001; Litman, 2004; FHWA, 2004). The most importation objective in environmental dimension is the minimization of gas emissions that have negative impacts on human health and climate. There are mainly two approaches in the literature to measure the emission of cars. The simplest approach is the use of emission factors (Nagurney, 2000a,b; Rahman & Grol, 2005; de Ceuster et al., 2007). This approach only considers the number of cars using a road discarding the travel speed and the congestion effects. But most of the emission occurs on congested networks while cars travel at slower speeds. So, instead of emission factors, emission functions are proposed (Rilett & Benedek, 1994;

Gkatzoias et al., 2007). Using emission functions, travel speed is also considered in the calculation of the emissions. As a result, the negative effects of congestion can be calculated more accurately. Yin & Lawphongpanich (2006) propose an emission function in terms of traffic flow, where the coefficients are equivalent to those in TRANSYT 7F (Rilett & Benedek, 1994). Afandizadeh et al. (2012) propose a multi objective model including environmental objective and use the VISUM software (PTV, 2013) to calculate the emissions. Kolak et al. (2013) consider the EURO standard issued by EEA (Gkatzoias et al., 2007) in the calculation of road vehicle emissions.

Although there are some articles studying multiple objectives in one model (Afandizadeh et al., 2012; Chen & Yang, 2012) using DUE, the models with SUE are missing in the literature. Moreover, existing models convert the multi-objective optimization model to single objective. As a result, only one optimal solution is proposed to the decision makers. But the trade-offs resulting from this conversion may not always be desirable for decision makers. Our approach to the problem is to offer a set of solutions to the decision makers. Not any member of this set of solutions should be worse than any other solution in the set with respect to all the objectives. This solutions are called Pareto-optimal solutions (Deb et al., 2002) and they offer decision makers a great flexibility in making the final decision. Our model offers this flexibility. We propose a model which deal with multiple objectives and we consider stochastic user equilibrium. In this thesis, we use this model to solve a problem with two objectives but the model can easily be expanded to include additional sustainability objectives.

# 3 MULTICRITERIA SUSTAINABILITY EVALUATION OF TRANSPORT NETWORKS

## 3.1 Evaluation Framework

It is crucial to select appropriate indicators in order to identify objectively if a transportation system is sustainable. The indicators selected in this study capture economic, social and environmental objectives, mostly rely on existing data from the European statistical databases. The selected indicators are related to the most transportation sectors, but they mainly concentrate on the road transport, which is mostly held responsible for unsustainable trends. We have expressed indicators in units that would allow comparing countries objectively; for example, some indicators are expressed relative to the GDP or the population size. The GDP is the best known measure of macro-economic activity and a standard benchmark used by policy makers. For some indicators, we have taken into account their change towards sustainability over a certain time period. Some indicators are based on the statistical data and some are based on the survey results and the perception of network users. In summary, we have identified eight economic, thirteen social indicators and fourteen environmental as given in Table 3.1 and Table 3.2. Environmental indicators are related to energy usage and emission data, economic indicators are more related to transportation habits and consumption, and social indicators reflect accidents (with injuries or fatalities), quality of transport or time spend for transportation.

**Table 3.1**: Indicators selected to evaluate the transportation network sustainability

| | | | |
|---|---|---|---|
| ECO | Economic Dimension | | |
| | EC1 | Use of alternative modes of transport | |
| | | EC11 | Road share of inland freight transport |
| | | EC12 | Car share of inland passenger transport |
| | | EC13 | Share of non-motorized individual transport |
| | EC2 | Economic support of transport to the economy | |
| | | EC21 | Volume of freight transport relative to GDP |
| | | EC22 | Volume of passenger transport relative to GDP |
| | | EC23 | Contribution of transport sector to GDP |
| | EC3 | Efficiency of operations | |
| | | EC31 | Share of non-road transport infrastructure investments |
| | | EC32 | Logistics performance index |
| SOC | Social dimension | | |
| | SC1 | Safety | |
| | | SC11 | People killed in road accidents |
| | | SC12 | Number of deaths per million inhabitants |
| | SC2 | Affordability | |
| | | SC21 | Price indices for transport (All Items) |
| | | SC22 | Price indices for transport - Railways |
| | | SC23 | Price indices for transport – Sea and inland waterways |
| | | SC24 | Total household consumption for transport |
| | SC3 | Ease of use | |
| | | SC31 | % of people taking 20 mn or less time to get to work/training place |
| | | SC32 | Rural Access Index |
| | SC4 | Quality of use | |
| | | SC41 | Satisfaction with public transport |
| | | SC42 | Quality of roads |
| | | SC43 | Quality of rail infrastructure |
| | | SC44 | Quality of port infrastructure |
| | | SC45 | Quality of air transport infrastructure |

| | | | |
|---|---|---|---|
| ENV | Environment dimension | | |
| | EN1 | Use of energy | |
| | | EN11 | Energy consumption of transport relative to GDP |
| | | EN12 | Energy consumption of transport per capita |
| | | EN13 | Energy consumption of road transport |
| | | EN14 | Share of renewable energy in fuel consumption of transport |
| | EN2 | Reuse and Recycling | |
| | | EN21 | End of life vehicles : Total waste per capita |
| | | EN22 | End of life vehicles : Reuse and recovery rate |
| | | EN23 | End of life vehicles : Reuse and recycle rate |
| | EN3 | Impacts on ecosystem | |
| | | EN31 | Greenhouse gases emission from all transport modes |
| | | EN32 | Greenhouse gases emission from all transport modes per capita |
| | | EN33 | Greenhouse gases emission from road transport |
| | | EN34 | Average CO2 emissions per km from new passenger cars |
| | EN4 | Impacts on human health | |
| | | EN41 | Emissions of carbon monoxide (CO) |
| | | EN42 | Emissions of nitrogen oxides (NOx) |
| | | EN43 | Emissions of particulate matter from transport |

**Table 3.2**: Details about the indicators

| Indicator | Year(s) | Unit | Improving Direction | Source |
|---|---|---|---|---|
| EC11 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EC12 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EC13 | 2009 | av. % | $\Uparrow$ | Eurobarometer |
| EC21 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EC22 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EC23 | 2000-2010 | av. % | $\Uparrow$ | Eurostat, WIOD* |
| EC24 | 2008-2011 | av. % | $\Uparrow$ | Eurostat |
| EC31 | 2000-2009 | av. % | $\Uparrow$ | OECD |
| EC32 | 2007, 2010 | av. % | $\Uparrow$ | World Bank |
| SC11 | 2000-2009 | av. % change | $\Downarrow$ | Eurostat |
| SC12 | 2000-2008 | average | $\Downarrow$ | Eurostat |
| SC21 | 2000-2011 | av. % change | $\Downarrow$ | Eurostat |
| SC22 | 2000-2011 | av. % change | $\Downarrow$ | Eurostat |
| SC23 | 2000-2011 | av. % change | $\Downarrow$ | Eurostat |
| SC24 | 2000-2010 | av. % | $\Downarrow$ | Eurostat |
| SC31 | 2009 | av. % | $\Uparrow$ | Eurobarometer |
| SC32 | 1999-2003 | % | $\Uparrow$ | World Bank |
| SC41 | 2009 | av. % | $\Uparrow$ | Eurobarometer |
| SC42 | 2009-2010 | % | $\Uparrow$ | WEF |
| SC43 | 2009-2010 | % | $\Uparrow$ | WEF |
| SC44 | 2009-2010 | % | $\Uparrow$ | WEF |
| SC45 | 2009-2010 | % | $\Uparrow$ | WEF |
| EN11 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EN12 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EN13 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EN14 | 2006-2010 | av. % | $\Uparrow$ | Eurostat |
| EN21 | 2009 | kg | $\Downarrow$ | Eurostat |
| EN22 | 2006-2009 | av. % | $\Uparrow$ | Eurostat |
| EN23 | 2006-2009 | av. % | $\Uparrow$ | Eurostat |
| EN31 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EN32 | 2000-2010 | kg (average ) | $\Downarrow$ | Eurostat |
| EN33 | 2000-2010 | av. % change | $\Downarrow$ | Eurostat |
| EN34 | 2000-2009 | av. % change | $\Downarrow$ | Eurostat |
| EN41 | 2000-2010 | av. % change | $\Downarrow$ | EEA |
| EN42 | 2000-2010 | av. % change | $\Downarrow$ | EEA |
| EN43 | 2000-2010 | av. % change | $\Downarrow$ | EEA |

## 3.2 Methodology

Let us consider a finite set of alternatives $\mathcal{A} = \{a_1, \ldots, a_m\}$ and a finite set of criteria $\mathcal{N} = \{c_1, \ldots, c_n\}$ for a multicriteria decision problem. In our setup, an alternative represents the transport system of a country, and a criterion corresponds to a sustainability indicator. Each alternative $a_j \in \mathcal{A}$ is associated with a profile $\mathbf{x}^j = \left(x_1^j, \ldots, x_n^j\right) \in [0,1]^n$, where $x_i^j$ denotes the partial score of $a_j$ associated with the criterion $c_i$. Defining the scores on the interval $[0,1]$ does not detract from the generality of our analysis; it is only required to define all the partial scores on the same interval scale; i.e., using same linear transformation (Marichal & Roubens, 2000).

An aggregate score associated with each profile can be computed by using an aggregation operator which takes into account the importance weights of criteria. The alternatives can then be ranked and the best alternative is selected according to the aggregate scores. If the criteria are independent, then the most often used aggregation operators are the weighted arithmetic means (Marichal, 2000). The aggregate score associated with the profile $\mathbf{x}^j$ is then given by $C_{\mathbf{w}}(\mathbf{x}^j) = \sum_{i=1}^n w_i x_i^j$, where $w_i \geq 0$ is the weight of the criterion $c_i$ , $i = 1, \ldots, n$, and $\sum_{i=1}^n w_i = 1$. However, the assumption of criteria independence is rarely justified. To model the interaction between multiple criteria, it has been proposed to substitute the weight vector $\mathbf{w}$ with a monotonic set function $\mu$ on $\mathcal{N}$. This approach allows us to model not only the importance of each criterion but also the importance of coalitions of criteria (Grabisch, 1997; Marichal, 2000; Marichal & Roubens, 2000). Such a monotonic set function $\mu$ is called the Choquet capacity (Choquet, 1953) or a fuzzy measure (Sugeno, 1977). A suitable aggregation operator that generalizes the weighted arithmetic mean, when the interactions between the criteria exist, is the discrete Choquet integral with respect to the fuzzy measure $\mu$ (Grabisch, 1996; Marichal, 2000). Indeed, the aggregation operations based on the family of fuzzy integrals include many operators such as weighted mean, min, max, median, or ordered weighted average. Thus, these operations express a variety of decision maker behaviors (severity, compromise, tolerance) and various effects of interaction between criteria (Grabisch, 1997). In section 3.2.2, we briefly present the definition of the Choquet integral and its principal properties as a multicriteria aggregation operator. In section 3.2.1 we discuss another multicriteria decision making method, namely the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS).

This technique is based on the assumption of criteria independence, and we shall utilize it to compare the results obtained through the Choquet Integral method.

### 3.2.1 TOPSIS

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method is presented in (Chen & Hwang, 1992), with a reference to Hwang & Yoon (1981). The basic principle is that the chosen alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution. The TOPSIS procedure consists of the following steps:

1. Assuming that $x_i^j$ values are normalized, the weighted normalized value $v_i^j$ is calculated as

$$v_i^j = w_i x_i^j \quad i = 1, \dots, n, \ j = 1, \dots, m. \tag{3.1}$$

2. Let us denote the set of benefit type of criteria and the set of cost type of criteria by $\mathcal{N}'$ and $\mathcal{N}''$, respectively. Basically, $\mathcal{N}'$ and $\mathcal{N}''$ form a partition of the set of criteria $\mathcal{N}$, i.e., $\mathcal{N}' \cup \mathcal{N}'' = \mathcal{N}$ and $\mathcal{N}' \cap \mathcal{N}'' = \emptyset$. Without loss of generality, we assume that the first $|\mathcal{N}'|$ indicators are of benefit type, where $|\mathcal{N}'|$ denotes the cardinality of $\mathcal{N}'$. Then the ideal and negative-ideal solutions are defined as

$$\begin{aligned} \mathbf{v}^+ &= \left(v_1^+, \dots, v_n^+\right) \\ &= \left(\max_j v_1^j, \max_j v_2^j, \dots, \max_j v_{|\mathcal{N}'|}^j, \min_j v_{|\mathcal{N}'|+1}^j, \dots, \min_j v_n^j\right) \end{aligned} \tag{3.2}$$

and

$$\begin{aligned} \mathbf{v}^- &= \left\{v_1^-, \dots, v_n^-\right\} \\ &= \left(\min_j v_1^j, \min_j v_2^j, \dots, \min_j v_{|\mathcal{N}'|}^j, \max_j v_{|\mathcal{N}'|+1}^j, \dots, \max_j v_n^j\right). \end{aligned} \tag{3.3}$$

3. The distances of each alternative to the ideal and the negative-ideal solutions are calculated using the Euclidean norm

$$d_+^j = \sqrt{\sum_{i=1}^n (v_i^j - v_i^+)^2}, \quad j = 1, \dots, m \tag{3.4}$$

and

$$d_-^j = \sqrt{\sum_{i=1}^n (v_i^j - v_i^-)^2}, \quad j = 1, \dots, m. \tag{3.5}$$

4. The relative closeness of each alternative to the negative-ideal solution is given by

$$C^j = d_-^j / (d_+^j + d_-^j), \quad j = 1, \dots, m. \tag{3.6}$$

The best alternative is considered to be the one with the highest $C^j$ value.

### 3.2.2 The Choquet Integral

As emphasized before, we consider the interaction among criteria and propose to model it using a discrete fuzzy measure. Let $P(\mathcal{N})$ denote the power set of $\mathcal{N}$ . A discrete fuzzy measure on $\mathcal{N}$ is a set function $\mu : P(\mathcal{N}) \to [0, 1]$ satisfying the following conditions: (i) $\mu(\emptyset) = 0$, $\mu(\mathcal{N}) = 1$, and (ii) $\mu(\mathcal{N}_1) \leq \mu(\mathcal{N}_2)$ whenever $\mathcal{N}_1 \subseteq \mathcal{N}_2 \subseteq \mathcal{N}$ (monotonicity condition). For each subset of indicators $\tilde{\mathcal{N}} \subseteq \mathcal{N}$, $\mu(\tilde{\mathcal{N}})$ can be interpreted as the weight of the importance of the coalition $\tilde{\mathcal{N}}$. Basically, the monotonicity means that the weight of a subset of criteria cannot decrease when a new criterion is added to it. The discrete Choquet integral of the profile $\mathbf{x}^j$ with respect to the fuzzy measure $\mu$ is defined by

$$C_\mu^j = C_\mu(\mathbf{x}^j) = \sum_{i=1}^n \mu\left(\mathcal{N}_{[i]}^j\right)\left(x_{[i]}^j - x_{[i-1]}^j\right), \tag{3.7}$$

where [.] indicates a permutation such that $0 \leq x_{[1]}^j \leq \ldots \leq x_{[n]}^j \leq 1$ with the convention that $x_{[0]}^j = 0$ and $\mathcal{N}_{[i]}^j = \{c_{[i]}, \dots, c_{[n]}\}$ for all $i = 1, \dots, n$. When

$\mu$ is additive, that is, when the criteria are independent, the Choquet integral is equivalent to the weighted arithmetic mean; i.e., $C_\mu^j = \sum_{i=1}^n \mu(\{c_i\})x_i^j$.

In real-life applications, it is really hard to estimate the higher order interactions between the multiple sustainability indicators. Therefore, we focus only on the pairwise interactions and use a special case of the Choquet integral, which is known as the 2-additive Choquet integral (Grabisch, 1997) and expressed in the following interpretable form:

$$\begin{aligned} C_\mu^j = \quad & \sum_{i=1}^n \Big( w_i - \frac{1}{2} \sum_{k \neq i} |u_{ik}| \Big) x_i^j \\ & + \sum_{u_{ik}>0} u_{ik} \min\{x_i^j, x_k^j\} + \sum_{u_{ik}<0} |u_{ik}| \max\{x_i^j, x_k^j\}. \end{aligned} \tag{3.8}$$

Here, $u_{ik}$ represents the interaction between the criteria $c_i$ and $c_k$ that takes values in the interval $[-1, 1]$. The $u_{ik}$ parameters satisfy the condition that $w_i - (1/2)\sum_{k\neq i} |u_{ik}| \geq 0$ for all $i = 1, \ldots, n$. This condition ensures that the overall importance of interactions associated with a specific criterion is always smaller than the weight of that criterion. The interpretations of the interaction terms can be summarized as follows:

• $u_{ik}$ takes a positive value for a pair of criteria $(c_i, c_k)$, if the alternative with better scores for both criteria is preferable by the decision maker. To reflect the importance of having better scores on both criteria, the overall performance is calculated based on the worse score and the level of importance is quantified by specifying the value of $u_{ik}$.

• $u_{ik}$ takes a negative value, if the decision maker is satisfied with the alternative, which has a reasonably good score in at least one of the criteria $c_i$ and $c_k$. When $u_{ik}$ takes a larger negative value, the effect of the lower score gets less significant.

• the value of zero implies that there is no interaction between the two criteria considered, and it leads to the classical weighted sum based on the $w_i$ parameters.

The normalized scores $x_i^j$ and the coefficients of importance $w_i$ and $u_{ik}$ are specified using a special evaluation method named as MACBETH which is described in section 3.2.3.

### 3.2.3 The MACBETH Procedure

The Measuring Attractiveness by a Categorical Based Evaluation TecHnique (MACBETH), is a Multi-Attribute Utility Theory (MAUT) method, which is based on the comparisons between different situations (which identify the context) made by the decision-makers. MACBETH describes these situations with, on one hand, elementary performance expressions, and on the other hand the aggregated ones. The principle is to translate the qualitative information generally obtained from the experts, into quantitative information (Bana e Costa et al., 2005). In this study, we use MACBETH to determine the criteria weights and interactions and to obtain the normalized performance values of alternatives with respect to attributes.

#### 3.2.3.1 Elementary Performance Expression Step

The first decision is the preference determination between available options. Once the preference determination is made, the preference strengths are determined by the experts. Let $a_j$ and $a_l$ denote alternative (or situation) $j$ and alternative $l$ respectively. Let $x_i^j$ and $x_i^l$ be partial scores (or performance values) for criterion $i$ of alternative $j$ and alternative $l$, respectively. Let $h$ be the preference strength where the strength can take value between 0 and 6 (*null, very weak, weak, moderate, strong, very strong, extreme*). Then, if the experts for criterion $i$ prefers $a_j$ to $a_l$ with strength $h$ then $a_j \succ^h a_l \Leftrightarrow x_i^j - x_i^l = h\alpha$ where $\alpha$ is a coefficient necessary to meet the condition $x_i^j, x_i^l \in [0, 1]$. If the decision maker is indifferent (*null*) between the situations, then $a_j \approx a_l \Leftrightarrow x_i^j = x_i^l$.

The quantification of the performance expressions is made by solving the equation system resulting from the expressions of all the preference strengths $h$ between $a_j$ and $a_l$, written as $x_i^j - x_i^l = h\alpha$. We briefly illustrate the procedure with a numerical example.

Consider alternatives $a_1, a_2, a_3$ with the following order and strengths of preferences: $a_{\text{good}} \succ^{\text{strong}} a_3 \succ^{\text{very strong}} a_2 \succ^{\text{moderate}} a_1 \succ^{\text{week}} a_{\text{neutral}}$. Then we have to solve the following equation system to find $mathrmx_i$.

$$
\begin{aligned}
x_i^{\text{good}} - x_i^3 = 1 - x_i^3 &= 4\alpha \\
x_i^3 - x_i^2 &= 5\alpha \\
x_i^2 - x_i^1 &= 3\alpha \\
x_i^1 - x_i^{\text{neutral}} = x_i^1 - 0 &= 2\alpha
\end{aligned}
$$

By using any standard technique that solves system of equations, we have: $x_i^1 = 0.1429, x_i^2 = 0.3571, x_i^3 = 0.7143$ and $\alpha = 0.0714$.

This procedure enables that the elementary performance scores are defined defined on the interval $[0, 1]$ in a commensurate way.

As the number of alternatives increases, pairwise comparisons become a cumbersome task. In that case, if the alternatives are evaluated with quantitative values, a simpler method to obtain the elementary performance scores is advised by Clivillé et al. (2007). First, good and neutral values are identified for a given criterion. Then, a few number of intermediate threshold values between the good and the neutral values are selected. All these good, neutral and intermediate values form the dummy alternatives. At the next step, the preference strengths among the dummy alternatives are evaluated using pairwise comparison and their elementary performance scores are obtained by solving the equation system as previously described in this section. Finally, the performance score of each real alternative is determined using linear interpolation in the interval of corresponding dummy alternatives.

#### 3.2.3.2 Weight Determination Step

MACBETH requires pairwise comparison between the characteristic situations. The results of each comparison are an equation, which can take the following form:

$$x^i_{\text{Ag}} - x^g_{\text{Ag}} = h\alpha = w_i - w_g \tag{3.9}$$

leading to a system of $n$ independent equations. Hence, the decision-maker has to provide $n$ relations to determine the weights of criteria.

Example: Consider three criteria $(c_1, c_2, c_3)$ and $c_0$ neutral situation. The decision-makers rank the characteristic situations then express their strengths of preferences as follows:

$$c_3 \succ^{\text{strong}} c_1 \succ^{\text{weak}} c_2 \succ^{\text{very weak}} c_0$$

Considering the strength of preference $h$ as integer, we can write the following system:

$$\begin{aligned} x^3_{\text{Ag}} - x^1_{\text{Ag}} &= 5\alpha = w_3 - w1, \\ x^1_{\text{Ag}} - x^2_{\text{Ag}} &= 2\alpha = w_1 - w2, \\ x^2_{\text{Ag}} - x^0_{\text{Ag}} &= \alpha = w_2, \\ w_1 + w_2 + w_3 &= 1. \end{aligned}$$

Solving this system of equations, we find: $w_1 = 0.2500$, $w_2 = 0.0833$, $w_3 = 0.6667$ and $\alpha = 0.0833$.

#### 3.2.3.3 Extensions of MACBETH to the 2-Additive Choquet Integral

Instead of simple weighted average formulation, 2-Additive Choquet Integral method can be incorporated into the MACBETH method. In the case of the 2-additive Choquet Integral, the aggregation formula of the performance expression is given by the following formulation:

$$x^j_{\text{Ag}} = \sum_{i=1}^{n} w_i x^j_i - \frac{1}{2}\sum_{i=1}^{n} u_{ik}|x^j_i - x^j_k|. \tag{3.10}$$

Example: Let $c_i$ and $(c_i, c_k)$ be criterion $i$ and interaction between criterion $i$ and criterion $k$ $(i \neq k)$, respectively $(i, k = 1, 2, 3)$. Consider the following order and strengths of preferences: $(c_2, c_3) \succ^4 (c_1, c_2) \succ^1 (c_1, c_3) \succ^2 c_2 \succ^2 c_3 \succ^4 c_1 \succ^2 c_0$. Then we have to solve the following system of equations:

$$\begin{aligned}
&\left[w_2 + w_3 - \frac{1}{2}(u_{12} + u_{13})\right] - \left[w_1 + w_2 - \frac{1}{2}(u_{13} + u_{23})\right] &&= 4\alpha \\
&\left[w_1 + w_2 - \frac{1}{2}(u_{13} + u_{23})\right] - \left[w_1 + w_3 - \frac{1}{2}(u_{12} + u_{23})\right] &&= \alpha \\
&\left[w_1 + w_3 - \frac{1}{2}(u_{12} + u_{23})\right] - \left[w_2 - \frac{1}{2}(u_{12} + u_{23})\right] &&= 2\alpha \\
&\left[w_2 - \frac{1}{2}(u_{12} + u_{23})\right] - \left[w_3 - \frac{1}{2}(u_{13} + u_{23})\right] &&= 2\alpha \\
&\left[w_3 - \frac{1}{2}(u_{13} + u_{23})\right] - \left[w_1 - \frac{1}{2}(u_{12} + u_{13})\right] &&= 4\alpha \\
&\left[w_1 - \frac{1}{2}(u_{12} + u_{13})\right] - 0 &&= 2\alpha \\
&w_1 + w_2 + w_3 &&= 1
\end{aligned}$$

which can be simplified as:

$$\begin{aligned}
&-w_1 + w_3 &&-\frac{1}{2}(u_{12} - u_{23}) &&= 4\alpha \\
&w_2 - w_3 &&-\frac{1}{2}(-u_{12} + u_{13}) &&= \alpha \\
&w_1 - w_2 + w_3 && &&= 2\alpha \\
&w_2 - w_3 &&-\frac{1}{2}(u_{12} - u_{13}) &&= 2\alpha \\
&-w_1 + w_3 &&-\frac{1}{2}(-u_{12} + u_{23}) &&= 4\alpha \\
&w_1 &&-\frac{1}{2}(u_{12} + u_{13}) &&= 2\alpha \\
&w_1 + w_2 + w_3 && &&= 1
\end{aligned}$$

Solving this system of equations, we find: criterion weights $w_1 = 0.175$, $w_2 = 0.45$, $w_3 = 0.375$, and interactions $u_{12} = 0.05$, $u_{13} = 0.1$, $u_{23} = 0.05$ and $\alpha = 0.05$.

### 3.2.4 Elucidation of the Results

Apart from the challenging task of evaluating and ranking the alternatives with several conflicting criteria, it is also essential to identify which partial scores have contributed more to the final aggregate score of a specific alternative (absolute elucidation) or which dimensions have been more influential in defining the rank of an alternative compared to the other dimensions (relative elucidation). Along these lines, the elucidation phase is to help the decision makers understand the reasons behind the results. Such reasoning can be expressed qualitatively and/or quantitatively in multiple ways (for more details, see (Dasarathy, 2000)).

Suppose that according to the Choquet integral given in equation 3.7, the alternative $a_s$ is ranked as the best one; i.e., $C_\mu^s \geq C_\mu^j$ for all $j = 1, \ldots, m$. In order to provide absolute and relative elucidations about why $a_s$ has such a rank, it is first crucial to reformulate $C_\mu^s$ as the sum of marginal contributions Akharraz (2002); Büyüközkan et al. (2003):

$$\begin{aligned} C_\mu^s &= \left(\mu_{[1]}^s - \mu_{[2]}^s\right) x_{[1]}^s + \ldots + \left(\mu_{[i]}^s - \mu_{[i+1]}^s\right) x_{[i]}^s + \ldots + \mu_{[n]}^s x_{[n]}^s \\ &= \sum_{i=1}^{n} \Delta\mu_{[i]}^s x_{[i]}^s, \end{aligned} \tag{3.11}$$

where $\mu_{[i]}^s = \mu\big(\mathcal{N}_{[i]}^s\big)$, $\mu_{[n+1]}^s = 0$, and $\Delta\mu_{[i]}^s = \mu_{[i]}^s - \mu_{[i+1]}^s$. Given that $\mathcal{N}_{[i]}^s \supseteq \mathcal{N}_{[i+1]}^s$ and the measure $\mu$ satisfies the monotonicity condition, we have $\Delta\mu_{[i]}^s \geq 0$ for $i = 1, \ldots, n$. By simple manipulations we can derive that

$$\sum_{i=1}^{n} \Delta\mu_{[i]}^s = \sum_{i=1}^{n} \left(\mu_{[i]}^s - \mu_{[i+1]}^s\right) = \mu_{[1]}^s - \mu_{[n+1]}^s = 1 - 0 = 1. \tag{3.12}$$

We refer to the term $\Delta\mu_{[k]}^s x_{[k]}^s$ as the absolute potential of criterion $c_{[k]}$. We can simply re-rank the terms of the sum in equation 3.11 so that

$$\Delta\mu^s_{[k]}x^s_{[k]} \geq \Delta\mu^s_{[k+1]}x^s_{[k+1]}, \quad k = 1, \ldots, n-1. \tag{3.13}$$

Then we can rank the absolute contributions of the scores, $\Delta\mu^s_{[k]}x^s_{[k]},\ k = 1, \ldots, n$, with respect to the values of the $\Delta\mu^s_{[k]}x^s_{[k]}/\Delta\mu^s_{[1]}x^s_{[1]}$ ratio. The closer this ratio to 1, the greater the contribution of the score of criterion $c_{[k]}$, and the more $c_{[k]}$ represents an essential dimension in the decision process (local interpretation of elucidation). In the case of 2-additive fuzzy measure, the expression $\Delta\mu^s_{[i]}$ in Eq.(9) becomes

$$\Delta\mu^s_{[i]} = w_{[i]} + \frac{1}{2}\sum_{k>i} u_{[i][k]} - \frac{1}{2}\sum_{k<i} u_{[k][i]}, \tag{3.14}$$

where $w_{[i]}$ is the relative importance of criterion $c_{[i]}$ and $u_{[i][k]}$ is the interaction between criteria $c_{[i]}$ and $c_{[k]}$.

To provide insights about how much each criterion has been influential to prefer the alternative $a_s$ over $a_j$, we use the following equation:

$$\Delta C^{sj}_\mu = \Delta C_\mu\left(\mathbf{x}^s, \mathbf{x}^j\right) = C^s_\mu - C^j_\mu = \sum_{i=1}^{n} R^{sj}_i, \quad a_s, a_j \in A, s \neq j, \tag{3.15}$$

where $R^{sj}_i = \Delta\mu^s_{[i]}x^s_{[i]} - \Delta\mu^j_{[i]}x^j_{[i]}$. Similar to $C^s_\mu$, which is formulated as the sum of the absolute potentials in equation 3.11, $\Delta C^{sj}_\mu$ is expressed as the sum of the individual relative potentials $R^{sj}_i$.

## 3.3 Case Study

Country based data collection on the indicators is a demanding task that requires a considerable amount of resources and the involvement of many local agencies. Moreover, a cross comparison is meaningful only if the definitions of the indicators accepted by countries' authorities are consistent. It is possible to extract data regarding the transportation industry within Europe from some publicly available databases such as Eurostat. Unfortunately, not all of the local agencies collect data on all transport indicators. Due to the limited available data, seventeen indicators are considered in this study and the data sources used are mentioned in Table (3.2).

We then construct a case to apply the methods described in the previous sections for the following selected European countries: Austria (AT), Belgium (BE), Bulgaria (BL), Denmark (DK), Estonia (EI), Finland (FI), France (FR), Germany (DE), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Slovakia (SK), Slovenia (SI), Spain (ES), Sweden (SE) and United Kingdom (UK). The idea behind selecting this set of countries is to compare the countries with large, moderate and small economic activities, and to assure a geographic dispersion.

To transform the values of the indicators into scores for the mentioned countries, the MACBETH method that is discussed in section 3.2.3 is utilized. The derived statistics are presented in apendix A and the corresponding scaled values are given in Tables (3.3), (3.4) and (3.5).

Determining the weights to quantify the relative importance of the sustainability indicators is an integral part of the analysis. The sustainability dimensions and also the indicators within each dimension are also evaluated in a pairwise fashion using the MACBETH method based on consultations with a group of experts in the field. The weights and interactions of criteria are presented in apendix A.

**Table 3.3**: Economic indicators and associated scaled scores for the selected countries

| | EC11 | EC12 | EC13 | EC21 | EC22 | EC23 | EC24 | EC31 | EC32 |
|---|---|---|---|---|---|---|---|---|---|
| AT | 0.91 | 0.41 | 0.51 | 0.75 | 0.39 | 0.33 | 0.69 | 0.97 | 0.86 |
| BE | 0.87 | 0.51 | 0.41 | 0.91 | 0.36 | 0.48 | 0.78 | 0.80 | 0.87 |
| BL | 0.17 | 0.13 | 0.40 | 0.25 | 0.51 | 0.61 | 0.76 | 0.66 | 0.36 |
| DK | 0.69 | 0.37 | 0.88 | 0.96 | 0.38 | 0.59 | 0.68 | 0.69 | 0.84 |
| EI | 0.16 | 0.23 | 0.03 | 0.88 | 0.38 | 0.71 | 0.89 | 0.76 | 0.48 |
| FI | 0.45 | 0.37 | 0.65 | 0.77 | 0.36 | 0.43 | 0.78 | 0.71 | 0.84 |
| FR | 0.34 | 0.45 | 0.34 | 0.79 | 0.37 | 0.29 | 0.72 | 0.63 | 0.82 |
| DE | 0.43 | 0.38 | 0.45 | 0.57 | 0.35 | 0.21 | 0.67 | 0.70 | 0.94 |
| IE | 0.38 | 0.38 | 0.38 | 0.84 | 0.33 | 0.12 | 0.68 | 0.40 | 0.86 |
| IT | 0.39 | 0.41 | 0.31 | 0.65 | 0.38 | 0.36 | 0.67 | 0.76 | 0.74 |
| LV | 0.02 | 0.33 | 0.33 | 0.53 | 0.71 | 0.84 | 0.94 | 0.81 | 0.53 |
| LT | 0.20 | 0.29 | 0.23 | 0.39 | 0.10 | 0.81 | 0.83 | 0.61 | 0.42 |
| NL | 0.47 | 0.38 | 0.78 | 0.70 | 0.42 | 0.33 | 0.68 | 0.66 | 0.95 |
| PL | 0.11 | 0.23 | 0.20 | 0.34 | 0.19 | 0.37 | 0.74 | 0.35 | 0.59 |
| PT | 0.39 | 0.35 | 0.58 | 0.38 | 0.23 | 0.24 | 0.51 | 0.64 | 0.64 |
| RO | 0.24 | 0.29 | 0.41 | 0.49 | 0.48 | 0.64 | 0.70 | 0.37 | 0.38 |
| SK | 0.11 | 0.23 | 0.32 | 0.70 | 0.92 | 0.56 | 0.80 | 0.60 | 0.50 |
| SI | 0.29 | 0.35 | 0.52 | 0.23 | 0.40 | 0.39 | 0.75 | 0.29 | 0.45 |
| ES | 0.37 | 0.38 | 0.49 | 0.50 | 0.42 | 0.26 | 0.68 | 0.67 | 0.73 |
| SE | 0.66 | 0.40 | 0.55 | 0.68 | 0.46 | 0.50 | 0.71 | 0.77 | 0.93 |
| UK | 0.47 | 0.38 | 0.35 | 0.80 | 0.48 | 0.29 | 0.70 | 0.84 | 0.89 |

**Table 3.4**: Social indicators and associated scaled scores for the selected countries

| | SC11 | SC12 | SC21 | SC22 | SC23 | SC24 | SC31 | SC32 | SC41 | SC42 | SC43 | SC44 | SC45 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 0.83 | 0.83 | 0.92 | 0.94 | 0.64 | 0.42 | 0.57 | 0.86 | 0.88 | 0.3 | 0.51 | 0.61 | 0.36 |
| BE | 0.83 | 0.79 | 0.90 | 0.97 | 0.66 | 0.48 | 0.57 | 1 | 0.68 | 0.47 | 0.47 | 0.26 | 0.32 |
| BL | 0.54 | 0.76 | 0.53 | 0.71 | 0.67 | 0.27 | 0.61 | 0.95 | 0.23 | 1 | 0.86 | 0.76 | 0.71 |
| DK | 0.80 | 0.92 | 0.91 | 0.93 | 0.57 | 0.47 | 0.68 | 0.97 | 0.81 | 0.32 | 0.49 | 0.34 | 0.26 |
| EI | 0.89 | 0.74 | 0.67 | 0.70 | 0.54 | 0.47 | 0.54 | 0.58 | 0.7 | 0.66 | 0.77 | 0.45 | 0.64 |
| FI | 0.74 | 0.92 | 0.93 | 0.92 | 0.62 | 0.48 | 0.68 | 0.44 | 0.82 | 0.39 | 0.41 | 0.26 | 0.32 |
| FR | 0.90 | 0.83 | 0.93 | 0.94 | 0.69 | 0.35 | 0.58 | 0.97 | 0.86 | 0.17 | 0.21 | 0.39 | 0.30 |
| DE | 0.89 | 0.93 | 0.94 | 0.93 | 0.67 | 0.36 | 0.54 | 0.69 | 0.82 | 0.26 | 0.32 | 0.26 | 0.17 |
| IE | 0.87 | 0.86 | 0.90 | 0.88 | 0.64 | 0.48 | 0.29 | 0.81 | 0.67 | 0.69 | 0.80 | 0.6 | 0.54 |
| IT | 0.86 | 0.82 | 0.89 | 0.88 | 0.46 | 0.39 | 0.72 | 0.95 | 0.01 | 0.70 | 0.79 | 0.74 | 0.69 |
| LV | 0.98 | 0.56 | 0.56 | 0.77 | 0.58 | 0.55 | 0.40 | 0.73 | 0.56 | 0.86 | 0.74 | 0.63 | 0.49 |
| LT | 0.84 | 0.58 | 0.81 | 0.77 | 0.58 | 0.28 | 0.53 | 0.92 | 0.22 | 0.51 | 0.69 | 0.63 | 0.79 |
| NL | 0.87 | 0.99 | 0.9 | 0.91 | 0.73 | 0.50 | 0.38 | 1 | 0.87 | 0.49 | 0.43 | 0.17 | 0.30 |
| PL | 0.73 | 0.71 | 0.84 | 0.87 | 0.61 | 0.70 | 0.47 | 0.86 | 0.70 | 1 | 0.91 | 0.83 | 0.79 |
| PT | 0.95 | 0.76 | 0.87 | 0.80 | 0.57 | 0.33 | 0.78 | 0.65 | 0.39 | 0.32 | 0.66 | 0.6 | 0.51 |
| RO | 0.11 | 0.79 | 0.16 | 0.24 | 0.26 | 0.37 | 0.53 | 0.69 | 0.46 | 1 | 0.94 | 0.87 | 0.74 |
| SK | 0.87 | 0.80 | 0.70 | 0.84 | 0.59 | 0.80 | 0.61 | 0.92 | 0.37 | 0.74 | 0.63 | 0.73 | 0.83 |
| SI | 0.88 | 0.75 | 0.70 | 0.79 | 0.54 | 0.29 | 0.53 | 0.86 | 0.62 | 0.61 | 0.84 | 0.51 | 0.61 |
| ES | 0.95 | 0.80 | 0.85 | 0.89 | 0.56 | 0.49 | 0.60 | 0.86 | 0.77 | 0.43 | 0.49 | 0.45 | 0.41 |
| SE | 0.87 | 0.98 | 0.93 | 0.94 | 0.63 | 0.39 | 0.43 | 0.58 | 0.90 | 0.43 | 0.49 | 0.32 | 0.32 |
| UK | 0.82 | 0.98 | 0.89 | 0.86 | 0.58 | 0.30 | 0.42 | 0.89 | 0.77 | 0.56 | 0.63 | 0.47 | 0.43 |

**Table 3.5**: Environmental indicators and associated scaled scores for the selected countries

| | EN11 | EN12 | EN13 | EN14 | EN21 | EN22 | EN23 | EN31 | EN32 | EN33 | EN34 | EN41 | EN42 | EN43 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 0.25 | 0.48 | 0.44 | 0.74 | 0.62 | 0.87 | 0.42 | 0.38 | 0.35 | 0.50 | 0.68 | 0.78 | 0.53 | 0.72 |
| BE | 0.64 | 0.57 | 0.53 | 0.28 | 0.73 | 0.84 | 0.73 | 0.48 | 0.44 | 0.64 | 0.77 | 0.67 | 0.65 | 0.83 |
| BL | 0.34 | 0.31 | 0.32 | 0.08 | 0.61 | 0.78 | 0.53 | 0.30 | 0.80 | 0.35 | 0.31 | 0.76 | 0.54 | 0.71 |
| DK | 0.34 | 0.56 | 0.53 | 0.03 | 0.48 | 0.41 | 0.40 | 0.43 | 0.45 | 0.58 | 0.91 | 0.74 | 0.74 | 0.95 |
| EI | 0.46 | 0.37 | 0.38 | 0.03 | 0.51 | 0.64 | 0.64 | 0.31 | 0.66 | 0.39 | 0.63 | 0.79 | 0.29 | 0.30 |
| FI | 0.59 | 0.52 | 0.51 | 0.31 | 0.69 | 0.41 | 0.40 | 0.43 | 0.41 | 0.57 | 0.73 | 0.65 | 0.93 | 0.69 |
| FR | 0.85 | 0.91 | 0.60 | 0.64 | 0.47 | 0.41 | 0.32 | 0.71 | 0.51 | 0.72 | 0.86 | 0.85 | 0.72 | 0.77 |
| DE | 0.91 | 0.86 | 0.98 | 0.80 | 0.60 | 0.83 | 0.67 | 0.95 | 0.57 | 0.93 | 0.79 | 0.75 | 0.75 | 0.78 |
| IE | 0.75 | 0.58 | 0.49 | 0.17 | 0.84 | 0.38 | 0.28 | 0.42 | 0.28 | 0.57 | 0.67 | 0.75 | 0.70 | 0.79 |
| IT | 0.65 | 0.90 | 0.70 | 0.35 | 0.69 | 0.43 | 0.32 | 0.60 | 0.53 | 0.68 | 0.71 | 0.82 | 0.64 | 0.72 |
| LV | 0.16 | 0.24 | 0.29 | 0.20 | 0.08 | 0.73 | 0.66 | 0.26 | 0.72 | 0.29 | 0.76 | 0.91 | 0.01 | 0.01 |
| LT | 0.63 | 0.30 | 0.33 | 0.47 | 0.39 | 0.70 | 0.65 | 0.31 | 0.73 | 0.35 | 0.85 | 0.49 | 0.65 | 0.13 |
| NL | 0.75 | 0.58 | 0.53 | 0.36 | 0.84 | 0.60 | 0.51 | 0.43 | 0.53 | 0.59 | 0.79 | 0.56 | 0.64 | 0.79 |
| PL | 0.07 | 0.22 | 0.20 | 0.43 | 0.66 | 0.47 | 0.39 | 0.20 | 0.80 | 0.22 | 0.45 | 0.4 | 0.34 | 0.70 |
| PT | 0.28 | 0.54 | 0.53 | 0.43 | 0.45 | 0.66 | 0.45 | 0.58 | 0.60 | 0.69 | 0.81 | 0.81 | 0.53 | 0.75 |
| RO | 0.32 | 0.31 | 0.26 | 0.25 | 0.86 | 0.55 | 0.39 | 0.30 | 0.89 | 0.33 | 0.11 | 0.11 | 0.18 | 0.06 |
| SK | 0.36 | 0.18 | 0.27 | 0.87 | 0.96 | 0.72 | 0.68 | 0.24 | 0.77 | 0.26 | 0.77 | 0.7 | 0.26 | 0.39 |
| SI | 0.18 | 0.36 | 0.33 | 0.22 | 0.73 | 0.65 | 0.53 | 0.29 | 0.49 | 0.36 | 0.39 | 0.81 | 0.32 | 0.39 |
| ES | 0.73 | 0.62 | 0.50 | 0.33 | 0.40 | 0.59 | 0.37 | 0.42 | 0.51 | 0.58 | 0.68 | 0.91 | 0.35 | 0.55 |
| SE | 0.89 | 0.57 | 0.52 | 0.91 | 0.94 | 0.78 | 0.53 | 0.44 | 0.49 | 0.60 | 0.84 | 0.73 | 0.36 | 0.53 |
| UK | 0.91 | 0.82 | 0.62 | 0.25 | 0.46 | 0.49 | 0.43 | 0.62 | 0.55 | 0.70 | 0.88 | 0.92 | 0.68 | 0.69 |

The emissions of the greenhouse gases, the energy consumption and the safety issues are identified as the three most important criteria in the context of sustainable transport. Transport causes more than one-fifth of the greenhouse-gas emissions and around one-third of the overall energy consumption in the European countries. Regarding to the greenhouse gas (GHG) emissions in the European, all main emitting sectors except the transport sector have made progress area between 1990 and 2006. Another fact is that the new EU Member States contribute to the total GHG emissions less than the older EU Member States, but the increase in the rate of their contributions is higher due to their developing transportation systems. As with emissions, the increase in passenger- and freight-transport demand has resulted in a rapid growth in the total energy consumption. As transport mainly depends on the fossil fuels, the energy consumption and the GHG emissions are closely related. To reflect the economic aspect of the energy consumption and distinguish it from the environmental indicator of GHS emissions, the energy consumption is scaled by the GDP. Finally, the safety is also regarded as an important factor. The main consequences of traffic accidents are not only social but economic as well. Although the number of road fatalities per year is gradually falling on average for the EU countries, a significant effort is needed especially for the east European countries.

We believe that the interaction parameters reflect the level of conservativeness of the decision makers' preferences. That is, a pessimistic (conservative) decision maker prefers that the scores of all (or most) of the criteria are satisfactory, while an optimistic one is satisfied when a satisfactory performance is observed for at least one criterion. In fact, when dealing with sustainability evaluation, the conservative approach is more suitable, since attaining reasonable scores in most of the sustainability criteria is preferable. This discussion explains why the specified values of the interaction parameters are in general positive.

**Table 3.6**: Aggregate scores and rankings

| | TOPSIS | | Choquet Integral | |
|---|---|---|---|---|
| | $C$ | Rank | $C_\mu$ | Rank |
| AT | 0.3584 | 8 | 0.5619 | 9 |
| BE | 0.3144 | 3 | 0.6043 | 1 |
| BL | 0.4890 | 15 | 0.4538 | 16 |
| DK | 0.3087 | 2 | 0.5704 | 6 |
| EI | 0.5448 | 17 | 0.4665 | 15 |
| FI | 0.3671 | 9 | 0.5553 | 10 |
| FR | 0.3284 | 4 | 0.5671 | 8 |
| DE | 0.2932 | 1 | 0.5916 | 3 |
| IE | 0.3801 | 11 | 0.5185 | 13 |
| IT | 0.3535 | 7 | 0.5704 | 7 |
| LV | 0.6035 | 19 | 0.4380 | 17 |
| LT | 0.6229 | 20 | 0.4283 | 20 |
| NL | 0.3295 | 5 | 0.5876 | 4 |
| PL | 0.4862 | 14 | 0.4355 | 19 |
| PT | 0.3988 | 12 | 0.5239 | 12 |
| RO | 0.7175 | 21 | 0.3238 | 21 |
| SK | 0.4950 | 16 | 0.4997 | 14 |
| SI | 0.5643 | 18 | 0.4362 | 18 |
| ES | 0.4329 | 13 | 0.5305 | 11 |
| SE | 0.3778 | 10 | 0.5874 | 5 |
| UK | 0.3385 | 6 | 0.5945 | 2 |

**Table 3.7**: Absolute potentials

| | ENV | ECO | SOC | Score | Rank |
|---|---|---|---|---|---|
| AT | 0.2795 | 0.1642 | 0.1182 | 0.5619 | 9 |
| BE | 0.3204 | 0.0972 | 0.1867 | 0.6043 | 1 |
| BL | 0.1899 | 0.1561 | 0.1077 | 0.4538 | 16 |
| DK | 0.2827 | 0.0984 | 0.1893 | 0.5704 | 6 |
| EI | 0.2145 | 0.1345 | 0.1176 | 0.4665 | 15 |
| FI | 0.2859 | 0.0912 | 0.1783 | 0.5553 | 10 |
| FR | 0.1459 | 0.2038 | 0.2174 | 0.5671 | 8 |
| DE | 0.1754 | 0.2036 | 0.2126 | 0.5916 | 3 |
| IE | 0.2147 | 0.1801 | 0.1237 | 0.5185 | 13 |
| IT | 0.1379 | 0.2036 | 0.2289 | 0.5704 | 7 |
| LV | 0.1699 | 0.1522 | 0.1159 | 0.4380 | 17 |
| LT | 0.2106 | 0.1126 | 0.1051 | 0.4283 | 20 |
| NL | 0.3108 | 0.1595 | 0.1173 | 0.5876 | 4 |
| PL | 0.1612 | 0.1390 | 0.1354 | 0.4355 | 19 |
| PT | 0.2440 | 0.1664 | 0.1135 | 0.5239 | 12 |
| RO | 0.1196 | 0.1161 | 0.0881 | 0.3238 | 21 |
| SK | 0.2312 | 0.1381 | 0.1304 | 0.4997 | 14 |
| SI | 0.1695 | 0.1501 | 0.1165 | 0.4362 | 18 |
| ES | 0.2170 | 0.1927 | 0.1208 | 0.5305 | 11 |
| SE | 0.3116 | 0.0975 | 0.1783 | 0.5874 | 5 |
| UK | 0.2532 | 0.2211 | 0.1202 | 0.5945 | 2 |

**Table 3.8**: Relative potentials

| | ENV | ECO | SOC |
|---|---|---|---|
| R(BE,UK) | 0.0673 | -0.1239 | 0.0664 |
| R(BE,DE) | 0.1450 | -0.1064 | -0.0259 |
| R(BE,NL) | 0.0096 | -0.0623 | 0.0693 |
| R(BE,SE) | 0.0088 | -0.0003 | 0.0084 |
| R(BE,DK) | 0.0377 | -0.0012 | -0.0027 |
| R(BE,IT) | 0.1825 | -0.1064 | -0.0423 |
| R(BE,FR) | 0.1745 | -0.1066 | -0.0307 |
| R(BE,AT) | 0.0409 | -0.0670 | 0.0685 |
| R(BE,FI) | 0.0346 | 0.0060 | 0.0083 |
| R(BE,ES) | 0.1034 | -0.0955 | 0.0659 |
| R(BE,PT) | 0.0765 | -0.0692 | 0.0731 |
| R(BE,IE) | 0.1057 | -0.0829 | 0.0630 |
| R(BE,SK) | 0.0893 | -0.0409 | 0.0563 |
| R(BE,EI) | 0.1060 | -0.0373 | 0.0691 |
| R(BE,BL) | 0.1305 | -0.0589 | 0.0790 |
| R(BE,LV) | 0.1505 | -0.0550 | 0.0707 |
| R(BE,SI) | 0.1509 | -0.0529 | 0.0701 |
| R(BE,PL) | 0.1592 | -0.0418 | 0.0513 |
| R(BE,LT) | 0.1098 | -0.0154 | 0.0816 |
| R(BE,RO) | 0.2008 | -0.0189 | 0.0985 |

We obtain the country scores by using the Choquet integral method and provide the respective rankings in Table 3.6. Table 3.6 also presents the results obtained by the TOPSIS method. According to TOPSIS method, the top ranked countries are Germany, Denmark, Belgium, France and Netherlands. These results are not surprising as these countries are western European countries with a high socio-economic status. Estonia, Slovenia, Latvia, Lithuania and Romania which are eastern European countries with lowest socio-economic status are at the bottom of the list. It is seen that socio-economic status is a clear indication of the sustainability of traffic networks.

According to the Choquet integral method, the countries with highest rankings are Belgium, United Kingdom, Germany, Netherlands and Sweden. In this list we observe that France and Denmark are replaced by United Kingdom and Sweden. These results indicate that although France and Denmark have good scores on some indicators, the contribution of the interactions between indicators is smaller then the cases of United Kingdom and Sweden. United Kingdom and Sweden do not have very high levels on indicators but, as they have decent scores on all indicators, they benefit from the contribution of the interaction between indicators. At the bottom of the list, we have Latvia, Slovenia, Poland, Lithuania and Romania. These results are almost the same with TOPSIS except for Estonia is replaced by Poland. It is a clear indication that Poland has high scores on some indicators but does not benefit from interactions due to poor scores on others.

On the top of the list, although the rankings are very similar, we observe that Germany is ranked at the top according to TOPSIS and Belgium is at the top according to Choquet integral. This result should be investigated in more details. Other important differences between methods are Denmark which is 2nd according to TOPSIS and 6th according to Choquet integral, France which is 4th according to TOPSIS and 8th according to Choquet integral and Poland which is 14th according to TOPSIS and 19th according to Choquet integral. These three countries experience the highest drop between different methods and their results need further investigations. Another important case is United Kingdom which is 6th according to TOPSIS and 2th according to Choquet integral. This result also clearly indicates that United Kingdom may not have very high scores on all indicators but benefits the most from the interaction of different indicators.

In order to investigate the rationale behind these obtained rankings, we determine the absolute and relative potentials which are presented in Table 3.7 and Table 3.8, respectively. Investigating more carefully Table 3.7 for previously mentioned countries we can make following statements: Top three countries has very similar final scores according to Choquet integral. Belgium benefits the most from environmental indicators and economial and social scores also contributes to its final score. In the case of the United Kingdom, we observe that although it does not have very high scores on any single dimension, it has above average scores on all alternatives. As a result it is ranked second according to the Choquet integral.

France has above average scores on economical and social dimensions but has a lower score on environmental dimension. In order to improve its situation, we may advise France to concentrate on environmental indicators. Poland has above average score on environmental dimension but lacks on economical and social dimensions. We can say that thanks to its high scores on environmental dimension it is ranked better on TOPSIS method but as it could not benefit from the interactions because of its lower scores on economical and social dimensions. The top priorities of Poland should be economical and social dimensions.

Using Table 3.8, we can determine the dimensions that countries should concentrate in order to obtain the same level of Belgium which has the highest ranking according to Choquet integral method. United Kingdom, Germany, Denmark and France are ahead on economical and social dimension but lack on environmental dimension. No country is ahead on environmental dimension compared to Belgium. Spain, Portugal, Ireland, Slovakia, Estonia, Belgium, Latvia, Slovenia, Poland, Lithuania and Romania are slightly better in economical dimension but they lack on environmental and social dimensions.

The method presented in this section provides a systematic method to evaluate the traffic network of different countries. The Choquet integral method permits to take the interactions into account and in our case study we can observe that the interactions in fact have an effect in the ranking. Also, examining the absolute and relative potentials, countries can determine the weak areas in order to improve their ranks. In this evaluation, we considered a total of 36 readily available indicators for 21 European countries. As more indicators become available for more countries this evaluation process can be easily expanded.

Several strategies are proposed in the literature to improve the performance of the transport systems in terms of the environmental issues. These strategies involve the vehicle and fuel technology changes, road operational improvements and demand management. Different policies (or set of actions) can be considered in line with a strategy (see, e.g., Deakin (2001)) and each has its advantages and drawbacks. The question is how effective would the alternate policies be in reducing congestion, cutting the fuel use, and hence, lowering the pollution. Basically, the main goal of the related studies is to alleviate congestion and transport emissions through the use of different policies.

In our study, we propose alternate optimization models that involve sustainability measures based on the gas emission amounts. We base our discussion on two major policies under elastic demand: toll pricing and capacity enhancement. Traffic management problems involving such policies are generally modeled using bilevel programming. In these models, an upper (system) level involves the decisions about a certain policy to achieve a predetermined objective and the lower (user) level reflects the decisions of the rational network users and their reactions to the upper level decisions (Patriksson, 1994). In this study, we also consider such a bilevel structure and focus on introducing different emission related objective functions to the upper level problem. It is important to point out that the emission concentrations are calculated using the emission functions, which we define in terms of the traffic flow in order to reflect the accumulations mainly in case of congestion. To define the proposed emission functions, we use the functions of emission amounts versus vehicle speeds provided by the European Environment Agency.

## 4.1 Deterministic User Equilibrium

The solution of the traffic assignment problem yields the optimum flow on the transportation network and is obtained when a stable pattern of travelers' choice is reached. This is called the user equilibrium (Wardrop, 1952). There are two different formulations of the traffic assignment problem (Dirkse & Ferris, 1997). The *path formulation* incorporates predetermined routes having specific order of links and this requires the enumeration of all possible paths which can be prohibitive even for moderate problem instances. In the *multi-commodity formulation*, the modeling structure is based on the numbers of users that are headed to each destination on each link. Though the general multi-commodity formulation is based on the origin-destination (O-D) pairs, the special structure of this transportation problem enables to distinguish the flows based only on the destination points (Dirkse & Ferris, 1997). In this computationally efficient formulation, a commodity is associated with each destination. Thus if we denote $\mathcal{D}$ as the set of destination points in the network, then we consider the decision variable $x_{ij}^s$ denoting the flow of commodity $s \in \mathcal{D}$ on link $(i, j) \in \mathcal{A}$ in the multi-commodity formulation .

The network is managed based on the peak-hour demand which is assumed to be variable, or more commonly addressed as *elastic*. For elastic demand, the number of trips from an origin to a destination depends on the associated travel cost. In general, the travel cost can be a function of several components including the travel time. However, it is common to focus only on the travel time while expressing the variable demand (see, e.g., (Sheffi, 1985; Babonneau & Vial, 2008)). Traditionally, it is assumed that the travel demand decreases as the travel time increases. This relation is represented by a demand function denoted by $g_{is}(\omega_{is})$ with $\omega_{is}$ being the travel time between O–D pair $(i, s)$. To the best of our knowledge, in literature two types of travel demand functions (Babonneau & Vial, 2008) are mainly used: exponential and linear. In this study, we use the widely-applied linear demand function

$$g_{is}(w_{is}) = \mu_{is}\omega_{is} + \nu_{is}, \tag{4.1}$$

where $\mu_{is}$ and $\nu_{is}$ are network specific parameters. Consequently, if we denote the travel demand between O–D pair $(i, s)$ by $d_i^s = g_{is}(\omega_{is})$, then $\omega_{is} = g_{is}^{-1}(d_i^s)$.

Lets denote $x_{ij}^s$ the flow on link $(i, j) \in \mathcal{A}$ to the destination $s \in \mathcal{D}$ and $f_{ij}$ total link flow on link $(i, j) \in \mathcal{A}$. Also, we define the travel time function on a particular link $(i, j) \in \mathcal{A}$ as $t_{ij}(f_{ij})$. Then, the link flows that satisfy the user-equilibrium can be obtained by solving the following mathematical programming formulation:

$$\begin{aligned}
\text{minimize} \quad & \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} t_{ij}(y)\,\mathrm{d}y - \sum_{i\in\mathcal{N}} \sum_{s\in\mathcal{D}} \int_0^{d_i^s} g_{is}^{-1}(v)\,\mathrm{d}v, && && \text{(4.2a)} \\
\text{subject to} \quad & \sum_{j:(i,j)\in\mathcal{A}} x_{ij}^s - \sum_{j:(j,i)\in\mathcal{A}} x_{ji}^s = d_i^s, && i \in \mathcal{N}, s \in \mathcal{D}, && \text{(4.2b)} \\
& \sum_{s\in\mathcal{D}} x_{ij}^s = f_{ij}, && (i, j) \in \mathcal{A}, && \text{(4.2c)} \\
& x_{ij}^s \geq 0, && (i, j) \in \mathcal{A}, s \in \mathcal{D}, && \text{(4.2d)} \\
& d_i^s \geq 0, && i \in \mathcal{N}, s \in \mathcal{D}. && \text{(4.2e)}
\end{aligned}$$

Here the set of constraints (4.2b) is for the flow conservation and constraints (4.2c) link the total flow on an arc to the flows resulting from individual destination points. Constraints (4.2d) and (4.2e) ensure that the link flows and travel demands are nonnegative.

### 4.1.1 Equivalence Conditions

In order to ensure that the equilibrium conditions are met at the point where program 4.2 is minimized, the order conditions of the program must be equivalent to the equilibrium conditions. Let the objective function in program 4.2 be decomposed as follows:

$$\min\{z_1(\mathbf{f}) - z_2(\mathbf{d})\} \tag{4.3a}$$

where

$$z_1(\mathbf{f}) = \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} t_{ij}(y)\,\mathrm{d}y \tag{4.3b}$$

$$z_2(\mathbf{d}) = \sum_{i\in\mathcal{N}} \sum_{s\in\mathcal{D}} \int_0^{d_i^s} g_{is}^{-1}(v)\,\mathrm{d}v \tag{4.3c}$$

Note that $z_1(\mathbf{f})$ can be written in terms of path flows by using the incidence relationships, and thus $f_{ij} = f_{ij}(\mathbf{x})$. The Lagrangian associated with 4.2 can be written as

$$L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda}) = z_1(\mathbf{f}(\mathbf{x})) - z_2(\mathbf{d}) + \sum_{i\in\mathcal{N}} \sum_{s\in\mathcal{D}} \lambda_i^s \left( d_i^s - \sum_{j:(i,j)\in\mathcal{A}} x_{ij}^s + \sum_{j:(j,i)\in\mathcal{A}} x_{ji}^s \right) \tag{4.4a}$$

where $\boldsymbol{\lambda} = (\ldots, \lambda_i^s, \ldots)$ is the vector of Lagrange multipliers associated with constraints 4.2b. This Lagrangian should be minimized with respect to the flow variables (and maximized with respect to dual variables) subject to the following constraints:

$$x_{ij}^s \geq 0, \qquad (i,j) \in \mathcal{A}, s \in \mathcal{D}, \tag{4.4b}$$

$$d_i^s \geq 0, \qquad i \in \mathcal{N}, s \in \mathcal{D}. \tag{4.4c}$$

The first-order conditions for this program are:

$$
\begin{aligned}
x_{ij}^s \frac{\partial L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})}{\partial x_{ij}^s} &= 0 \qquad && (i,j) \in \mathcal{A}, s \in \mathcal{D}, && \text{(4.5a)}\\
\frac{\partial L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})}{\partial x_{ij}^s} &\geq 0 \qquad && (i,j) \in \mathcal{A}, s \in \mathcal{D}, && \text{(4.5b)}\\
d_i^s \frac{\partial L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})}{\partial d_i^s} &= 0 \qquad && i \in \mathcal{N}, s \in \mathcal{D}, && \text{(4.5c)}\\
\frac{\partial L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})}{\partial d_i^s} &\geq 0 \qquad && i \in \mathcal{N}, s \in \mathcal{D}, && \text{(4.5d)}\\
\frac{\partial L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})}{\partial \lambda_i^s} &= 0 \qquad && i \in \mathcal{N}, s \in \mathcal{D}, && \text{(4.5e)}\\
x_{ij}^s &\geq 0, \qquad && (i,j) \in \mathcal{A}, s \in \mathcal{D}, && \text{(4.5f)}\\
d_i^s &\geq 0, \qquad && i \in \mathcal{N}, s \in \mathcal{D}. && \text{(4.5g)}
\end{aligned}
$$

The derivative of the Lagrangian with respect to a general path-flow variable, $x_{ij}^s$, is:

$$
\frac{\partial L(\cdot)}{\partial x_{ij}^s} = \frac{\partial}{\partial x_{ij}^s} \left\{ z_1(\mathbf{f}(\mathbf{x})) - z_2(\mathbf{d}) + \sum_{i \in \mathcal{N}} \sum_{s \in \mathcal{D}} \lambda_i^s \left( d_i^s - \sum_{j:(i,j) \in \mathcal{A}} x_{ij}^s + \sum_{j:(j,i) \in \mathcal{A}} x_{ji}^s \right) \right\} \tag{4.6}
$$

The first-order conditions expressed in eq.(4.5a) and eq.4.5b) can be obtained explicitly by calculating the partial derivatives of $L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})$ with respect to the flow variables, $x_{ij}^s$, and substituting the result into (4.5a) and (4.5b). This derivative is given by

$$
\frac{\partial L(\mathbf{x}, \mathbf{d}, \boldsymbol{\lambda})}{\partial x_{ij}^s} = \frac{\partial}{\partial x_{ij}^s} z_1(\mathbf{f}(\mathbf{x})) - \frac{\partial}{\partial x_{ij}^s} z_2(\mathbf{d}) + \frac{\partial}{\partial x_{ij}^s} \sum_{i \in \mathcal{N}} \sum_{s \in \mathcal{D}} \lambda_i^s \left( d_i^s - \sum_{j:(i,j) \in \mathcal{A}} x_{ij}^s + \sum_{j:(j,i) \in \mathcal{A}} x_{ji}^s \right) \tag{4.7}
$$

The second term, $z_2(\mathbf{d})$, is not a function of $\mathbf{f}$ and can therefore be dropped from the derivative.

$$\frac{\partial L(\mathbf{x},\mathbf{d},\boldsymbol{\lambda})}{\partial x_{ij}^s} = \frac{\partial L(\mathbf{x},\boldsymbol{\lambda})}{\partial x_{ij}^s} = t_{ij}(f_{ij}) - \lambda_i^s + \lambda_j^s \tag{4.8}$$

The first-order derivative of the Lagrangian with respect to $d_i^s$, can be simplified to $\partial L(\mathbf{d},\boldsymbol{\lambda})/\partial d_i^s$, since $z_1(\mathbf{f})$ can be dropped from the derivative. This derivative is therefore

$$\frac{\partial L(\mathbf{d},\boldsymbol{\lambda})}{\partial d_i^s} = \frac{\partial}{\partial d_i^s}\left\{-z_2(\mathbf{d}) + \sum_{i\in\mathcal{N}}\sum_{s\in\mathcal{D}}\lambda_i^s\left(d_i^s - \sum_{j:(i,j)\in\mathcal{A}} x_{ij}^s + \sum_{j:(j,i)\in\mathcal{A}} x_{ji}^s\right)\right\} = -g_{is}^{-1}(d_i^s) + \lambda_i^s \tag{4.9}$$

The first-order conditions are thus

$$\begin{aligned}
x_{ij}^s\left[t_{ij}(f_{ij}) - \lambda_i^s + \lambda_j^s\right] &= 0, & (i,j)\in\mathcal{A}, s\in\mathcal{D}, && \text{(4.10a)}\\
t_{ij}(f_{ij}) - \lambda_i^s + \lambda_j^s &\geq 0, & (i,j)\in\mathcal{A}, s\in\mathcal{D}, && \text{(4.10b)}\\
d_i^s\left[\lambda_i^s - g_{is}^{-1}(d_i^s)\right] &= 0, & i\in\mathcal{N}, s\in\mathcal{D}, && \text{(4.10c)}\\
\lambda_i^s - g_{is}^{-1}(d_i^s) &\geq 0, & i\in\mathcal{N}, s\in\mathcal{D}, && \text{(4.10d)}\\
\sum_{j:(i,j)\in\mathcal{A}} x_{ij}^s - \sum_{j:(j,i)\in\mathcal{A}} x_{ji}^s &= d_i^s, & i\in\mathcal{N}, s\in\mathcal{D}, && \text{(4.10e)}\\
\sum_{s\in\mathcal{D}} x_{ij}^s &= f_{ij}, & (i,j)\in\mathcal{A}, && \text{(4.10f)}\\
x_{ij}^s &\geq 0, & (i,j)\in\mathcal{A}, s\in\mathcal{D}, && \text{(4.10g)}\\
d_i^s &\geq 0, & i\in\mathcal{N}, s\in\mathcal{D}, && \text{(4.10h)}
\end{aligned}$$

where $\lambda_i^s$ $i\in\mathcal{N},\ s\in\mathcal{D}$, are the dual variables associated with constraints (4.2b). At optimality $\lambda_i^s$ gives the minimum travel time between O–D pair $(i,s)$. For more detailed information please refer to (Sheffi, 1985).

### 4.1.2 Uniqueness Conditions

To prove that the equivalent variable-demand UE program has a unique solution, it is sufficient to show that the objective function is strictly convex everywhere. The first part of the objective function,

$$z_1(\mathbf{f}) = \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} t_{ij}(y)\,\mathrm{d}y \tag{4.11}$$

is strictly convex if the functions $c_{ij}(f_{ij})$ are increasing in $f_{ij}$.

The demand function for each O–D pair, $g_{is}(\lambda_i^s)$, is a monotonically decreasing function of its argument. It follows that its inverse, $g_{is}^{-1}(\cdot)$, should also be a decreasing function. The integral of a decreasing function is strictly concave and the sum of strictly concave functions is a strictly concave function. Thus

$$z_2(\mathbf{d}) = \sum_{i\in\mathcal{N}}\sum_{s\in\mathcal{D}} \int_0^{d_i^s} g_{is}^{-1}(v)\,\mathrm{d}v \tag{4.12}$$

is strictly concave. The negative of a strictly concave function is, however, a strictly convex function. Thus

$$z(\mathbf{x},\mathbf{d}) = z_1(\mathbf{f}) - z_2(\mathbf{d}) \tag{4.13}$$

is the sum of two strictly convex functions, meaning that $z(\mathbf{x},\mathbf{d})$ is strictly convex.

The strict convexity of $z(\mathbf{x},\mathbf{d})$ implies that program (4.2) has a unique solution in terms of O–D trip rates and link flows.

## 4.2 Emission Functions

Environmental dimension is a critical part of a sustainable network, and the traffic emission is an important indicator of the environmental dimension. In this section emission functions and its implementation to the traffic assigment problem is presented.

Emission modeling is a wide research area. In one of the early studies, Guensler & Sperling (1994) show that vehicle emissions are highly dependent on the vehicle speed. Many researchers have studied the relation between transport emissions and vehicle types, speeds, driving styles, weather or several other factors (EPA, 2003b; Gkatzoflias et al., 2007; Gokhale & Khare, 2004; Ketzel et al., 2002). Akçelik (2003, 2006) has performed extensive studies to show that there is a direct relationship between the vehicle speed and the traffic flow on the link. In this study, we consider emission functions and express them in terms of the traffic flow. First, we express the emission of a specific pollutant in terms of the speed. Then, using the mathematical relationship between the traffic flow and the average vehicle speed, we obtain a single composite function of the pollutant emission with respect to the traffic flow.

European Environment Agency (EEA) is a major information source for those involved in developing, adopting, implementing and evaluating environmental policies. In the framework of the activities of the European Topic Centre for Air and Climate Change, EEA has financed COPERT 4, a software tool used world-wide to calculate air pollutant and greenhouse gas emissions from road transport. Vehicle emissions are expressed as a function of average speed for pre-EURO and EURO class vehicles in COPERT 4. Accordingly, the emission in *grams per kilometer* of an EURO (European emission standards) class vehicle is expressed as

$$e = \frac{\delta_1 + \delta_3 v + \delta_5 v^2}{1 + \delta_2 v + \delta_4 v^2} \tag{4.14}$$

where $v$ is vehicle speed in *kilometer per hour* and $\delta_1, \delta_2, \delta_3, \delta_4$ and $\delta_5$ are parameters depending on vehicle and fuel type. We use the well known travel time (cost) function defined by Bureau of Public Roads as in relation (4.15). If we denote the flow on link $(i, j)$ in vehicle per hour by $f_{ij}$ then the travel time in hours is given by

$$t_{ij}(f_{ij}) = a_{ij}\left(1 + 0.15\left(\frac{f_{ij}}{b_{ij}}\right)^4\right) \tag{4.15}$$

Here $a_{ij}$ is the free flow travel time in hours and $b_{ij}$ is the capacity given in vehicle per hour. Then we express the average speed on kilometers per hour on link $(i, j) \in \mathcal{A}$ as a function of the flow amount

$$v_{ij}(f_{ij}) = \frac{l_{ij}}{t_{ij}(f_{ij})}, \tag{4.16}$$

where $l_{ij}$ designate the length of link $(i, j)$ given in kilometers. Using the emission-vehicle speed function (4.14) and the vehicle speed-traffic flow function (4.16), we construct a composite function to express the total emission in terms of the traffic flow. Basically we estimate the total emission of a pollutant in grams per hour on a particular link $(i, j)$ with

$$e_{ij}(f_{ij}) = f_{ij} \times l_{ij} \times e(v_{ij}(f_{ij})). \tag{4.17}$$

In figure 4.1, the relation between flow/capacity ratio and emission in a network link is illustrated.

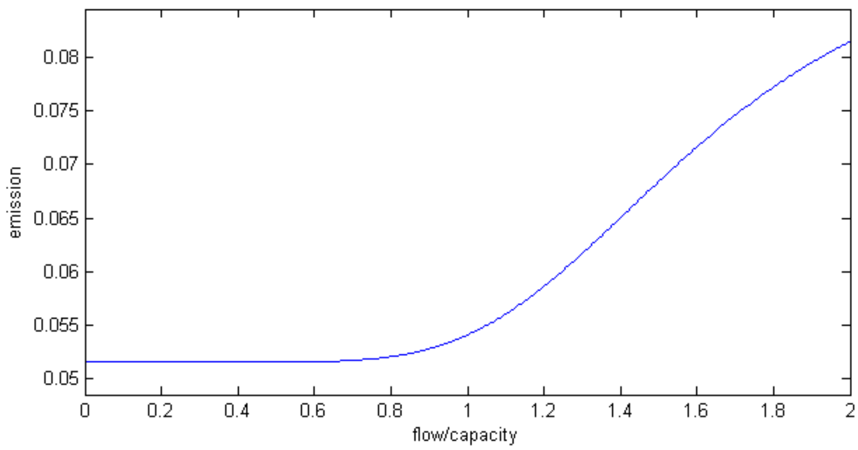



**Figure 4.1**: Relation between Flow and Emission on a Link

It is expected that when the road capacity is reached and congestion occurs, vehicles start to follow stop/go pattern which decreases the average vehicle speed and increases the total emission significantly.

## 4.3 Bilevel Traffic Assignment Problem

Bilevel programming is a branch of hierarchical mathematical optimization. In a bilevel model, the objective is to optimize the upper level objective while simultaneously optimizing the lower level problem. In a typical bilevel traffic equilibrium problem, the upper level problem involves the decisions about a certain policy (like toll pricing or capacity enhancement) to achieve a predetermined objective (like reducing the congestion or the investment cost). In the lower level we model the traffic equilibrium reflecting the decisions of the rational network users and their reactions to the upper level decisions. In other words, given an upper level decision, the lower level problem leads to the traffic assignment problem given in (4.2). A common approach to solve bilevel models is to reformulate the lower level problem in terms of its optimality conditions. In our case, these optimality conditions are given by (4.10). Due to the constraints (4.10a) and (4.10c), the resulting nonlinear programming problems are referred to as mathematical programs with complementarity constraints (MPCCs) (Birbil et al., 2006; Luo et al., 1996; Sun et al., 2012).

In the following subsections, we discuss several mathematical programming models in the form of typical MPCCs. In all these models, the objectives involve alternate sustainability measures based on the proposed emission functions, and the constraints involve the optimality conditions of the user equilibrium problem.

### 4.3.1 Total Network Emission.

In this section, we propose models with the objective of minimizing the total network emission. We try to achieve this objective via two policies: (i) toll pricing and (ii) capacity enhancement.

#### 4.3.1.1 Toll Pricing.

As mobility increases, not only each new driver pays a higher congestion cost compared to previously present drivers, but he/she also reduces the road space available to other drivers. This cost is external to the marginal driver. Thus, a road user's marginal private cost is lower than her marginal social cost (Knight, 1924; Pigou, 1920; Rouwendal & Verhoef, 2006; Vickrey, 1969). It is important to note that the concept of road pricing emerged from this idea. Toll pricing policies have recently become more practical due to the advent of electronic tolling, and hence, received significant attention from transportation planners and researchers. The *first-best* toll pricing problem assumes that all roads on the network can be tolled (Arnott & Small, 1994). There exist several first-best toll pricing models with various objective functions: minimizing the total tolls collected, minimizing the largest nonnegative toll to be collected, minimizing the total tolls collected while constraining this total to be zero and allowing negative tolls (allowing users to collect a payment on some links and pay a toll on others) and minimizing the number of toll booths (Hearn & Ramana, 1998). Nonetheless, the first-best toll pricing framework can hardly be applied in real life. Alternatively, it has been proposed to allow a subset of the roads to be tolled and the resulting problem is known as the *second-best* toll pricing problem (Brotcorne et al., 2001; Johansson-Stenman & Sterner, 1998; Labbe et al., 1998; Lawphongpanich & Hearn, 2004; Patriksson & Rockafellar, 2002). Here, we focus on this latter problem and use toll prices as disincentives to discourage travelers from choosing more congested links, and consequently, to reduce the emissions.

Let $\bar{\mathcal{A}}_\tau \subset \mathcal{A}$ be the subset of tollable links and $\tau_{ij}$ be the toll price on link $(i,j) \in \mathcal{A}$. We assume that $\tau_{ij}$ cannot exceed a prescribed upper bound $\tau_{ij}^{\max}$, where $\tau_{ij}^{\max} > 0$ if $(i,j) \in \bar{\mathcal{A}}_\tau$ and $\tau_{ij}^{\max} = 0$ otherwise. Our optimization model for minimizing the total emission is given as

$$\text{minimize} \sum_{(i,j)\in\mathcal{A}} e_{ij}(f_{ij}), \tag{4.18a}$$

$$\text{subject to} \sum_{(i,j)\in\bar{\mathcal{A}}_1} \tau_{ij} f_{ij} \geq \gamma_1 R^{\max}, \tag{4.18b}$$

$$0 \leq \tau_{ij} \leq \tau_{ij}^{\max}, \qquad (i,j) \in \mathcal{A}, \tag{4.18c}$$

$$x_{ij}^s \left[t_{ij}(f_{ij}) + \tau_{ij} - \lambda_i^s + \lambda_j^s\right] = 0, \qquad (i,j) \in \mathcal{A}, s \in \mathcal{D}, \qquad (4.18d)$$

$$t_{ij}(f_{ij}) + \tau_{ij} - \lambda_i^s + \lambda_j^s \geq 0, \qquad (i,j) \in \mathcal{A}, s \in \mathcal{D}, \qquad (4.18e)$$

$$(4.10c) - (4.10h), \qquad (4.18f)$$

where $R^{\max}$ denotes the maximum revenue that can be received from enforcing tolls and $\gamma_1 \in [0,1]$ is a parameter specified by the decision makers to represent a certain fraction of the maximum revenue. The parameter $R^{\max}$ can be obtained by solving the traditional toll pricing problem with the objective of revenue maximization (see also Section 4.4). Constraint (4.18b) ensures that the collected revenue is above a fraction of the maximum possible revenue. Constraints (4.18d)-(4.18f) are similar to the optimality conditions (4.10) with the addition of toll $\tau_{ij}$ to the travel time $t_{ij}(f_{ij})$ in equations (4.18d) and (4.18e). We note that the tolls and the revenue parameter $R^{\max}$ are in time units.

#### 4.3.1.2 Capacity Enhancement.

Network design problems (NDPs) in transportation context deal with decisions about (re)structuring the underlying networks. Under budgetary constraints, *discrete* NDPs usually focus on decisions related to the link or lane additions, whereas *continuous* NDPs are limited to decisions on network improvements that can be modeled using continuous variables such as the lane and lateral clearance changes and also other enhancements that produce incremental changes in capacities. Due to the intrinsic complexity of the model formulation, NDP has been recognized as one of the most challenging problems in the literature (Abdulaal & LeBlanc, 1979; Chiou, 2005; Friesz et al., 1990; Magnanti & Wong, 1984; Marcotte, 1986; Yang & Bell, 1998). As we are interested in introducing new models by mainly focusing on alternate objective functions based on emission amounts for environmental sustainability, we restrict our attention to the continuous case. However, we note that the proposed modeling approaches can also be applied for discrete network design problems.

We assume that the investment and operating cost function associated with the capacity enhancement on link $(i,j)$ is given by $k_{ij}\sigma_{ij}^2$, where $\sigma_{ij}$ represents the capacity enhancement and $k_{ij}$ the associated cost coefficient (Abdulaal & LeBlanc, 1979). Note that this type of quadratic cost functions are frequently used in the literature (see, e.g., (Gao & Song, 2002; Zhang & Gao, 2009)), but other types can easily be incorporated into the proposed models. Capacity enhancement naturally affects the travel time on link $(i, j)$ and leads to

$$\bar{t}_{ij}(f_{ij}, \sigma_{ij}) = a_{ij} \left(1 + 0.15 \left(f_{ij}/(b_{ij} + \sigma_{ij})\right)^4\right). \tag{4.19}$$

We next denote the set of link capacities that could be enhanced by $\bar{\mathcal{A}}_\sigma \subset \mathcal{A}$ and the maximum capacity enhancement on link $(i, j)$ by $\sigma_{ij}^{\max}$. Then, $\sigma_{ij}^{\max} > 0$, if $(i, j) \in \bar{\mathcal{A}}_\sigma$ and $\sigma_{ij}^{\max} = 0$, otherwise. Using this new notation, our capacity enhancement model with the objective of minimizing the total emission is given by

$$\begin{aligned}
\text{minimize} \sum_{(i,j)\in\mathcal{A}} & e_{ij}(f_{ij}, \sigma_{ij}), && && (4.20\text{a})\\
\text{subject to} \sum_{(i,j)\in\bar{\mathcal{A}}_\sigma} & k_{ij}\sigma_{ij}^2 \le \gamma_2 B^{\max}, && && (4.20\text{b})\\
& 0 \le \sigma_{ij} \le \sigma_{ij}^{\max}, && (i, j) \in \mathcal{A}, && (4.20\text{c})\\
& x_{ij}^s \left[\bar{t}_{ij}(f_{ij}, \sigma_{ij}) - \lambda_i^s + \lambda_j^s\right] = 0, && (i, j) \in \mathcal{A}, s \in \mathcal{D}, && (4.20\text{d})\\
& \bar{t}_{ij}(f_{ij}, \sigma_{ij}) - \lambda_i^s + \lambda_j^s \ge 0, && (i, j) \in \mathcal{A}, s \in \mathcal{D}, && (4.20\text{e})\\
& (4.10c) - (4.10h). && && (4.20\text{f})
\end{aligned}$$

Here $B^{\max}$ is the maximum budget that can be allocated for capacity enhancement and $\gamma_2 \in [0, 1]$ is a prespecified parameter to represent a certain fraction of the maximum budget. Constraint (4.20b) ensures that the total cost of enhancing the network is below the specified fraction of the budget. The parameter $B^{\max}$ can be calculated by solving model (CTE) after relaxing constraints (4.20b); see also Section 4.4. Constraints (4.20d)-(4.20f) are the optimality conditions of the traffic assignment problem as presented in (4.10), where (4.20d) and (4.20e) are obtained by replacing the travel time $t_{ij}(f_{ij})$ by $\bar{t}_{ij}(f_{ij}, \sigma_{ij})$. We note that the capacity enhancement cost coefficients and the budget parameter $B^{\max}$ are in time units.

#### 4.3.1.3 Simultaneous Toll Pricing and Capacity Enhancement.

As the toll pricing and capacity enhancement policies have conflicting effects (decreasing and increasing the demand, respectively), at first it may seem counterintuitive to simultaneously apply these policies in a hybrid fashion. However, the toll pricing policy may divert the vehicle flow to untolled areas of the network, whereas the capacity enhancement policy may attract the demand due to the decreased travel times. Therefore, the simultaneous application of these two policies enables us to push some of the flow from congested areas to less congested areas, and it proves to be effective in serving more demand and reducing the travel times. Other studies that propose models incorporating both policies also exist in the literature (see, e.g., (Chen & Subprasom, 2007; Yang & Meng, 2000, 2002)).

To observe the combined effect of the toll pricing and the capacity enhancement policies in reducing emission amounts, we develop a hybrid model and its mathematical programming formulation is given by

$$\begin{aligned}
\text{minimize} \quad & \sum_{(i,j)\in\mathcal{A}} e_{ij}(f_{ij}, \sigma_{ij}), && \text{(4.21a)}\\
\text{subject to} \quad & (4.18b), (4.18c), (4.20b), (4.20c), && \text{(4.21b)}\\
& x_{ij}^{s}\left[\bar{t}_{ij}(f_{ij}, \sigma_{ij}) + \tau_{ij} - \lambda_i^s + \lambda_j^s\right] = 0, \; (i,j) \in \mathcal{A}, s \in \mathcal{D}, && \text{(4.21c)}\\
& \bar{t}_{ij}(f_{ij}, \sigma_{ij}) + \tau_{ij} - \lambda_i^s + \lambda_j^s \geq 0, \qquad (i,j) \in \mathcal{A}, s \in \mathcal{D}, && \text{(4.21d)}\\
& (4.10c) - (4.10h). && \text{(4.21e)}
\end{aligned}$$

The parameters $R^{\max}$ and $B^{\max}$ are the same as in the models (TTE) and (CTE), respectively. The underlying idea in developing this model is similar to the one that defines simultaneous positive and negative tolls: encouraging the users by enhancing the capacity of some links and discouraging them by collecting toll on some other links. If the traffic authority follows the strategy to toll only those links, of which the capacities are enhanced, this can be interpreted as the intent to recover the capacity enhancement costs by collecting tolls.

### 4.3.2 Emission Dispersion.

Directing the vehicle flow to other parts of the transportation network through the toll pricing policy may lead to high emission accumulations in the wider area of the network. Therefore, it may be preferable to disperse the emission rather than minimizing the total emission. In this regard, we propose alternate models under the toll pricing and capacity enhancement policies, where we focus on the pollutant concentration in different areas of the network instead of the total emission amount. We refer to these models as the emission dispersion models. The emission concentration is defined as the emission amount per unit link length, and the concentration on link $(i, j)$ is given as

$$\bar{e}_{ij}(f_{ij}) = f_{ij} e(v_{ij}(f_{ij})). \tag{4.22}$$

Basically, $\bar{e}_{ij}$ is measured in *grams per kilometer and hour.*

We start with two new models that are obtained by modifying the objective function (4.18a) of the toll-pricing model (TTE). The main difference between these models is their scope of evaluating the emission concentration. The objective of the first model is based on minimizing the maximum link emission concentration over the whole network. The first model then becomes

$$\min \left\{ \max_{(i,j)\in\mathcal{A}} \bar{e}_{ij}(f_{ij}) : (4.18b) - (4.18f) \right\}. \tag{4.23}$$

With this objective, the solution of the model is biased towards policies, which may lead to a more balanced concentration over the entire network. The objective of the second model is differentiating the emission concentrations in different sections of the network. Traffic flows with reasonable emission levels in a highly populated section of a network may sum up to excessive amounts in that section. Due to the land use characteristics (such as; residential, commercial, and so on), the network management authorities may determine upper limits on the emission amount at certain sections of the network. Let $\zeta_{ij}$ denote the threshold on the emission concentration level for link $(i, j)$. The product of this amount with the link length gives the threshold on the emission level for that link. As the public health is at stake, it would be natural to set different levels of restrictions on the emission amounts for different parts of the network. For example, one may enforce smaller concentration levels for harmful pollutants in highly populated areas. Note that in practice the decision makers may specify a threshold for each section (zone) of the network and consider the same zone-based threshold for each link belonging to that specific zone. With this dispersion type of objective, we penalize the amount of emission on each link that exceeds the specified upper limit. This discussion leads to our second model as

$$\min \left\{ \sum_{(i,j)\in\mathcal{A}} \max\{\, e_{ij}(f_{ij}) - \zeta_{ij} l_{ij},\, 0 \,\} : (4.18b) - (4.18f) \right\}. \tag{4.24}$$

The dispersion of the emission throughout the network may also be attained by capacity enhancement. Similar to the toll pricing models as described above, we modify the capacity enhancement model (CTE) by incorporating the proposed two types of objective functions. The corresponding capacity enhancement models then become

$$\min \left\{ \max_{(i,j)\in\mathcal{A}} \bar{e}_{ij}(f_{ij}, \sigma_{ij}) : (4.20b) - (4.20f) \right\}$$

and

$$\min \left\{ \sum_{(i,j)\in\mathcal{A}} \max\{\, \bar{e}_{ij}(f_{ij}, \sigma_{ij}) - \zeta_{ij} l_{ij},\, 0 \,\} : (4.20b) - (4.20f) \right\},$$

respectively.

Finally, by replacing the objective function of the model (TCTE) we obtain the simultaneous toll pricing and capacity enhancement models with the emission dispersion based objectives as

$$\min \left\{ \max_{(i,j)\in\mathcal{A}} \bar{e}_{ij}(f_{ij}, \sigma_{ij}) : (4.21b) - (4.21e) \right\}$$

and

$$\min \left\{ \sum_{(i,j)\in\mathcal{A}} \max \{ \bar{e}_{ij}(f_{ij}, \sigma_{ij}) - \zeta_{ij} l_{ij},\, 0 \} : (4.21b) - (4.21e) \right\},$$

respectively.

In the next section, we elaborate on how the solutions provided by the total emission and emission dispersion models perform in terms of the resulting emission amounts.

## 4.4 Solution Method

The main difficulty of solving the proposed models come from the complementarity constraints, since these constraints induce a *nonconvex* feasible region (Luo et al., 1996). Fortunately, there exists a meta-solver, namely NLPEC, to handle MPCCs automatically. NLPEC reformulates the complementarity constraints of a MPCC model with a user specified reformulation option. The default option for NLPEC is `reftype mult`, which we use also in our computational study. According to this option, the optimality conditions in (4.10a)-(4.10h) are reformulated as

$$\begin{aligned}
t_{ij}(f_{ij}) - \lambda_i^s + \lambda_j^s &= r_{ij}^{1,s}, && (i,j) \in \mathcal{A}, s \in \mathcal{D},\\
\lambda_i^s - g_{is}^{-1}(d_i^s) &= r_i^{2,s}, && i \in \mathcal{N}, s \in \mathcal{D},\\
r_{ij}^{1,s} x_{ij}^s &\leq \upsilon, && (i,j) \in \mathcal{A}, s \in \mathcal{D},\\
r_i^{2,s} d_i^s &\leq \upsilon, && i \in \mathcal{N}, s \in \mathcal{D},\\
r_{ij}^{1,s} &\geq 0, && (i,j) \in \mathcal{A}, s \in \mathcal{D},\\
r_i^{2,s} &\geq 0, && i \in \mathcal{N}, s \in \mathcal{D},\\
(4.10e)&-(4.10h).
\end{aligned}$$

In the above formulation, $r_{ij}^{1,s}$ and $r_i^{2,s}$, $i \in \mathcal{N}, s \in \mathcal{D}$ are just auxiliary variables automatically generated by NLPEC. Similar reformulations can be easily given for (4.18d)-(4.18f), (4.20d)-(4.20e) and (4.21c)-(4.21e). We set $\upsilon$ to a positive value at first, and thus, start with a "nearly-complementary" solution and aim at pushing the complementarity gap down to zero. This is achieved by choosing additional options `initmu 1, numsolves 5, finalmu 0`. Finally, NLPEC calls a user-specified nonlinear programming solver to solve the reformulated model. The results from the nonlinear programming solver are then translated back into the original MPCC model and the complementarity constraints are checked for violation. Among all available solvers, CONOPT (Drud, 1985) performed the best in our experiments. For several combinations of reformulations and option files, we refer the reader to (Ferris et al., 2005) and the current version of NLPEC manual[1]. We note that NLPEC solver is accessible through GAMS modeling language (Rosenthal, 2014).

## 4.5 Case Study

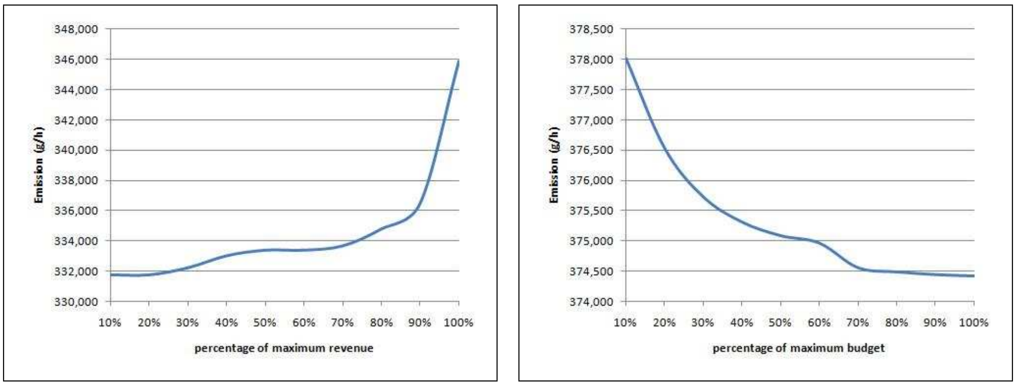
We conduct a computational study to analyze the effects of the proposed models on the emission amounts, and evaluate the toll pricing and capacity enhancement policies with respect to the specified sustainability measures. We use the well-known Sioux Falls network (see Figure 4.3) which consists of 24 nodes, 76 links and 552 O–D pairs. The data of this model is suplied in Apendix B. Its trip table is nearly symmetric, all the connections are bi-directional and represented by two arcs each of which has identical characteristics. It is important to note that the presented map is not to scale, so the length of links is not related to the free flow time between pairs of nodes. The original Sioux Falls network data includes the fixed peak hour demand for O–D pairs. To obtain the problem instances of our models under the elastic demand, we generate parameters of the linear demand function given in (4.1) as follows: We first solve the model (REG) with the original fixed demand data to optimality by omitting the second term in the objective function (4.2a). With the optimal link flow values at hand, we then calculate the associated travel time for each link. In the next step, the path(s) with minimum travel time are identified for each O–D pair. Denoting this minimum travel time as $\bar{\lambda}_i^s$ and the

[1] `http://www.gams.com/dd/docs/solvers/nlpec.pdf` (last accessed on November 2011)

original fixed demand for O–D pair $(i, s)$ as $\bar{d}_i^s$, the parameters of the elastic demand function in (4.1) are calculated from the linear interpolation of points $(\bar{\lambda}_i^s, \bar{d}_i^s)$ and $(\rho\bar{\lambda}_i^s, \bar{d}_i^s/\rho)$, where $\rho$ is a random number generated from the uniform distribution on the interval $(2, 3)$. We also use the optimal solution of the modified (REG) model to calculate the threshold value $\zeta_{ij}$ on the emission concentration for each link $(i, j) \in \mathcal{A}$. For this optimal solution, we calculate the total emission in each zone and divide it by the total length of the links in that zone to estimate the zone emission concentration. We scale these emission concentrations by zone dependent coefficients to determine the zone based threshold values. The zone coefficients are specified as inversely proportional to the corresponding population density. We assume that the population density decreases in the following order of zones: residential, commercial, industrial and non-urban. In particular, the coefficients are selected as 0.7, 0.9, 1.1 and 1.3, respectively. Then the threshold value of each link is set equal to the corresponding zone based threshold value. Notice that the zone coefficients indicate our preferences with respect to the concentration levels associated with the optimal solution of the modified (REG), which can be considered as a reference solution. Basically, we would like to obtain a new solution which performs better than the reference one with respect to decision makers' preferences. When a zone coefficient is less than 1, this indicates that the decision makers prefer a solution with lower emission concentrations in that zone with respect to the reference solution. In our implementation, we assume that it is more preferable to reduce the concentration levels in residential and commercial zones, and therefore, we set the corresponding coefficients to be less than 1. To achieve the desired improvements in the selected zones, we compromise on the concentration levels in the other less dense zones by assigning zone coefficients which are larger than 1.

We choose the following arcs to be tolled: (6,8), (8,6), (10,15), (11,4), (14,11), (15,10), (15,22) (22,15). The same set of arcs is also considered for capacity expansion. In the subsequent figures, all these arcs are also marked with appropriate symbols depending on the problem solved (toll pricing (T), capacity enhancement (C), both policies (X)). We note that the results obtained by the proposed models depend on the arcs to be tolled and/or whose capacities to be enhanced. To determine the maximum revenue parameter $R^{\max}$, we solve an auxiliary model that is obtained from (TTE) by relaxing the constraint (4.18b) and replacing the objective (4.18a) by the maximization of $\sum_{(i,j)\in\bar{\mathcal{A}}_\tau} \tau_{ij} f_{ij}$. The optimum objective function value of this auxiliary model provides the value of the parameter $R^{\max}$.

In a similar fashion, the model (CTE) is solved without constraint (4.20b), and the total capacity enhancement cost associated with its optimum solution is used to set the maximum budget parameter $B^{\max}$. In all our experiments, we consider the accumulated emission for a single pollutant, namely NOx. The variation of the total NOx emission with respect to $\gamma_1$ and $\gamma_2$ values are plotted in Figures 4.2(a) and 4.2(b), respectively. Based on these figures, we set $\gamma_1$ to 0.70 and $\gamma_2$ to 0.80.




(a) Emission versus ratio of the maximum revenue.

(b) Emission versus ratio of the allocated budget.

**Figure 4.2**: The experiments conducted to determine the parameters $\gamma_1$ and $\gamma_2$.

The optimum link emissions are illustrated on the graphical representations of the Sioux Falls network in Figures 4.3-4.6, and some comparative emission statistics are provided in Tables 4.1-4.3. In all of the figures, the network is colored such that the least emission values are observed on green links, whereas very high emission amounts are observed on red links. All other colors represent intermediate values. The average concentration is calculated by dividing the total network emission by the total length of links. The average vehicle emission is calculated as the total network emission divided by the total number of trips. In all of the tables, for each model the values of various criteria and their relative differences with respect to those of the model (REG) are presented in columns “Value”, and “Change”, respectively.

As the model (REG) corresponds to the case where there is no intervention from a traffic authority, its optimal solution is used as a benchmark and the associated emission amounts are depicted in Figure 4.3. As it is common for many cities, we observe that most of the NOx emission is concentrated around the city center. We use these benchmark amounts to analyze the efficiency of applying different policies that we propose in this study.

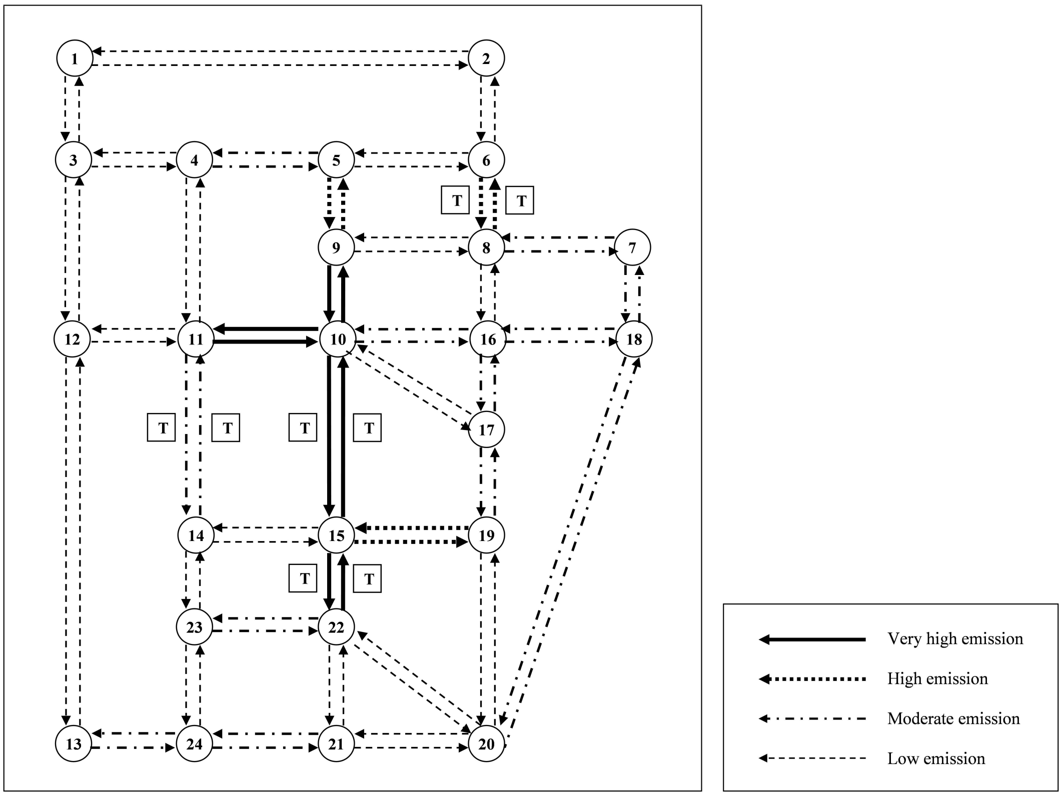



**Figure 4.3**: Pictorial representation of link emissions for model (REG).

First we investigate the results associated with the solutions of three models aiming to minimize the total network emission: (TTE), (CTE) and (TCTE). Emission amounts corresponding to the optimum solutions of these models are illustrated in Figure 4.4, and the statistics about emission amounts are provided in Table 4.1. The main conclusion is that toll pricing based policies are more effective in reducing the total emission. From the total network emission row of Table 4.1, it can be observed that models (TTE) and (TCTE) achieve an emission decrease of about 8.2% and 9.0% respectively compared to (REG). Meanwhile, only 1.1% decrease was achieved with the capacity enhancement model (CTE). A close examination shows that the success of toll pricing policies can be attributed to their potential for reducing the number of trips. As the demand is assumed to be variable and depending on the travel time, pricing type policies direct some of the trips to alternative transportation means, which in turn leads to a reduction in total emission level. On the other hand, the enhancement type policies generate additional demand due the increased capacity. For example, the total number of trips at the optimal solution of the model (CTE) is 2.6% higher than the one obtained by the model (REG) as given in

**Table 4.1**: Statistics for models with the objective of minimizing the total emission

| | (REG) | (TTE) | | (CTE) | | (TCTE) | |
|---|---|---|---|---|---|---|---|
| | Value | Value | Change | Value | Change | Value | Change |
| Tot. Net. Emission | 378.556 | 347.668 | -8.2% | 374.488 | -1.1% | 344.529 | -9.0% |
| Ave. Concentration | 1.206 | 1.107 | -8.2% | 1.193 | -1.1% | 1.097 | -9.0% |
| Min. Concentration | 0.368 | 0.233 | -36.7% | 0.382 | -3.9% | 0.225 | -38.7% |
| Max. Concentration | 2.802 | 2.172 | -22.5% | 2.663 | -5.0% | 2.244 | -19.9% |
| Number of Trips | 360,608 | 329,949 | -8.5% | 369,891 | +2.6% | 336,552 | -6.7% |
| Ave. Veh. Emission | 1.050 | 1.054 | +0.4% | 1.012 | -3.6% | 1.024 | -2.5% |

Table 4.1. This behavior limits their effectiveness in decreasing the total emission. Meanwhile, the model (CTE) is only superior in terms of the average vehicle emission criterion as the total network emission slightly decreases and the total number of trips increases when compared against the model (REG). As the demand decrease is restricted while the emission decrease is substantial, the solution associated with the hybrid policy considered in the model (TCTE) seems to be the most effective one.

Next, we contrast the models (TED1), (CED1) and (TCED1), which have the common objective of minimizing the maximum emission concentration. The optimum solutions are illustrated in Figure 4.5 and the corresponding outcomes are summarized in Table 4.2. Inferences similar to those made for the models minimizing the total emission are also valid here. First of all, the maximum link emission concentrations are significantly lower for all three models due to their objective functions. The model (TED1) provides a solution with the least total emission, and also the least number of trips and the highest average vehicle emission. The solution of the model (CED1) results in a total emission and demand almost equal to those of (REG). Moreover, it can be noticed from the results that (CED1) requires concentration increase on some links to reduce the concentration of others, which is not really a desirable outcome. Finally, the solution provided by the hybrid policy model (TCED1) is moderate in terms of the total emission and the demand decrease, and also leads to a higher decrease in the maximum emission amount.

Finally, we compare the remaining models (TED2), (CED2) and (TCED2) based on the results given in Figure 4.6 and Table 4.3. In terms of both the total emission

**Table 4.2**: Statistics for models with the objective of minimizing the maximum emission concentration

| | (REG) | (TED1) | | (CED1) | | (TCED1) | |
|---|---|---|---|---|---|---|---|
| | Value | Value | Change | Value | Change | Value | Change |
| Tot. Net. Emission | 378.556 | 349.941 | -7.6% | 381.123 | +0.7% | 357.545 | -5.6% |
| Ave. Concentration | 1.206 | 1.114 | -7.6% | 1.214 | +0.7% | 1.139 | -5.6% |
| Min. Concentration | 0.368 | 0.122 | -66.8% | 0.412 | +12.0% | 0.228 | -37.9% |
| Max. Concentration | 2.802 | 2.138 | -23.7% | 2.472 | -11.8% | 2.059 | -26.5% |
| Number of Trips | 360,608 | 325,325 | -9.8% | 365,614 | +1.4% | 340,235 | -5.6% |
| Ave. Veh. Emission | 1.050 | 1.076 | +2.5% | 1.042 | -0.7% | 1.051 | +0.1% |

and total excess emission, the hybrid policy incorporated into the model (TCED2) is the most effective. It seems that by successfully diverting the actual traffic, the undesirable excess emission in a relatively populated commercial zone is dramatically reduced and shifted to non-urban areas. Additionally, excess emission is moderately reduced in residential and industrial zones. The model (TED2) produces quite similar outcomes as the model (TCED2) but it is less effective. The last model (CED2) provides similar results with (REG) in terms of the total emission amount. Moreover, both the total and excess emissions are highly increased for the non-urban areas, and the excess emission is significantly reduced in the commercial area. To summarize, the capacity enhancement is not as effective as the pricing policies but accomplishes its emission dispersion mission when compared against the do-nothing strategy of solving the model (REG).

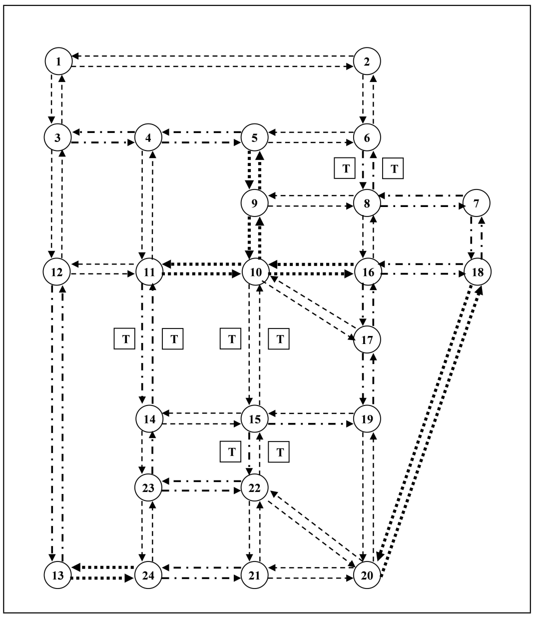
In this study, we propose several new optimization models to support the management of urban transportation networks with environmental sustainability concerns. We derive emission functions in terms of the traffic flow in order to reflect the emission amounts in the congested networks more accurately. Based on the proposed emission functions, we also introduce alternate objective functions into the optimization models. We investigate two main policies: toll pricing and capacity enhancement. The proposed models based on the toll pricing policy provide good results in terms of the emission amounts as tolling reduces the total demand on the network. We have also observed that under the capacity enhancement policy, the increased capacity of a link decreases the travel time on that specific link, and hence, increases the associated travel demand and the emission. This limits the

**Table 4.3**: Statistics for models with the objective of minimizing the zonal excess emission

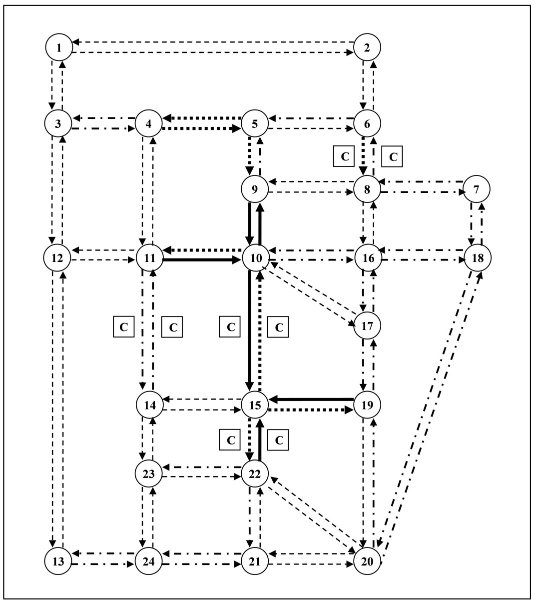
| | (REG) | (TED2) | | (CED2) | | (TCED2) | |
|---|---|---|---|---|---|---|---|
| | Value | Value | Change | Value | Change | Value | Change |
| *Zonal Emission* | | | | | | | |
| Whole Network | 378.556 | 356.686 | -5.8% | 378.659 | +0.0% | 352.712 | -6.8% |
| Residential | 73.907 | 73.951 | +0.1% | 74.452 | +0.7% | 72.921 | -1.3% |
| Commercial | 124.636 | 102.332 | -17.9% | 119.131 | -4.4% | 99.803 | -19.9% |
| Industrial | 140.079 | 142.239 | +1.5% | 136.837 | -2.3% | 141.591 | 1.1% |
| Non-urban | 39.934 | 38.164 | -4.4% | 48.239 | +20.8% | 38.397 | -3.8% |
| *Excess Emission* | | | | | | | |
| Whole Network | 75.080 | 49.765 | -33.7% | 71.272 | -5.1% | 48.640 | -35.2% |
| Residential | 24.402 | 22.593 | -7.4% | 25.015 | +2.5% | 22.211 | -9.0% |
| Commercial | 25.389 | 2.428 | -90.4% | 20.108 | -20.8% | 2.382 | -90.6% |
| Industrial | 21.631 | 20.146 | -6.9% | 19.931 | -7.9% | 19.808 | -8.4% |
| Non-urban | 3.659 | 4.599 | +25.7% | 6.218 | +69.9% | 4.239 | +15.9% |
| Number of Trips | 360,608 | 346,826 | -3.8% | 369,634 | +2.5% | 349,377 | -3.1% |
| Ave. Veh. Emission | 1.050 | 1.028 | -2.0% | 1.024 | -2.4% | 1.010 | -3.8% |

capacity enhancement policy, but still some improvement could be achieved even if the demand increases. The best results are obtained by applying toll pricing and capacity enhancement simultaneously.

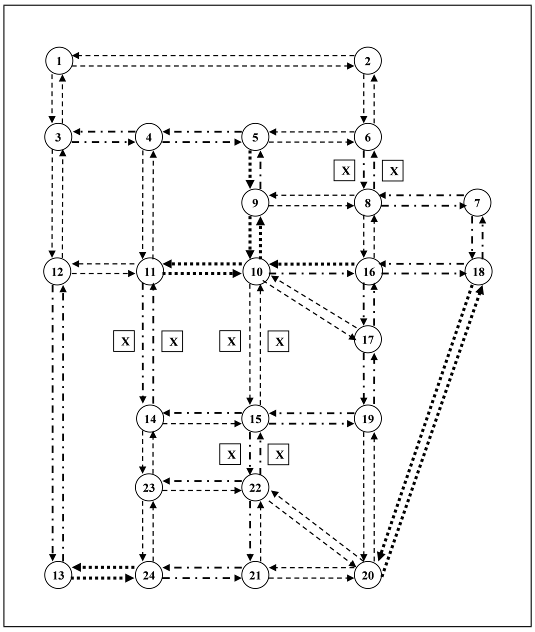
Note that determining the set of arcs to be tolled and/or enhanced is a significant issue to obtain effective policies. As a future research, decisions on selecting the arcs to be tolled and/or enhanced can also be incorporated into the proposed models. As the users of a transportation network drive different types of vehicles or commute by means of public transport, the proposed models could be extended with considering the multi-modal nature of the problem. This shall also increase the accuracy of the models in terms of accumulated emissions, since different vehicles have different emission profiles. Moreover, the road types, such as belt lines, highways, and so on, could also have an impact on the emission profiles. Finally, we intend to investigate fast solution methods that utilize the special structure of the proposed models to solve the large scale real-life problems efficiently.




(a) Toll pricing (TTE).

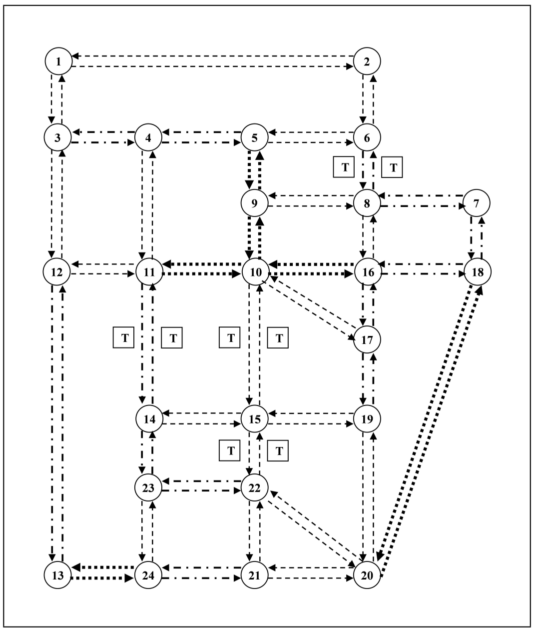



(b) Capacity enhancement (CTE).

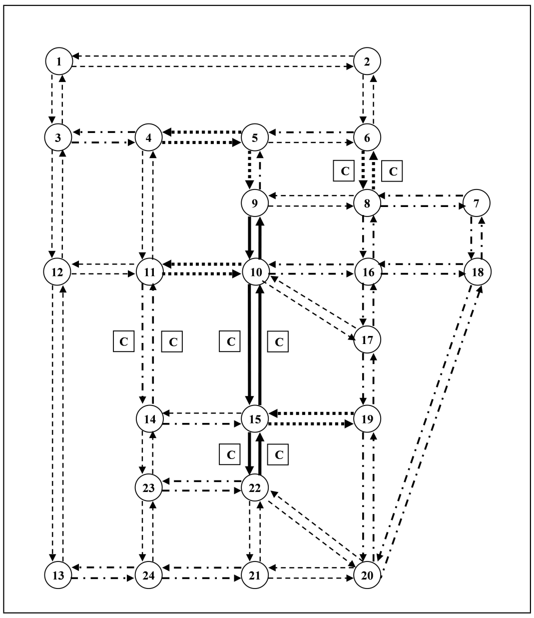



(c) Toll pricing and capacity enhancement (TCTE).

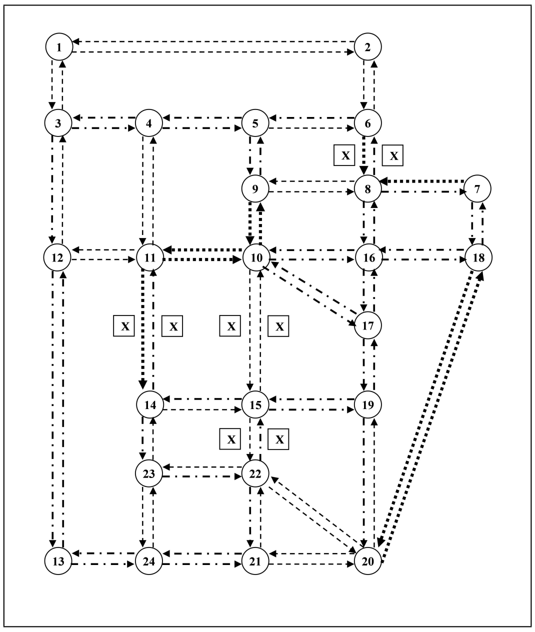
**Figure 4.4**: Pictorial representation of link emissions for models aiming to minimize the total emission.




(a) Toll pricing (TED1).

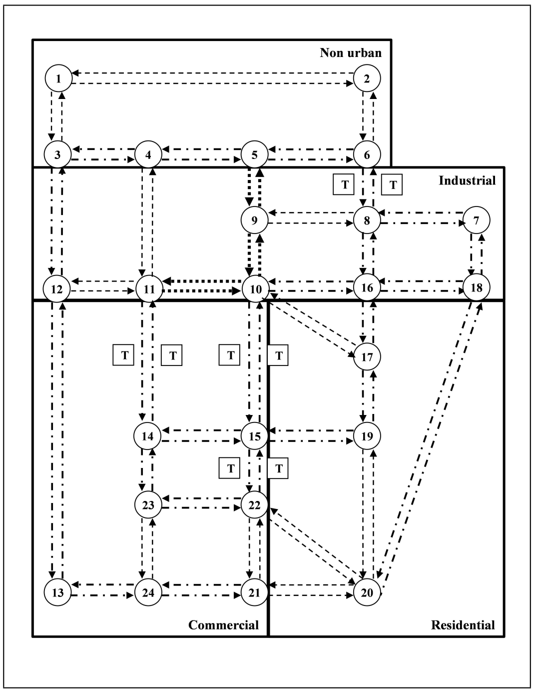



(b) Capacity enhancement (CED1).

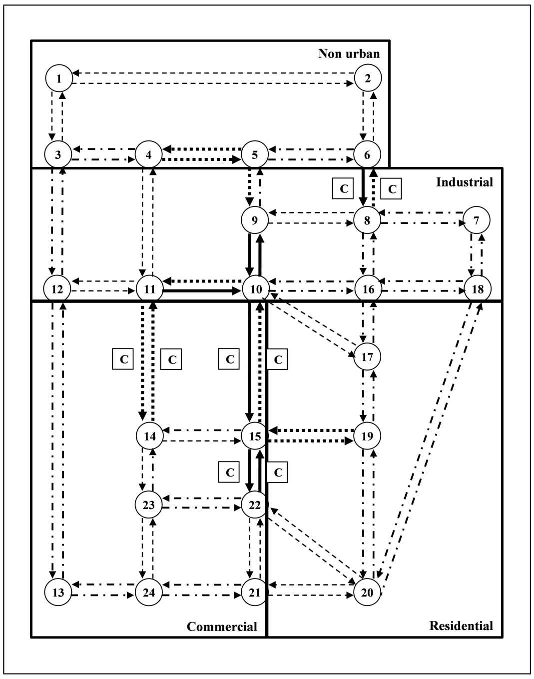



(c) Toll pricing and capacity enhancement (TCED1).

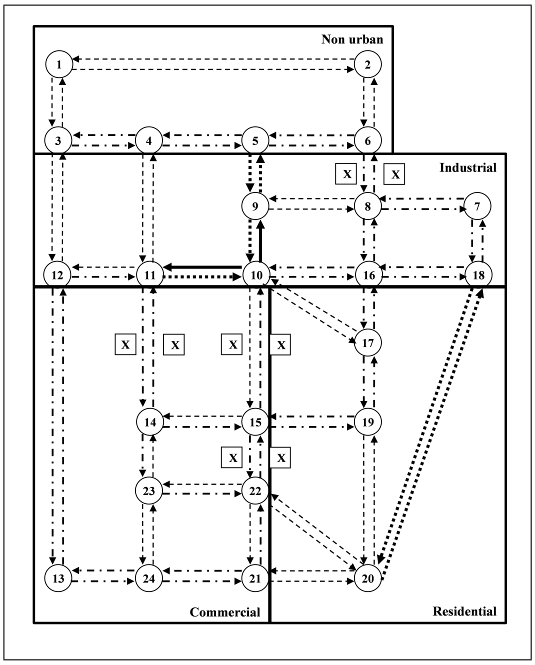
**Figure 4.5**: Pictorial representation of link emissions for models aiming to minimize the maximum emission concentration.




(a) Toll pricing (TED2).




(b) Capacity enhancement (CED2).




(c) Toll pricing and capacity enhancement (TCED2).

**Figure 4.6**: Pictorial representation of link emissions for models aiming to minimize the zonal excess emission.

# 5 SUSTAINABLE TRAFFIC ASSIGNMENT WITH SUE

In chapter 4, we covered Deterministic User Equilibrium (DUE) in which the users are supposed to have a perfect knowledge of the traffic network and the are assumed to make their decisions rationally. Against this ideal solution, users usually don't have a perfect knowledge of the network and don't always make rational decisions. To model this later case, Stochastic User Equilibrium (SUE) model is proposed and this model is presented in this chapter.

The perfect knowledge assumption can be relaxed when the user equilibrium is reached in the stochastic sense. In this case, it is assumed that the users make their decisions according to the travel time they *perceive* and thus any path relating an origin and a destination has a positive probability to be taken (Sheffi, 1985).

Recently, Kolak et al. (2013) proposed a bi-level traffic assignment model with an environmental objective. This model consists of a single objective and assumes deterministic user equilibrium. The objective was to minimize emission in the traffic network. As sustainability has many dimensions, here we propose a new model with multiple objectives, and we drop the assumption that users have a perfect knowledge of the traffic network and extend the former model with stochastic user equilibrium.

To solve the multi-objective model, we consider an evolutionary algorithm, namely the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002). The main reason for the choosing of this algorithm is its ability to produce a set of non-dominated solutions instead of a single solution. This algorithm is also considered to be one of the best multi-objective evolutionary algorithms being efficient and flexible (Ghodratnama et al., 2014).

## 5.1 Stochastic User Equilibrium

We cover here two different SUE models. In the first model (SUE-FD), the demand between any origin and destination on the network has a fixed value. In the second model (SUE-ED), the demand between any origin and destination is elastic and varies according to the travel time between corresponding origin and destination.

### 5.1.1 Stochastic User Equilibrium with Fixed Demand (SUE-FD)

Let $\mathcal{N}$ the set of nodes and $\mathcal{A}$ the set of links on a traffic network. Let $f_{ij}$ be the traffic flow and $t_{ij}(f_{ij})$ the travel time function on link $(i,j) \in \mathcal{A}$, $\mathbf{c}^{rs}$ the vector of actual travel times on all paths $k$ between origin $r$ and destination $s$, $C_k^{rs}$ the perceived travel time on path $k$ between origin $r$ and destination $s$ and $S_{rs}$ the satisfaction function of origin destination pair $(r,s) \in \mathcal{W}$. $d^{rs}$ travel demand between origin $r$ and destination $s$. Then the unconstrained optimization model (5.1) solves the SUE-FD (Sheffi, 1985):

$$\min_{\mathbf{f}} z(\mathbf{f}) = -\sum_{(r,s)\in\mathcal{W}} d_{rs} S_{rs}[\mathbf{c}^{rs}(\mathbf{f})] + \sum_{(i,j)\in\mathcal{A}} f_{ij} t_{ij}(f_{ij}) - \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} t_{ij}(\omega) \mathrm{d}\omega \quad (5.1)$$

where

$$S_{rs}[\mathbf{c}^{rs}(\mathbf{f})] = E\left[min_{k\in\mathcal{K}_{rs}} \{C_k^{rs}\} \,|\mathbf{c}^{rs}(\mathbf{f})\right] \quad \forall (r,s) \in \mathcal{W}. \quad (5.2)$$

### 5.1.2 Stochastic User Equilibrium with Elastic Demand (SUE-ED)

The model in (5.1) is formulated by assuming that the travel demand for a destination is fixed. However, users tend to postpone or cancel their travel demand in practice when the duration of a trip is perceived as long. To consider this situation, we assume that there exist a nonnegative and strictly decreasing demand function $D_{rs}$ with respect to the path cost OD pair $(r,s)$. Then, $d^{rs} = D_{rs}(S^{rs})$ and $S^{rs} = D_{rs}^{-1}(d^{rs}) \quad \forall (r,s) \in \mathcal{W}$.

Rosa & Maher (2002) propose SUE-ED that can be formulated as the unconstrained optimization model (5.3):

$$\begin{aligned}\min_{\mathbf{f},\mathbf{d}} Z(\mathbf{f},\mathbf{d}) = & \sum_{(i,j)\in\mathcal{A}} t_{ij}(f_{ij})f_{ij} - \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} t_{ij}(\omega)\mathrm{d}\omega + \sum_{(r,s)\in\mathcal{W}} D_{rs}^{-1}(d^{rs})D_{rs}\left(S^{rs}\left(\mathbf{x}\right)\right) \\ & - \sum_{(r,s)\in\mathcal{W}} S^{rs}(\mathbf{f})D_{rs}\left(S^{rs}\left(\mathbf{f}\right)\right) + \sum_{(r,s)\in\mathcal{W}} \int_0^{d^{rs}} dD_{rs}^{-1}(d)\mathrm{d} - \sum_{(r,s)\in\mathcal{W}} d^{rs}D_{rs}^{-1}(d^{rs})\end{aligned} \tag{5.3}$$

where all variables are as defined earlier.

## 5.2 Formulating Multiple Sustainability Objectives and Flow Management Strategies

### 5.2.1 Sustainability Objectives

In a very compact way, a sustainable transportation system should respond to mobility needs, but at the same time should attend to the habitat, the equity in the society, and the economic advancement in the present as well as in the future Deakin (2001). Within the context of sustainability, objectives can be classified under three dimensions: environmental, social and economical Litman & Burwell (2006). And under these three dimensions, different objectives can be considered. These objectives are usually conflicting, in other words, while one objective improves, others can get deteriorate. In that case, instead of finding a single optimal solution, it is more useful to find a set of non-dominated solutions. This topic will be discussed in details in following sections. Here, we present the objective functions considered within the scope of this study.

**a) The Environmental Objective** As urban transportation is mainly based on fossil fuels, environmental costs should also be considered in the framework of sustainable transportation. An importation objective in the environmental dimension is the minimization of gases emissions that have negative impacts on human health and climate. Mainly two approaches are referred in the literature to include the emission of vehicles in the mathematical models. The simplistic approach is the use of emission factors (Nagurney, 2000a,b; Rahman & Grol, 2005; de Ceuster et al., 2007). This approach only considers the number of vehicles using a network discarding the travel speed and the congestion effects. But it is well known that high emission occurs in congested networks while vehicles travel at slower speeds. Instead of emission factors, emission functions are also proposed (Rilett & Benedek, 1994; Gkatzoias et al., 2007). Using emission functions, travel speed can also be considered in the calculation of the emissions. As a result, the negative effects of the congestion can be exposed more accurately. Kolak et al. (2013) consider the EURO standard issued by European Environment Agency (EEA) (Gkatzoias et al., 2007) in the calculation of traffic emissions.

The emission function is defined as:

$$Z_1 = \sum_{(i,j)\in\mathcal{A}} e_{ij}(f_{ij}, \sigma_{ij}) \tag{5.4}$$

where $(i, j) \in \mathcal{A}$ is a link in the traffic network, $f_{ij}$ is the flow on link $(i, j)$, $\sigma_{ij}$ is the capacity enhancement on link $(i, j)$ and $e_{ij}$ is the amount of emission on link $(i, j)$.

**b) The Social Objective** The most common social objective is the minimization of total network travel time which is widely researched in the literature (Chen & Alfa, 1991b; Fumero et al., 1999; Chen et al., 2004; Maher et al., 2005; Long et al., 2010). With SUE, the minimization of *perceived* travel time is considered Stewart (2007). But travel time by itself is not sufficient in the framework of social dimension. More recent studies also consider the equity as a social objective. Equity can be measured in many ways. As for example, toll pricing affects more people with limited budgets, so Wu et al. (2012) propose the equity in congestion pricing. Users also may not benefit equally from the road improvements in the context of spacial accessibility, so Delafontaine et al. (2011) propose the equity in accessibility. Another negative effect of urban transportation is the road accidents which are also considered a major social cost to the community (Shefer, 1994; Noland et al., 2008). Here, we focus on the equity of accessibility. Keeble et al. (1982) define accessibility of a traffic network as:

$$A = \sum_{r \in \mathcal{N}} P_r \times A_r \tag{5.5}$$

where

$$A_r = \sum_{\substack{s \neq r \\ s,r \in \mathcal{N}}} \frac{P_s}{C_{rs}} \quad \forall r \in \mathcal{N}. \tag{5.6}$$

In equation (5.5), $A_r$ denotes the the accessibility of node $r$ to all other nodes $s$. The accessibility to the node is inversely proportional to the expected perceived travel times $C_{rs}$. Moreover, the accessibility is proportional to the destination link population $P_s$ to give more importance to centers where more people live. The node accessibility $A_r$ defines the accessibility for an individual living on node $r$. By multiplying $A_r$ by $P_r$ in equation (5.5), overall accessibility of node $r$ can be obtained. Finally, general network accessibility $A$ can be calculated by summing the accessibility of all nodes (Santos et al., 2008).

Many equity measures have been proposed in the literature expressing different perceptions of fairness like Gini coefficient, Theil index, Atkinson index etc. (D. Gkatzoias & Samaras, 2007). But there is little agreement about the best measure to apply in various situations. In a perfect, fully equitable region, all centers would have exactly same accessibility. A good way to measure the inequality of a situation is to compare it with a perfect region. Wu et al. (2012) propose the Gini coefficient or Gini index, one of the most widely used measures of inequality. The Gini coefficient is formulated as:

$$Z_2 = \frac{\sum_{r \in \mathcal{N}} \sum_{s \in \mathcal{N}} P_r P_s \left| A_r - A_s \right|}{2 \left( \sum_{r \in \mathcal{N}} P_r \right)^2 \bar{A}} \tag{5.7}$$

where

$$\bar{A} = \frac{\sum_{r \in \mathcal{N}} A_r}{n} \tag{5.8}$$

where $n$ in the total number of nodes and $\bar{A}$ is the average accessibility of the network.

The Gini coefficient can be defined as a measure of dispersion scaled by twice the value of the mean. In practice, it measures the relative difference between the actual and a perfect situation. The value of the coefficient belongs to the interval $[0, 1]$, and the lower the value is, the closer the situation is to perfect. In a perfect network, equity would be equal to zero. Our second objective is then to minimize the value of $Z_2$.

### 5.2.2 Bi-Level Multi-Objective Optimization Model

The Traffic Assignment Problem discussed in section 5.2 can be formulated as a bi-level multi-objective optimization model. This model consists of two problems, the upper level problem which represents the traffic authority decisions with multiple objectives and the lower level problem which represents the traffic users decisions.

The lower level problem consists of SUE. As the number of nodes and links in a real traffic network is high, solving this problem can become a very cumbersome task. Fortunately, there are algorithms that allows to solve such problems very efficiently. The efficiency of this algorithm is crucial as it is called many times to solve the upper level model.

Let $\bar{\mathcal{A}}_\tau \subset \mathcal{A}$ be the subset including the toll priced links and $\bar{\mathcal{A}}_\sigma \subset \mathcal{A}$ be the subset including the capacity enhanced links. Let $\tau_{ij}^{\max} > 0$ be the maximum amount of toll price on link $(i, j) \in \bar{\mathcal{A}}_\tau$ and $\sigma_{ij}^{\max} > 0$ be the maximum amount of capacity enhancement on link $(i, j) \in \bar{\mathcal{A}}_\sigma$. Let $\tau_{ij}^{\max} = 0$ for $(i, j) \in \mathcal{A}/\bar{\mathcal{A}}_\tau$ and $\sigma_{ij}^{\max} = 0$ for $(i, j) \in \mathcal{A}/\bar{\mathcal{A}}_\sigma$.

The bi-level multi-objective optimization model for SUE-FD with TPCE can be formulated as follows:

$$\min Z_1 = \sum_{(i,j)\in\mathcal{A}} e_{ij}(f_{ij}, \sigma_{ij}) \tag{5.9a}$$

$$\min Z_2 = \frac{\sum_{r\in\mathcal{A}}\sum_{s\in\mathcal{A}} P_r P_s \left|A_r - A_s\right|}{2\left(\sum_{r\in\mathcal{A}} P_r\right)^2 \bar{A}} \tag{5.9b}$$

ST:

$$0 < \tau_{ij} < \tau_{ij}^{max} \qquad \forall(i,j)\in\mathcal{A} \tag{5.9c}$$

$$0 < \sigma_{ij} < \sigma_{ij}^{max} \qquad \forall(i,j)\in\mathcal{A} \tag{5.9d}$$

$$\begin{aligned}\min_{\mathbf{f}} z(\mathbf{f}) = &- \sum_{(r,s)\in\mathcal{W}} d_{rs} S_{rs}[\mathbf{c}^{rs}(\mathbf{f})] + \sum_{(i,j)\in\mathcal{A}} f_{ij}\left(\bar{t}_{ij}(f_{ij},\sigma_{ij}) + \tau_{ij}\right) \\ &- \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} \left(\bar{t}_{ij}(f_{ij},\sigma_{ij}) + \tau_{ij}\right)(\omega)\mathrm{d}\omega.\end{aligned} \tag{5.9e}$$

In order to construct the bi-level multi-objective optimization model for SUE-ED with TPCE, the model should be constructed as:

$$\min Z_1 = \sum_{(i,j)\in\mathcal{A}} e_{ij}(f_{ij}, \sigma_{ij}) \tag{5.10a}$$

$$\min Z_2 = \frac{\sum_{r\in\mathcal{A}}\sum_{s\in\mathcal{A}} P_r P_s \left|A_r - A_s\right|}{2\left(\sum_{r\in\mathcal{A}} P_r\right)^2 \bar{A}} \tag{5.10b}$$

ST:

$$0 < \tau_{ij} < \tau_{ij}^{max} \qquad \forall(i,j)\in\mathcal{A} \tag{5.10c}$$

$$0 < \gamma_{ij} < \gamma_{ij}^{max} \qquad \forall(i,j)\in\mathcal{A} \tag{5.10d}$$

$$\begin{aligned}\min_{\mathbf{f},\mathbf{d}} Z(\mathbf{f},\mathbf{d}) = &\sum_{(i,j)\in\mathcal{A}} \left(\bar{t}_{ij}(f_{ij},\sigma_{ij}) + \tau_{ij}\right) - \sum_{(i,j)\in\mathcal{A}} \int_0^{f_{ij}} \left(\bar{t}_{ij}(f_{ij},\sigma_{ij}) + \tau_{ij}\right)(\omega)\mathrm{d}\omega \\ &+ \sum_{(r,s)\in\mathcal{W}} D_{rs}^{-1}(d^{rs}) D_{rs}\left(S^{rs}(\mathbf{f})\right) - \sum_{(r,s)\in\mathcal{W}} S^{rs}(\mathbf{f}) D_{rs}\left(S^{rs}(\mathbf{f})\right) \\ &+ \sum_{(r,s)\in\mathcal{W}} \int_0^{d^{rs}} D_{rs}^{-1}(d)\mathrm{d}d - \sum_{(r,s)\in\mathcal{W}} d^{rs} D_{rs}^{-1}(d^{rs})\end{aligned} \tag{5.10e}$$

Note that, both toll pricing and capacity enhancement strategies influence the decisions of traffic users and necessary adjustments must be applied to the lower level model which represents the traffic user decisions. But, it is assumed that toll pricing does not actually affect the travel speed of a vehicle using a link, as a result it does not change the travel time of the vehicles and consequently has no direct effect on vehicle emissions and node accessibilities. Contrary to the toll pricing, capacity enhancements directly affect the vehicle speeds and travel times so must be incorporated in both objective functions in upper level model.

## 5.3 Solution Method

### 5.3.1 Solving the Stochastic User Equilibrium

Most algorithms proposed to solve SUE problems relies on the Method of Successive Averages (MSA). However, the slow convergence speed of MSA is its main disadvantage that limits its application. The reason for its poor performance is mainly due to the predetermined sequence of step size used in the search, which inspires researchers to develop alternative methods. Recently, Liu et al. (2009a) propose the Self-Regulated Averaging (SRA) Scheme for solving SUE. In SRA method, the step sizes are dynamically updated by evaluating a potential function. When the potential function detects that the step size in previous iteration is effective to the convergence, it maintains current step size slowly converging to zero; otherwise, it speeds up the reduction of the step size.

#### 5.3.1.1 Self-Regulated Averaging Algorithm

Lets denote $\kappa$ the current iteration, $\mathbf{f}^{\kappa}$ and $\mathbf{y}^{\kappa}$, current and auxiliary solutions respectively and $\alpha_{\kappa} = 1/\beta_{\kappa}$ step size at iteration $\kappa$. The most convenient measurement that can be used to monitor the convergence is the distance between auxiliary point $\mathbf{y}^{\kappa}$ and current solution $\mathbf{f}^{\kappa}$, due to the fact that $\mathbf{y}^{\kappa} \to \mathbf{f}^{*}$ (where $\mathbf{f}^{*}$ denotes the optimal solution). Therefore, SRA regulates the increment of $\beta_{\kappa}$ according to the information of absolute error $||\mathbf{f}^{\kappa} - \mathbf{y}^{\kappa}||$. The increment of $\beta_{\kappa}$ should be greater than 1, if the iterate tends to diverge, or whenever the distance

$||\mathbf{f}^\kappa - \mathbf{y}^\kappa||$ becomes larger; otherwise, the increment of $\beta_\kappa$ should be smaller than 1, when the solution series tend to converge, or whenever the distance $||\mathbf{f}^\kappa - \mathbf{y}^\kappa||$ becomes smaller. That is:

$$\beta_\kappa = \left\{ \begin{array}{l} \beta_{\kappa-1} + \Gamma, \Gamma > 1, \text{if } ||\mathbf{f}^\kappa - \mathbf{y}^\kappa|| \geq ||\mathbf{f}^{\kappa-1} - \mathbf{y}^{\kappa-1}|| \\ \beta_{\kappa-1} + \gamma, \gamma < 1, \text{if } ||\mathbf{f}^\kappa - \mathbf{y}^\kappa|| < ||\mathbf{f}^{\kappa-1} - \mathbf{y}^{\kappa-1}|| \end{array} \right\}. \tag{5.11}$$

The choice of step size increment parameters $\Gamma$ and $\gamma$ is flexible, e.g., $\Gamma \in [1.5, 2]$ and $\gamma \in [0.01, 0.5]$.

Let $\mathbf{F}(\mathbf{f}^\kappa, \mathbf{d}^\kappa)$ denote the stochastic network loading function: It takes as input, the current network link flows $\mathbf{f}^\kappa$ and travel demands $\mathbf{d}^\kappa$ at iteration $\kappa$, calculates link travel times $t(\mathbf{f}^\kappa)$ and finally determines and returns resulting network flows $\mathbf{y}^\kappa$ corresponding these link travel times. We will discuss this function in section 5.3.1.2. $\mathbf{y}^\kappa$ is then used as the auxiliary solution for the next iteration. The algorithm stops when the distance between the current network link flows $\mathbf{f}^\kappa$ and the auxiliary network link flows $\mathbf{y}^\kappa$ is small i.e. $||\mathbf{f}^\kappa - \mathbf{y}^\kappa|| < \varepsilon$. In SUE with elastic demand, the travel demand is dependent on minimum expected perceived travel times $S^{rs}(\mathbf{f})$. Travel demand in every iteration is updated according to current minimum expected perceived travel times. It should also be noted that as $\mathbf{f}$ converges to $\mathbf{y}$, the demand $D_{rs}(S^{rs}(\mathbf{f}))$ converges to $D_{rs}(S^{rs}(\mathbf{y}))$. Consequently the convergence of the demand function doesn't need to be checked.

The implementation details of SRA method to solve SUE-ED are described in Algorithm 1. Also, we can modify Step 10 in this algorithm as $\mathbf{d}^{\kappa+1} = \mathbf{d}$ in order to solve SUE-FD where $\mathbf{d}$ denotes the fixed demands between origin and destination pairs.

#### 5.3.1.2 Stochastic Network Loading

In the DUE, all of the travel demand related to an OD pair is assumed to take on least cost path. As it is assumed that the users don't have perfect knowledge about the network in SUE, the demand can take many paths relating an origin to a

**Algorithm 1:** Self-Regulated Averaging Method for SUE with Elastic Demand

Initialization: Set $\kappa = 1$; $\Gamma > 1$; $0 < \gamma < 1$; the stop criteria $\varepsilon > 0$;

Set the initial point $\mathbf{x}^1 = 0$; calculate the initial demand $\mathbf{d}^1 = D_{rs}(S^{rs}(\mathbf{f}^1))$ and auxiliary point $\mathbf{y}^1 = \mathbf{F}(\mathbf{f}^1, \mathbf{d}^1)$;

**while** $||\mathbf{f}^\kappa - \mathbf{y}^\kappa|| \geq \varepsilon$ **do**

  **if** $||\mathbf{f}^\kappa - \mathbf{y}^\kappa|| \geq ||\mathbf{f}^{\kappa-1} - \mathbf{y}^{\kappa-1}||$ **then**

    $\beta_\kappa = \beta_{\kappa-1} + \Gamma$;

  **else**

    $\beta_\kappa = \beta_{\kappa-1} + \gamma$;

  $\alpha_\kappa = 1/\beta\kappa$;

  $\mathbf{f}^{\kappa+1} = \mathbf{f}^\kappa + \alpha_\kappa(\mathbf{y}^\kappa - \mathbf{f}^\kappa)$ ;

  $\mathbf{d}^{\kappa+1} = D_{rs}(S^{rs}(\mathbf{f}^{\kappa+1}))$ ;

  $\mathbf{y}^{\kappa+1} = \mathbf{F}(\mathbf{f}^{\kappa+1}, \mathbf{d}^{\kappa+1})$; ;

  $\kappa = \kappa + 1$;

**output**: $\mathbf{f}^\kappa$

destination. The flow that occurs on a given path depends to the probability that users choose this path, an this probability in turns depends to the cost (time) that occurs if this path is chosen. The probability distribution function of the (perceived) travel time on each path has to be known so that the path choice probability can be calculated.

There are two type of network loading models widely used in the literature. The main assumption of *logit based* models is that the alternatives in the choice set are identically and independently distributed Gumbel variates. Logit based models are widely researched (Chen & Alfa, 1991b; Yang et al., 2001; Meng et al., 2004; Maher et al., 2005; Wu et al., 2009; Sumalee et al., 2009; Long et al., 2010) in the literature so there exist an abundant number of efficient algorithms developed to solve these models. Also, these models yield realistic results on medium and large scale networks even though they do not consider the interaction between different overlapping paths. *Probit based* models are also developed in recent years (Wu et al., 2006; Ren et al., 2009). The assumption of probit based models is that the perceived travel times are normally distributed. The main advantage of these models is that they also consider the interaction of overlapping paths. Monte Carlo simulation or similar simulation techniques are usually used to solve these models. In this study, we consider the logit based model as it is widely used in practice.

*Logit-based Network Loading Model.* Recall that $c_k^{rs}$ and $C_k^{rs}$ corresponds to the actual and perceived travel times on path $k$ between origin $r$ and destination $s$, respectively. Let, $\theta$ be a positive parameter and $\rho_k^{rs}$ a random term, the distribution of which is given by the Gumbel density function. Then, the perceived travel time can be expressed as

$$C_k^{rs} = c_k^{rs} - \frac{1}{\theta}\rho_k^{rs} \tag{5.12}$$

The parameter $\theta$ is in fact a constant that scales the perceived travel time. If $\theta$ is very large, the perceived error is small and users will tend to select the minimum measured travel-time path. A small value of $\theta$ indicates a large perception variance, with travelers using many routes, including some that may be significantly longer than the true shortest path. In the limit, where $\theta \to 0$, the share of flow on all paths will be equal, regardless of path travel times (Sheffi, 1985).

On a small network with few nodes and links, it may be possible to enumerate all the paths. Unfortunately, in more realistic settings, enumeration of all paths may not be practical. An alternative approach is to determine *reasonable* paths and to use only this subset of paths for network loading. In this study however, we use Bell's Second Algorithm (Bell, 1995). This algorithm is link based and instead of path choice probabilities, it use link choice probabilities. This approach offer significant advantages. It does not require path enumeration in every iteration of the algorithm, hence works very efficiently and fast. The efficiency of network loading algorithm is a crucial issue because it takes part in SRA and called many times as a subprocedure.

Bell's algorithms (Bell, 1995) are based on Dial's algorithm (Dial, 1971). Dial's method requires that travel times on all paths between origins and destinations be calculated beforehand. This requires the determination of all paths between origins and destination and calculation of travel times. This problem have to be solved iteratively with forward or backward passes. The need to calculate the travel times on all paths between origins and destination in a medium or large scale network affects negatively the efficiency of network loading algorithms which uses the Dial's network loading algorithm.

Bell (1995) proposes two methods for finding a logit assignment that dispense with the need for either a forward or a backward pass. As with Dial's method, path enumeration is not required. There is no need to know minimum costs beforehand. The first method considers a finite number of paths including all those without loops and some with. The second method considers all paths, which will be an infinite number in the presence of loops.

It should also be noted that, on small networks, the presence of paths with loops can lead to unrealistic results. However, on medium and large networks, the inclusion of paths with loops induces negligible or no difference on network flows. The implementation details of Bell's second algorithm are presented in Algorithm 2:

**Algorithm 2:** Bell's Second Algorithm

**input** : link flows $f_{ij}$ and O–D demands $d_{rs}$

Set $\kappa = 1$ ;

Calculate $t_{ij}(f_{ij}) \quad \forall i, j$ ;

Define a matrix $W^1 = [w^1_{ij}]$ with elements

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

**while** $\max(w^{\kappa}_{ij}) > \varepsilon$ **do**

  $W^{\kappa+1} = W^{\kappa} \times W^1$ ;

  $\kappa = \kappa + 1$ ;

$W = \sum_{\kappa'=1}^{\kappa} W^{\kappa'}$ ;

$p^{rs}_{ij} = \dfrac{w_{ri} \times \exp(-\theta t_{ij}(f_{ij})) \times w_{js}}{w_{rs}}$ ;

$y_{ij} = \sum_{rs} d_{rs} p^{rs}_{ij}$ ;

**output**: auxiliary link flows $y_{ij}$

### 5.3.2 Solving Upper Level Problem

SUE-FD and SUE-ED are optimization models with multiple objective functions. A model with multiple conflicting objectives has a set of optimal solutions (known as Pareto-optimal solutions) instead of a single optimal solution. None of the solutions in the Pareto-optimal set is better than other solutions. It cab be beneficial to identify as many Pareto-optimal solution as possible to enable the decision makers making a selection based on their conditions.

Solving the Multi-Objective Optimization (MOO) problems requires considerable amount of computations. In order to solve MOO problems, several authors have proposed different evolutionary and swarm intelligence based MOO algorithms (Patel & Savsani, 2014). Dynamical Multi-Objective Evolutionary Algorithm (Liu et al., 2009b), Multiple Trajectory Search (Tseng & Chen, 2009), Multi-Objective Evolutionary Programming (Qu & Suganthan, 2009), Nondominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al., 2002), Local Search Based Evolutionary Multi-Objective Optimization Algorithm (Sindhya et al., 2009), Multi objective Biogeography-Based Optimization (Silva et al., 2012), etc. are some of the evolutionary MOO algorithms that aimed to obtain approximate Pareto front for multi-objective problems. Similarly, PSO-based multi-objective optimization with dynamic population size and adaptive local archives (Coello et al., 2004), Dynamic Multiple Swarms in Multi-Objective Particle Swarm Optimization (Yen & Leong, 2009), Autonomous bee colony optimization for multi-objective function (Zeng et al., 2010), Particle swarm inspired evolutionary algorithm (PS-EA) for multi-objective optimization problem (Srinivasan & Seow, 2003), Interactive Particle Swarm Optimization (Agrawal et al., 2008), Multi-objective artificial bee colony algorithm (Akbari et al., 2012), etc. are some of the swarm intelligence algorithms which efficiently solved the multi-objective problems.

In this study, we consider the Multi-Objective Evolutionary Algorithms (MOEA). Various MOEAs (Li et al., 2010) are proposed in the litterature (Fonseca & Fleming, 1993; Horn et al., 1994; Srinivas & Deb, 1994; Deb, 2001). The main advantage of MOEAs is the ability to find multiple Pareto-optimal solutions in a single run. As Evolutionary Algorithms (EA) work with a population of solutions, a simple EA can be extended to find multi-objective solutions. The nondominated sorting genetic algorithm (NSGA) proposed in (Srinivas & Deb, 1994) is one of the first such EAs. NSGA can find Pareto-optimal solutions in a single run, but the main disadvantage of this algorithm is the high computational complexity of $O(MN^3)$ (where $M$ is the number of objectives and $N$ is the population size) (Deb et al., 2002). NSGA-II (Deb et al., 2002) discussed in this section is an improvement over the original NSGA and has a computational complexity of $O(MN^2)$.

*Nondomination rank*: "Non-dominated sorting" is one of the main characteristics of the NSGA-II. A vector $u = (u_1, u_2, \ldots, u_N)$ is said to dominate another vector, $v = (v_1, v_2, \ldots, v_N)$ if and only if $u_i \leq v_i$ for all $i = 1, \ldots, N$ and there exists at least an element $k$ such that $u_k < v_k$ (Coello et al., 2007). To find the nondominated rank of a solution $u$, two quantities should be calculated: 1) domination count $n_u$, the number of solutions dominating $u$, and 2) $\mathcal{S}_u$, a set of solutions that $u$ dominates.

All solutions in the first nondominated front will have their domination count as zero. Then, for each solution $u$ with $n_u = 0$, $n_v$ of each $v \in \mathcal{S}_u$ is reduced by one. While doing so, if for any $v \in \mathcal{S}_u$, the domination count becomes zero, it is added to a set $\mathcal{Q}$. These solutions belong to the second nondominated front. This process continues until all fronts are identified. The front that a particular solution belongs determines this solution's *nondomination rank* ($u_{\text{rank}}$).

*Crowding distance*: Another important concept is "crowding distance" for NSGA-II implementation. It measures the density of an individual through all the individuals in a particular front (rank). An EA is desired to maintain a good spread of solutions in the obtained set of nondominated solutions. NSGA-II introduces a density-estimation metric for the crowded-distance approach.

For each solution in the pareto optimal front, the average distance to the neighboring solutions in the same pareto optimal front is calculated. This quantity $u_{\text{distance}}$ serves as an estimate of the perimeter of the cuboid formed using the nearest neighbors as the vertices (call this the *crowding distance*).

*Crowded-Comparison Operator*: The crowded-comparison operator ($\prec_n$) guides the selection process at the various stages of the algorithm toward a uniformly spread-out Pareto-optimal front.

We now define a partial order $\prec_n$ as

$$\begin{aligned}
&u \prec_n \upsilon \\
&\quad \text{if } (u_{\text{rank}} < \upsilon_{\text{rank}}) \\
&\quad \text{or } ((u_{\text{rank}} = \upsilon_{\text{rank}}) \\
&\qquad \text{and } (u_{\text{distance}} > \upsilon_{\text{distance}})).
\end{aligned}$$

That is, between two solutions with different nondomination ranks, we prefer the solution with the lower (better) rank. Otherwise, if both solutions belong to the same front, then we prefer the solution that is located in a lesser crowded region.

*Genetic Operators*: We use *Simulated Binary Crossover (SBX)* (Deb & Agrawal, 1995; Deb, 2001; Deb et al., 2002) operator for crossover and *polynomial mutation* (Deb, 2001; Deb et al., 2002).

Let $p_{1,k}$ and $p_{2,k}$ be the values of $k^{\text{th}}$ attribute of parents 1 and 2 respectively. Let $c_{1,k}$ and $c_{2,k}$ be the value of $k^{\text{th}}$ attribute of children 1 and 2 respectively. We use Algorithm 3 for crossover:

**Algorithm 3:** Simulated Binary Crossover (SBX)

1 Generate a uniformly sampled random number $\rho_k$ ;

2 Calculate $\varrho_k = \begin{cases} (2\rho_k)^{\frac{1}{(\eta_c+1)}} & \text{if } \rho_k \leq 0.5 \\ \frac{1}{[2(1-\rho_k)]^{\frac{1}{(\eta_c+1)}}} & \text{if } \rho_k > 0.5 \end{cases}$ ;

3 Calculate $\begin{aligned} c_{1,k} &= \tfrac{1}{2}[(1-\varrho)p_{1,k} + (1+\varrho)p_{2,k}) \\ c_{2,k} &= \tfrac{1}{2}[(1+\varrho)p_{1,k} + (1-\varrho)p_{2,k}) \end{aligned}$ .

where $\eta_c$ is the distribution index for crossover which determine how well spread the children will be from their parents. We use $\eta_c = 20$ in this study.

Let $p_k$ and $c_k$ the values of $k^{\text{th}}$ attribute of parent and child respectively. Let $p_k^u$ and $p_k^l$ be the upper bound and lower bound on the parent component respectively. We use Algorithm 4 for mutation:

where $\eta_m$ is mutation distribution index. We use $\eta_m = 20$ in this study.

**Algorithm 4:** Polynomial Mutation

Generate a uniformly sampled random number $\rho_k$ ;

Calculate $\sigma_k = \begin{cases} (2\rho_k)^{\frac{1}{(\eta_m+1)}} - 1 & \text{if } \rho_k < 0.5 \\ 1 - [2(1-\rho_k)]^{\frac{1}{(\eta_m+1)}} & \text{if } \rho_k \geq 0.5 \end{cases}$ ;

Calculate $c_k = p_k + (p_k^u - p_k^l)\sigma_k$.

The decision variables for the upper level problem are the toll prices and/or capacity enhancements. Each solution is represented by a vector of size $|\mathcal{A}'|$ where $\mathcal{A}'$ is the set of tolled and/or capacity enhanced arcs of the network. The general description of the adapted NSGA-II is given in the Algorihm 5 (Bhattacharya & Bandyopadhyay, 2010).

**Algorithm 5:** Pseudo-code of NSGA-II

Let $M$ number of generations and $N$ the size of the population.

Generate the initial parent population $\mathcal{P}_0$ of size of $N$ by randomly choosing toll pricing and/or capacity enhancement between predetermined lower and upper bounds.

Use selection, crossover and mutation to create a new offspring population $\mathcal{Q}_0$.

**for** $\kappa = 0 : M$ **do**

    Combine parent and offspring population, $\mathcal{R}_\kappa = \mathcal{P}_\kappa \cup \mathcal{Q}_\kappa$

    Assess the objective function. To realize this, first solve SUE model given toll prices and/or capacity enhancements for every individual of the population $\mathcal{R}_k$ using SRA algorithm. Then using optimal SUE flow values calculate the value of each objective function for every individual.

    Find all nondominated fronts $\mathcal{F} = \{\mathcal{F}_1, \mathcal{F}_2, \ldots\}$ of $\mathcal{R}_\kappa$.

    Calculate crowding distances for all fronts of $\mathcal{F}$.

    Sort in descending order using $\prec_n$.

    Choose the first $N$ elements of $\mathcal{F}$ and replace the parent population, $\mathcal{P}_{\kappa+1} = \mathcal{F}[1 : N]$.

    Use selection, crossover and mutation to create a new offspring population $\mathcal{Q}_{\kappa+1}$.

## 5.4 Case Study

In our study, we make use of a medium-sized network well-known in the literature, namely Sioux Falls (see Figure 5.1) which consists of 24 nodes, 76 links and 552 O-D pairs. Its original trip table is nearly symmetric and all the links come in bi-directional pairs with identical characteristics. It is important to note that the map of the network given in Figure 5.1 is not to scale, so the length of links is not related to the free flow time between pairs of nodes. We chose a subset of links to be tolled/capacity enhanced so we solve the second best problem. The chosen link set to toll is $\bar{\mathcal{A}}_\tau = \{13, 21, 23, 24, 28, 30, 43, 51\}$ and the chosen link set to enhance capacities is $\bar{\mathcal{A}}_\gamma = \{25, 26, 29, 34, 40, 48, 66, 75\}$. For the emission minization objective we considered the $NO_x$ emission for EURO3 gasoline vehicles which has the following emission function parameters: ($\delta_1 = 9.29E - 02$, $\delta_2 = -1.22E-02$, $\delta_3 = -1.49E-03$, $\delta_4 = 3.97E-5$, $\delta_5 = 6.53E06$) considering equation 4.14.

We solved this model for both fixed and elastic demand cases using NSGS-II. The algorithm is run for 2000 generations with a population size of 200. The results on each iteration for all models are presented in form of graphs in Appendix C.

### 5.4.1 Fixed Demand Case

In our first example, we assume that the trip demands are fixed and do not depend on path travel times. The Pareto solution sets are sketched in Figure 5.2 for SUE-FD-TP, SUE-FD-CE and SUE-FD-TPCE models. Also the solution is shown in this graph which represents the situation without any improvements and alterations to the network.

In Figure 5.2, the big purple dot represents the unaltered situation whereas the blue, red and green dots represent the Pareto optimal fronts of SUE-FD-TP, SUE-FD-CE and SUE-FD-TPCE models respectively. We see in this graph that the TP strategy can be used to improve the network for both objective functions. The main advantage of TP is that implementation is rather easy, cost efficient and has the benefit of generating revenue. But the improvement using TP strategy is limited. On

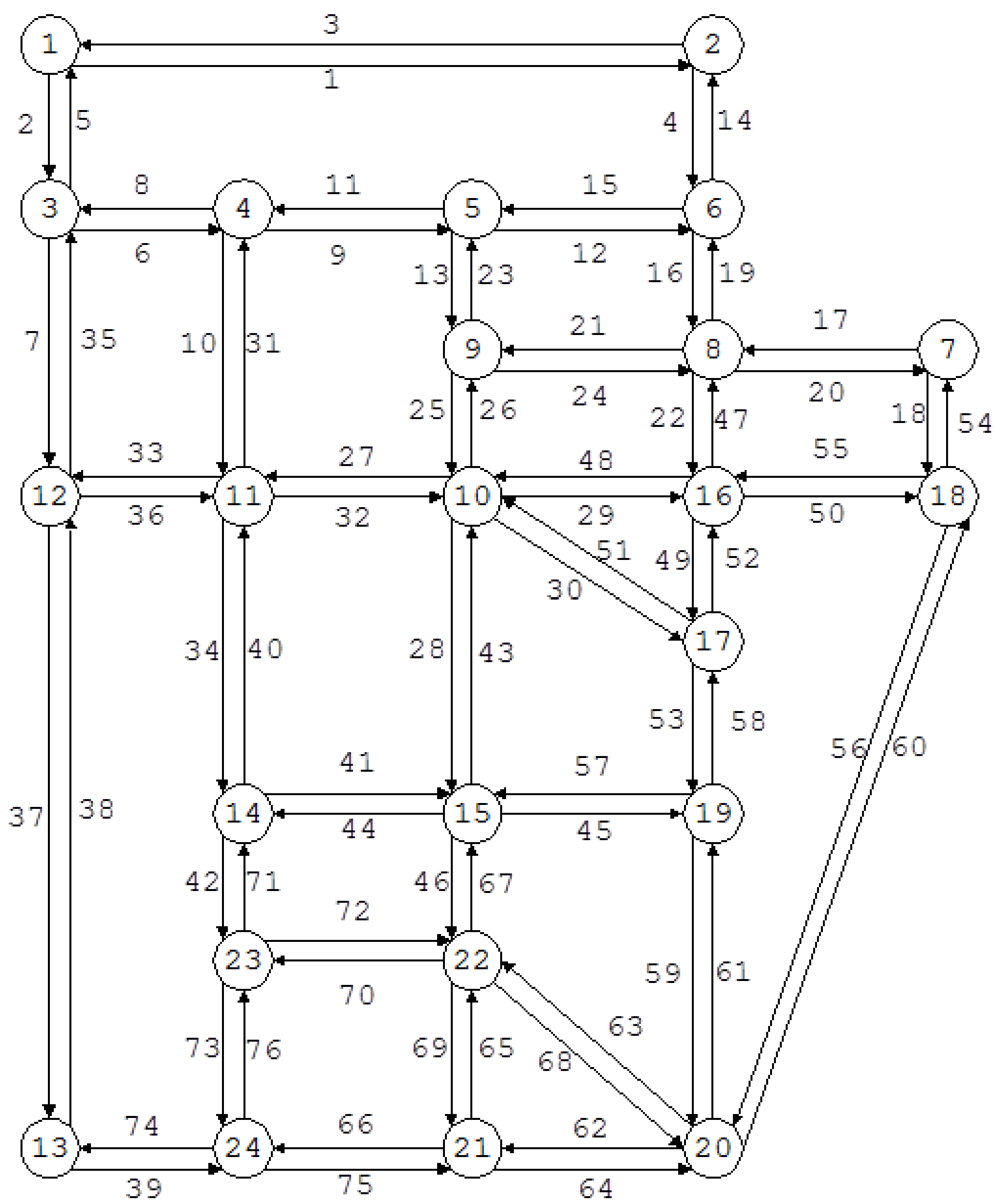



**Figure 5.1**: Sioux Falls Network

the other hand, we observe that CE strategy gives better results for both objective functions as the related Pareto front resides below. The main disadvantage of CE is that it is more difficult and costly to implement. As expected, when both strategies are implemented simultaneously in TPCE strategy, the improvements are far better for both objective functions.

In order to evaluate the results in more details, we provide Table 5.1 which presents the best possible improvements for SUE-FD models. For the social objective, using

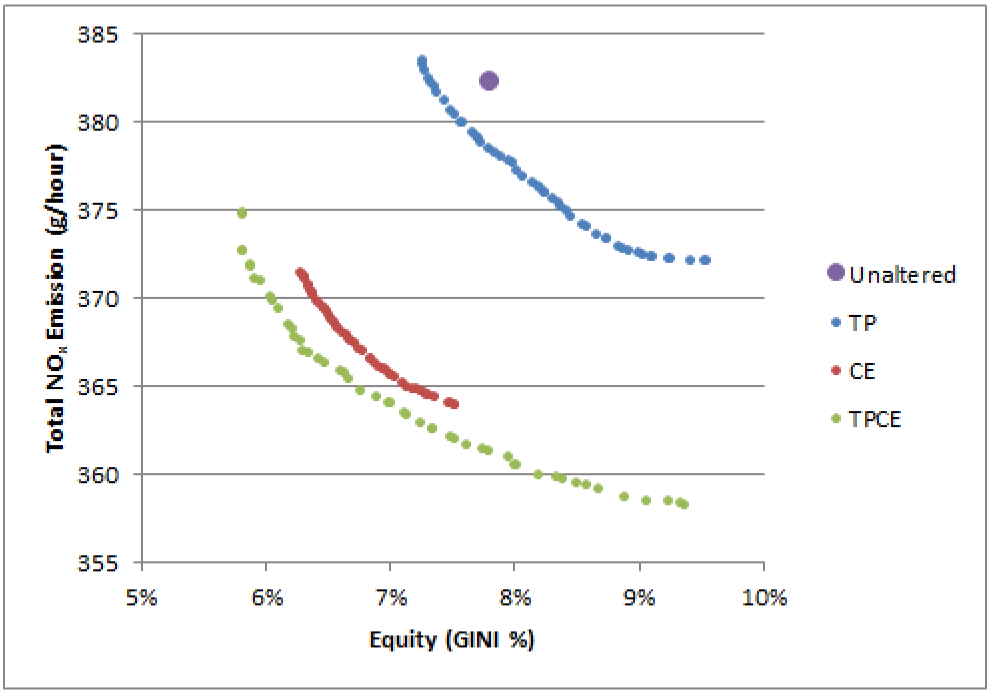



**Figure 5.2**: Pareto optimal fronts for SUE-FD models

**Table 5.1**: Best possible improvements for SUE-FD models

| | Equity | | NOx Emission | |
|---|---|---|---|---|
| | Value (GINI %) | Improvement | Value (g/hour) | Improvement |
| Original | 7.80% | - | 382.32 | - |
| TP | 7.25% | 6.99% | 372.14 | 2.66% |
| CE | 6.28% | 19.51% | 364.03 | 4.78% |
| TPCE | 5.81% | 25.56% | 358.34 | 6.25% |

the TP strategy it is possible to obtain an improvement of up to 6.99%. Using CE strategy, it is possible to obtain an improvement of up to 19.51% and finally using the TPCE strategy it is possible to obtain an improvement of 25.56%. We see clearly that CE strategy is more effective than the TP strategy and applying both strategies simultaneously we achieve a performance almost the sum of both strategies. For the environmental objective, using the TP strategy it is possible to obtain an improvement of up to 2.66%, using CE strategy it is possible to obtain an improvement of up to 4.78% and finally using TPCE strategy it is possible to obtain an improvement of 6.25%. Considering that the Kyoto Protocol (1997) has a goal to decrease the greenhouse gases emission by 5.2% worldwide, these results would contribute to these goal in a significant way. Also, the vehicle emission strongly depends of driving habits and technological advances. In this model however, only the road network is improved withoud changing vehicle technologies. Also the note that when both strategies are applied simultaneously the resulting improvement on emission is less than the sum of both strategies applied separately. Full results are provided in Appendix C.

### 5.4.2 Elastic Demand Case

To model the elastic demand case, we use the following linear demand function:

$$D_{rs}(S_{rs}) = \nu_{rs} - \mu_{rs} S_{rs} \tag{5.13}$$

where $\mu_{rs}$ and $\nu_{rs}$ are network specific parameters. $S_{rs}$ denotes the minimum expected travel time for O–D pair $(r, s)$. In this example, we set $\nu_{rs} = d_{rs}$ (where $d_{rs}$ is the travel demand used in fixed model) and $\mu_{rs} = 10^{-3}$. Clearly, this function is strictly decreasing. The Pareto solution sets are sketched in Figure 5.3 for SUE-ED-TP, SUE-ED-CE and SUE-ED-TPCE models. The unaltered solution is also included in this figure which represents the situation without any improvements and alterations to the network.

In Figure 5.3, the big purple dot represents the unaltered solution whereas the Pareto optimal fronts for models SUE-ED-TP, SUE-ED-CE and SUE-ED-TPCE are represented with blue, red and green dots respectively. Observing the graph, we again see an improvement using the TP strategy compared to the unaltered solution. CE strategy provides better solution on both objectives as the related Pareto optimal resides below compared to the TP strategy front. Finally, applying both strategies simultaneously in TPCE strategy, we observe far better solutions compared to the separate usage of strategies.

Table 5.2 shows us the best possible improvements for SUE-ED models. Using the TP and CE strategies the equity can be improved up to 6.90% and 16.76% respectively. Clearly the CE strategy offers more improvement over TP strategy but it is more difficult to implement and does not have direct economical advantages

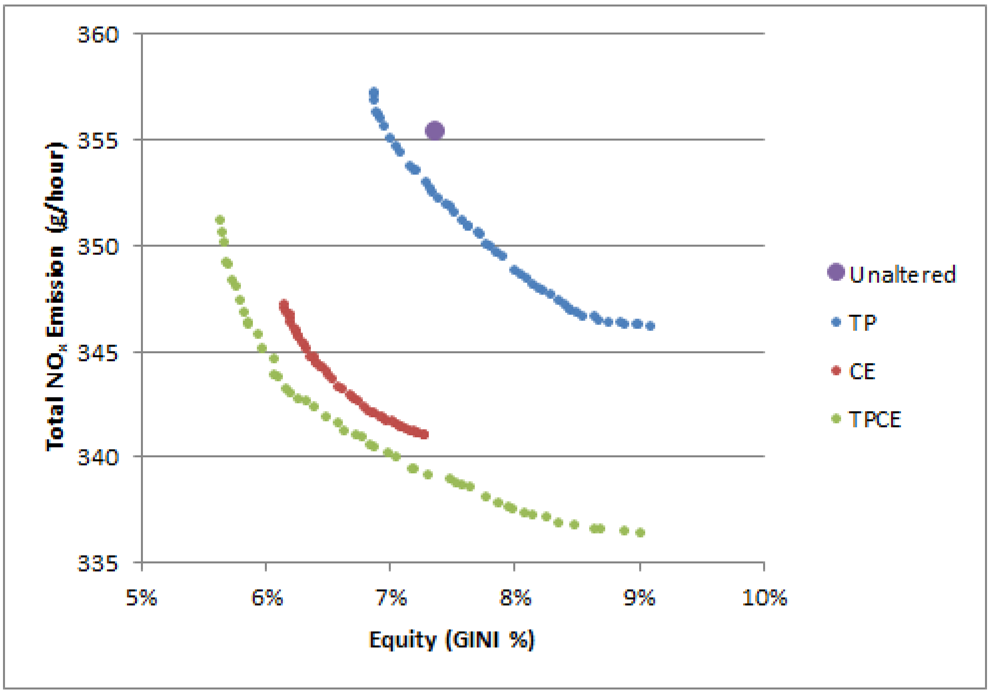



**Figure 5.3**: Pareto optimal fronts for SUE-ED models

**Table 5.2**: Best possible improvements for SUE-ED models

| | Equity | | NOx Emission | |
|---|---|---|---|---|
| | Value (GINI %) | Improvement | Value (g/hour) | Improvement |
| Original | 7.37% | - | 355.40 | - |
| TP | 6.86% | 6.90% | 346.18 | 2.59% |
| CE | 6.13% | 16.76% | 341.06 | 4.04% |
| TPCE | 5.63% | 23.66% | 336.46 | 5.33% |

like the TP strategy. When both strategies are applied simultaneously in TPCE strategy, an improvement of up to 23.66% is possible which is almost the sum of both strategies applied simultaneously. If we investigate the environmental objective, we see that the TP and CE strategies offer an improvement of up to 2.59% and 4.04% respectively. When both strategies are applied simultaneously in TPCE, it is possible to achieve an improvement of up to 5.33%. Note that, when applied simultaneously, the possible improvement in emission is less than the sum of possible improvements when applied seperatly. Again, considering the emission reduction goal of 5.5% in the Kyoto Protocol (1997), models proposed in this study offer a significant contribution to achive this goal.

The, proposed models offer multiple strategies and solutions to the decision makers. The flexibility of the models is high and decision makers have a wide range of choices. Full results are provided in Appendix C.

# 6 CONCLUSION

In this thesis, the sustainability of a traffic network is extensively studied. First the properties of sustainability is presented and the requirements of a sustainable traffic network are discussed. Three dimensions of sustainability – environmental, social, economical - are presented in details and associated indicators are studied. A literature survey on sustainable transportation systems is introduced. After this literature survey, we have been able to conclude that evaluation and optimization systems considering all sustainability dimensions are scarce in the literature. We then developed and presented models which allow the evaluation and optimization of traffic network with the sustainability perspective.

In chapter 3, a framework to evaluate and compare the sustainability of traffic networks using relevant indicators is presented. 35 sustainability related indicators are determined and are classified under sustainability dimensions. For a comprehensive evaluation of sustainability, all the dimensions must be in the evaluation process. The data on indicators for many European countries are readily available to the public. The main challenge is to integrate all data with an easily interpretable model. In this thesis, we propose a multi-criteria decision making model and use two methods for model evaluation. The TOPSIS method is based on arithmetic mean and uses the concepts of ideal and nadir solutions. The euclidean distances are used to rate and compare different alternatives in this method. The main drawback of this method is that it does not consider possible interactions between different indicators. However, the interactions between different indicators play an important role in the context of sustainability as compromise solutions are not desirable. To alleviate this problem, we consider the Choquet integral method which includes the interactions between indicators. In order to determine the criteria weights and interactions, we use the MACBETH procedure. The MACBETH procedure is based on the comparisons between different situations made by decision-makers. Involvement of the decision makers to the identification of criteria weights and interactions makes this method superior to simple scaling methods. A case study involving 21 European countries is presented. The relevant data is collected from many sources and are integrated into the evaluation model. Both TOPSIS and Choquet integral methods are utilized to evaluate the sustainability of transport system and rank selected countries. The results are contrasted in details. We observe that the interactions between indicators play an important role. Countries having good scores on many indicators are ranked higher than other countries that are very good on some indicators but have lower scores on the remaining indicators. With the elucidation part, improvement directions for countries are identified.

In chapter 4, we investigate the ways of improving the sustainability of traffic networks and focus on the traffic assignment stage. Traffic assignment models can be used for that. The main assumption in this chapter is that the drivers have a perfect knowledge of the traffic network and always make rational decisions. This corresponds to the DUE case. In this type of models, the travel times on all used paths between any origin and destination are equal and lower than the travel time on all unused paths. Another concern in this model is the demand elasticity. As an environmental objective, we study the vehicle emissions in this chapter. Generally, the emission objectives in the literature only consider the flow on a link but ignore the vehicle speed hence the congestions. However, it is known that the emission is higher in highly congested roads. Here we use the emission function determined by the European Environment Agency to predict the vehicle emissions in a traffic network. This function takes the vehicle speed into account, as a result the emission differs dramatically when a road reaches its capacity and the congestion occurs.

The objective of our mathematical model is to minimize the emission. Although we can not dictate the path choices to the drivers directly, it is possible to use some strategies to influence their decisions indirectly. The strategic decisions reflect the choices of the traffic authorities. In this thesis, we consider the toll pricing and capacity enhancement strategies. Using the traffic assignment methods, traffic authority can predict their reactions. Consequently, we build a bi-level optimization model where the lower level reflects the decisions of drivers and the upper level reflects the decisions of traffic authority. We use the GAMS modeling environment and NLPEC/CONOPT solver to solve these models deterministically. As a case study we consider the benchmark Sioux Falls Network. We conclude that using these strategies whether separately or simultaneously, it is possible to decrease the vehicle emissions considerably.

In chapter 5, we expand our previous models using SUE instead of DUE. Also we construct a multi objective model instead of a single objective. The assumption that users have perfect knowledge of the traffic network and they make rational decisions is relaxed in SUE. In multi-objective models, the objectives are generally contradictory, hence there is not a single optimum solution. Instead, it is expected to find solutions that form a Pareto optimal front. No solution in the Pareto optimal front is worst than any other solution. The existence of multiple solutions offers multiple choices to the decision makers, and thus offers a great flexibility. Using the vehicle emission and access equity objectives, we construct a multi objective bi-level optimization model. To solve the lower level model we use Bell's Second Algorithm and SRA Scheme. For the upper level model which is a multi objective model, we use the NSGA-II algorithm. This algorithm considers the nondomination rank as well as the crowding distance. The crowding distance ensures that similar solutions are eliminated between generations and more distant solutions pass to the next generation. We implement Simulated Binary Crossover and Polynomial Mutation to generate new generations. As a case study, a modified version of Sioux Falls Network is used. As in previous chapter, both toll pricing and capacity enhancement strategies are applied separately and simultaneously and the solutions are compared. It is observed that the constructed models offer significant improvements to the traffic network.

In this study, we show that it is possible to obtain a considerable improvement in the sustainability of an existing transportation network by altering and modifying several network parameters. Previous studies suggest various sustainability objectives but fail to provide a unified model that considers all these objectives simultaneously. Here, we provide two such sustainability objectives, and more importantly a model that integrates both objectives. This method offers a great flexibility to decision makers. Using the framework presented in this thesis, it is possible to integrate even more sustainability objectives. This allows the model to be adapted to different conditions and situations.

We focus our attention to offer improvements on an existing network. Although, the models developed offer considerable improvements to existing networks, sustainability related strategies should also be applied on initial planning stages of an urban environment. This approach would allow city planners to fully integrate all four steps of urban transportation planning. Especially, the mode choice step has a crucial importance in urban transportation planning. In addition to traffic vehicles, public transportation should be planned in accordance with sustainability objectives. The two modes of transport should be considered together and should be planned as an integrated system. This would allow more choices to users and greater flexibility to transportation authorities to obtain a sustainable transportation system.

Urban areas are not static environments, it is dynamic and ever changing. Traffic demands vary during the day, and depending on season and holidays. For example, during a weekday, users mostly travel to their works in the morning and back home in the evening. On the other hand, during the weekends and on holidays, they travel to entertainment or shopping areas. In this study, we focus on an instant of the traffic network. This model can be expanded with dynamic user equilibrium. In dynamic user equilibrium, traffic flow is not static but changes over time. Integrating these changes to the model would offer more useful insights to city planners.

The sustainability of transportation networks is an important topic in the European Union (EU). To assess the sustainability of the transportation networks, different indicators are proposed by various researchers. The main challenge in evaluating these indicators is the lack of data and standardization. Although, we have been able to evaluate most European countries, data availability of some countries are scarce or missing, especially, countries that join EU recently. The evaluation model in this study can easily be applied to additional countries as the relevant data becomes accessible and standardized.

Design and management of traffic networks is an important challenge for the modern world. Similarly, sustainability is an important issue for future progress of modern cities. Heavy traffic and congestions pose a negative impact on sustainable development. Although not sufficient by itself to assure the sustainable development, sustainable traffic network systems can make a significant contribution. All the models presented in this thesis can be applied to evaluate and to improve the current situation of traffic networks in real life.

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# A FULL DATA FOR MULTICRITERIA EVALUATION MODEL

**Table A.1**: Economic Indicators and associated raw values for the selected countries

| | EC11 | EC12 | EC13 | EC21 | EC22 | EC23 | EC24 | EC31 | EC32 |
|---|---|---|---|---|---|---|---|---|---|
| AT | -1.36% | -0.10% | 25.50% | -2.01% | -0.62% | 4.98% | 4.97% | 72.03% | 78.20% |
| BE | -1.03% | -0.54% | 19.67% | -3.94% | -0.38% | 6.21% | 6.12% | 51.46% | 78.30% |
| BL | 2.82% | 3.26% | 19.00% | 4.81% | -1.58% | 7.32% | 5.82% | 34.91% | 57.00% |
| DK | -0.56% | 0.25% | 53.00% | -4.50% | -0.56% | 7.06% | 4.85% | 38.35% | 77.10% |
| EI | 3.03% | 1.98% | 6.00% | -3.63% | -0.56% | 8.54% | 7.94% | 46.42% | 61.10% |
| FI | -0.09% | 0.20% | 35.00% | -2.37% | -0.38% | 5.79% | 6.17% | 40.75% | 77.10% |
| FR | 0.79% | -0.27% | 15.50% | -2.54% | -0.49% | 4.76% | 5.32% | 31.38% | 76.00% |
| DE | -0.05% | 0.12% | 21.86% | 0.29% | -0.29% | 4.28% | 4.74% | 39.50% | 82.10% |
| IE | 0.31% | 0.12% | 18.00% | -3.22% | -0.14% | 3.69% | 4.88% | 18.89% | 78.00% |
| IT | 0.16% | -0.13% | 14.33% | -0.80% | -0.56% | 5.23% | 4.73% | 46.71% | 72.20% |
| LV | 4.72% | 0.66% | 15.00% | 0.82% | -3.17% | 10.27% | 8.80% | 53.34% | 62.70% |
| LT | 2.50% | 1.27% | 12.00% | 2.83% | 2.02% | 9.77% | 6.75% | 28.97% | 59.10% |
| NL | -0.13% | 0.04% | 46.00% | -1.43% | -0.89% | 4.96% | 4.79% | 35.00% | 82.50% |
| PL | 3.64% | 2.00% | 11.00% | 3.49% | 1.16% | 5.32% | 5.66% | 17.33% | 64.80% |
| PT | 0.15% | 0.50% | 30.00% | 2.93% | 0.79% | 4.46% | 3.65% | 33.35% | 67.20% |
| RO | 2.00% | 1.27% | 19.67% | 1.37% | -1.32% | 7.64% | 5.06% | 17.93% | 57.50% |
| SK | 3.58% | 2.07% | 14.50% | -1.40% | -5.18% | 6.79% | 6.44% | 27.89% | 61.60% |
| SI | 1.40% | 0.50% | 26.00% | 5.03% | -0.71% | 5.49% | 5.75% | 15.24% | 60.10% |
| ES | 0.32% | 0.06% | 24.50% | 1.29% | -0.89% | 4.54% | 4.86% | 36.78% | 71.50% |
| SE | -0.49% | -0.05% | 28.00% | -1.20% | -1.21% | 6.36% | 5.22% | 48.26% | 81.60% |
| UK | -0.13% | 0.00% | 16.00% | -2.66% | -1.30% | 4.72% | 5.12% | 55.81% | 79.40% |

**Table A.2**: Social Indicators and associated raw values for the selected countries

| | SC11 | SC12 | SC21 | SC22 | SC23 | SC24 | SC31 | SC32 | SC41 | SC42 | SC43 | SC44 | SC45 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | -4.63% | 103.22 | 2.01% | 2.69% | 2.50% | 13.07% | 45.00% | 95.00% | 82.50% | 90.00% | 75.71% | 68.57% | 85.71% |
| BE | -4.56% | 115.56 | 2.21% | 1.70% | 2.03% | 12.01% | 45.33% | 100.00% | 70.67% | 78.57% | 78.57% | 91.43% | 88.57% |
| BL | -1.07% | 127.56 | 5.78% | 8.01% | 1.50% | 15.50% | 48.00% | 98.00% | 50.50% | 30.00% | 44.29% | 54.29% | 58.57% |
| DK | -4.21% | 74.89 | 2.04% | 2.76% | 5.01% | 12.24% | 52.50% | 99.00% | 78.50% | 88.57% | 77.14% | 87.14% | 91.43% |
| EI | -6.00% | 136.44 | 4.32% | 8.24% | 6.23% | 12.10% | 43.00% | 86.00% | 72.00% | 64.29% | 52.86% | 80.00% | 65.71% |
| FI | -3.34% | 73.22 | 1.85% | 3.01% | 3.42% | 11.99% | 52.50% | 82.00% | 79.00% | 84.29% | 82.86% | 91.43% | 88.57% |
| FR | -6.61% | 99.67 | 1.90% | 2.61% | 0.87% | 14.15% | 46.00% | 99.00% | 81.50% | 94.29% | 92.86% | 84.29% | 90.00% |
| DE | -6.31% | 72.33 | 1.69% | 2.89% | 1.38% | 13.99% | 43.29% | 89.00% | 79.00% | 91.43% | 88.57% | 91.43% | 94.29% |
| IE | -5.57% | 90.89 | 2.15% | 4.20% | 2.54% | 12.06% | 29.00% | 93.00% | 70.00% | 61.43% | 50.00% | 70.00% | 74.29% |
| IT | -5.20% | 105.89 | 2.30% | 4.04% | 9.00% | 13.47% | 54.67% | 98.00% | 40.33% | 60.00% | 51.43% | 55.71% | 61.43% |
| LV | -9.26% | 209.22 | 5.33% | 6.72% | 4.86% | 10.86% | 33.00% | 90.00% | 65.00% | 44.29% | 55.71% | 67.14% | 77.14% |
| LT | -4.81% | 202.67 | 3.16% | 6.63% | 4.74% | 15.41% | 42.00% | 97.00% | 50.00% | 75.71% | 61.43% | 67.14% | 51.43% |
| NL | -5.35% | 53.11 | 2.18% | 3.22% | -1.33% | 11.65% | 31.00% | 100.00% | 82.33% | 77.14% | 81.43% | 94.29% | 90.00% |
| PL | -3.24% | 147.44 | 2.94% | 4.42% | 3.69% | 9.05% | 37.75% | 95.00% | 72.25% | 30.00% | 38.57% | 47.14% | 51.43% |
| PT | -8.27% | 129.33 | 2.56% | 6.05% | 4.96% | 14.53% | 58.00% | 88.00% | 57.50% | 88.57% | 64.29% | 70.00% | 75.71% |
| RO | 1.49% | 118.33 | 11.83% | 16.03% | 11.95% | 13.82% | 42.33% | 89.00% | 60.67% | 30.00% | 35.71% | 42.86% | 55.71% |
| SK | -5.32% | 113.44 | 4.10% | 5.19% | 4.20% | 8.05% | 48.00% | 97.00% | 56.50% | 55.71% | 67.14% | 57.14% | 47.14% |
| SI | -5.64% | 133.56 | 4.06% | 6.15% | 5.93% | 15.25% | 42.00% | 95.00% | 68.00% | 68.57% | 45.71% | 75.71% | 68.57% |
| ES | -8.27% | 111.56 | 2.85% | 3.76% | 5.49% | 11.84% | 47.00% | 95.00% | 76.00% | 81.43% | 77.14% | 80.00% | 82.86% |
| SE | -5.30% | 55.67 | 1.87% | 2.58% | 3.05% | 13.58% | 35.00% | 86.00% | 84.00% | 81.43% | 77.14% | 88.57% | 88.57% |
| UK | -4.47% | 56 | 2.31% | 4.53% | 4.85% | 14.92% | 34.00% | 96.00% | 76.00% | 72.86% | 67.14% | 78.57% | 81.43% |

**Table A.3**: Environmental Indicators and associated raw values for the selected countries

| | EN11 | EN12 | EN13 | EN14 | EN21 | EN22 | EN23 | EN31 | EN32 | EN33 | EN34 | EN41 | EN42 | EN43 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 0.81% | 1.85% | 2.54% | 5.42% | 13.21 | 91.05% | 81.65% | 1.83% | 2.78 | 1.90% | -1.22% | -9.03% | -1.56% | -1.54% |
| BE | -0.51% | 0.27% | 0.92% | 2.08% | 8.88 | 90.22% | 88.00% | -0.05% | 2.47 | -0.03% | -1.74% | -5.99% | -2.63% | -4.86% |
| BL | 0.15% | 4.73% | 4.43% | 0.62% | 13.46 | 88.95% | 83.87% | 3.43% | 0.94 | 3.94% | 0.15% | -8.38% | -1.63% | -1.29% |
| DK | 0.16% | 0.38% | 0.89% | 0.22% | 19.32 | 81.45% | 81.35% | 0.73% | 2.44 | 0.78% | -2.53% | -7.87% | -3.86% | -8.57% |
| EI | -0.17% | 3.62% | 3.51% | 0.20% | 18.06 | 86.21% | 86.10% | 3.20% | 1.59 | 3.39% | -0.97% | -9.30% | 2.02% | 5.55% |
| FI | -0.42% | 1.01% | 1.19% | 2.24% | 9.99 | 81.50% | 81.25% | 0.59% | 2.56 | 0.88% | -1.54% | -5.49% | -6.49% | -0.67% |
| FR | -1.19% | -0.73% | -0.04% | 4.68% | 19.47 | 81.51% | 79.47% | -0.56% | 2.22 | -0.45% | -2.22% | -10.76% | -3.67% | -3.06% |
| DE | -1.50% | -0.57% | -0.95% | 5.84% | 14.06 | 89.88% | 86.75% | -1.65% | 2.01 | -1.62% | -1.83% | -8.17% | -4.08% | -3.40% |
| IE | -0.82% | 0.02% | 1.60% | 1.24% | 5.75 | 80.89% | 78.54% | 0.94% | 3.01 | 0.87% | -1.18% | -8.20% | -3.39% | -3.68% |
| IT | -0.54% | -0.69% | -0.23% | 2.56% | 10.29 | 81.88% | 79.68% | -0.29% | 2.15 | -0.22% | -1.41% | -10.13% | -2.53% | -1.48% |
| LV | 1.40% | 5.82% | 4.99% | 1.46% | 36.64 | 88.00% | 86.50% | 4.39% | 1.31 | 4.76% | -1.66% | -12.45% | 9.62% | 10.76% |
| LT | -0.48% | 4.90% | 4.41% | 3.44% | 22.97 | 87.43% | 86.35% | 3.26% | 1.27 | 3.99% | -2.19% | -2.26% | -2.64% | 8.75% |
| NL | -0.81% | 0.12% | 0.83% | 2.64% | 5.68 | 85.33% | 83.53% | 0.61% | 2.14 | 0.63% | -1.85% | -3.56% | -2.61% | -3.76% |
| PL | 2.05% | 6.28% | 6.50% | 3.18% | 11.36 | 82.73% | 81.04% | 5.71% | 0.97 | 5.95% | -0.32% | -0.71% | 0.62% | -1.02% |
| PT | 0.60% | 0.79% | 0.94% | 3.12% | 20.43 | 86.48% | 82.25% | -0.26% | 1.88 | -0.28% | -1.98% | -9.66% | -1.50% | -2.58% |
| RO | 0.27% | 4.61% | 5.48% | 1.80% | 5.04 | 84.43% | 81.14% | 3.59% | 0.62 | 4.17% | 0.71% | 7.09% | 5.18% | 9.96% |
| SK | 0.04% | 6.98% | 5.36% | 6.28% | 2.25 | 87.66% | 87.02% | 4.87% | 1.05 | 5.18% | -1.75% | -6.70% | 2.86% | 4.16% |
| SI | 1.24% | 3.79% | 4.27% | 1.58% | 9.01 | 86.32% | 83.93% | 3.73% | 2.3 | 3.77% | -0.08% | -9.64% | 1.28% | 4.20% |
| ES | -0.76% | -0.08% | 1.38% | 2.40% | 22.76 | 85.21% | 80.75% | 0.90% | 2.22 | 0.75% | -1.24% | -12.61% | 0.49% | 1.81% |
| SE | -1.40% | 0.16% | 1.03% | 6.48% | 2.67 | 89.00% | 83.85% | 0.45% | 2.3 | 0.51% | -2.13% | -7.54% | 0.10% | 2.00% |
| UK | -1.50% | -0.47% | -0.07% | 1.80% | 19.94 | 83.23% | 81.86% | -0.34% | 2.06 | -0.37% | -2.34% | -12.70% | -3.08% | -0.55% |

**Table A.4**: Weights and interactions for the sustainability dimensions

| ALL | ECO | SOC | ENV | Weight |
|---|---|---|---|---|
| ECO | 0 | 0.1154 | 0.1154 | 0.2692 |
| SOC | 0.1154 | 0 | 0.1923 | 0.3462 |
| ENV | 0.1154 | 0.1923 | 0 | 0.3846 |

**Table A.5**: Weights and interactions for the economic indicators

| ECO | EC1 | EC2 | EC3 | Weight |
|---|---|---|---|---|
| EC1 | | 0.05 | 0.1 | 0.175 |
| EC2 | 0.05 | | 0.05 | 0.45 |
| EC3 | 0.1 | 0.05 | | 0.375 |

**Table A.6**: Weights and interactions for the economic indicators (EC1)

| EC1 | EC11 | EC12 | EC13 | Weight |
|---|---|---|---|---|
| EC11 | | 0.0435 | 0.087 | 0.1957 |
| EC12 | 0.0435 | | 0 | 0.4565 |
| EC13 | 0.087 | 0 | | 0.3478 |

**Table A.7**: Weights and interactions for the economic indicators (EC2)

| EC2 | EC21 | EC22 | EC23 | EC24 | Weight |
|---|---|---|---|---|---|
| EC21 | | 0.0882 | 0.0735 | 0.1176 | 0.2132 |
| EC22 | 0.0882 | | 0.0735 | 0.1176 | 0.1838 |
| EC23 | 0.0735 | 0.0735 | | 0.1176 | 0.2647 |
| EC24 | 0.1176 | 0.1176 | 0.1176 | | 0.3382 |

**Table A.8**: Weights and interactions for the economic indicators (EC3)

| EC3 | EC31 | EC32 | Weight |
|---|---|---|---|
| EC31 | | 0.1 | 0.35 |
| EC32 | 0.1 | | 0.65 |

**Table A.9**: Weights and interactions for the social indicators

| SOC | SC1 | SC2 | SC3 | SC4 | Weight |
|---|---|---|---|---|---|
| SC1 | | 0.1045 | 0.0896 | 0.1045 | 0.3284 |
| SC2 | 0.1045 | | 0.0746 | 0.0896 | 0.2687 |
| SC3 | 0.0896 | 0.0746 | | 0.0896 | 0.1866 |
| SC4 | 0.1045 | 0.0896 | 0.0896 | | 0.2164 |

**Table A.10**: Weights and interactions for the social indicators (SC1)

| SC1 | SC11 | SC12 | Weight |
|---|---|---|---|
| SC11 | | -0.1538 | 0.3846 |
| SC12 | -0.1538 | | 0.6154 |

**Table A.11**: Weights and interactions for the social indicators (SC2)

| SC2 | SC21 | SC22 | SC23 | SC24 | Weight |
|---|---|---|---|---|---|
| SC21 | | 0.0278 | 0.0278 | 0.0556 | 0.2778 |
| SC22 | 0.0278 | | 0.0833 | 0.0556 | 0.1944 |
| SC23 | 0.0278 | 0.0833 | | 0.0556 | 0.1667 |
| SC24 | 0.0556 | 0.0556 | 0.0556 | | 0.3611 |

**Table A.12**: Weights and interactions for the social indicators (ES3)

| ES3 | ES31 | ES32 | Weight |
|---|---|---|---|
| ES31 | | -0.1111 | 0.6111 |
| ES32 | -0.1111 | | 0.3889 |

**Table A.13**: Weights and interactions for the social indicators (ES4)

| ES4 | ES41 | ES42 | ES43 | ES44 | ES45 | Weight |
|---|---|---|---|---|---|---|
| ES41 | | 0.0963 | 0.0963 | 0.0963 | 0.0963 | 0.2667 |
| ES42 | 0.0963 | | 0.0667 | 0.0667 | 0.0519 | 0.1852 |
| ES43 | 0.0963 | 0.0667 | | 0.0889 | 0.0741 | 0.2222 |
| ES44 | 0.0963 | 0.0667 | 0.0889 | | 0.0519 | 0.1741 |
| ES45 | 0.0963 | 0.0519 | 0.0741 | 0.0519 | | 0.1519 |

**Table A.14**: Weights and interactions for the environmental indicators

| ENV | EN1 | EN2 | EN3 | EN4 | Weight |
|---|---|---|---|---|---|
| EN1 | | 0.0455 | 0.0227 | 0.0682 | 0.2045 |
| EN2 | 0.0455 | | 0.0455 | 0.0682 | 0.1477 |
| EN3 | 0.0227 | 0.0455 | | 0.0909 | 0.2841 |
| EN4 | 0.0682 | 0.0682 | 0.0909 | | 0.3636 |

**Table A.15**: Weights and interactions for the environmental indicators (EN1)

| EN1 | EN11 | EN12 | EN13 | EN14 | Weight |
|---|---|---|---|---|---|
| EN11 | | 0.0612 | 0.0816 | 0.0612 | 0.1633 |
| EN12 | 0.0612 | | 0.0816 | 0.0816 | 0.2143 |
| EN13 | 0.0816 | 0.0816 | | 0.1224 | 0.3469 |
| EN14 | 0.0612 | 0.0816 | 0.1224 | | 0.2755 |

**Table A.16**: Weights and interactions for the environmental indicators (EN2)

| EN2 | EN21 | EN22 | EN23 | Weight |
|---|---|---|---|---|
| EN21 | | 0.1667 | 0.125 | 0.4375 |
| EN22 | 0.1667 | | 0.125 | 0.3125 |
| EN23 | 0.125 | 0.125 | | 0.25 |

**Table A.17**: Weights and interactions for the environmental indicators (EN3)

| EN3 | EN31 | EN32 | EN33 | EN34 | Weight |
|---|---|---|---|---|---|
| EN31 | | 0.1087 | 0.0652 | 0.1087 | 0.3587 |
| EN32 | 0.1087 | | 0.0435 | 0.087 | 0.2283 |
| EN33 | 0.0652 | 0.0435 | | 0.0435 | 0.25 |
| EN34 | 0.1087 | 0.087 | 0.0435 | | 0.163 |

**Table A.18**: Weights and interactions for the environmental indicators (EN4)

| EN4 | EN41 | EN42 | EN43 | Weight |
|---|---|---|---|---|
| EN41 | | -0.0625 | -0.1875 | 0.25 |
| EN42 | -0.0625 | | -0.125 | 0.1563 |
| EN43 | -0.1875 | -0.125 | | 0.5938 |

# B FULL DATA FOR DUE MODELS

**Table B.1**: Sioux Falls Network Parameters

| Origin | Destination | Capacity | Length | Free Flow Time |
|---|---|---|---|---|
| 1 | 2 | 25900.20064 | 6 | 6 |
| 1 | 3 | 23403.47319 | 4 | 4 |
| 2 | 1 | 25900.20064 | 6 | 6 |
| 2 | 6 | 4958.180928 | 5 | 5 |
| 3 | 1 | 23403.47319 | 4 | 4 |
| 3 | 4 | 17110.52372 | 4 | 4 |
| 3 | 12 | 23403.47319 | 4 | 4 |
| 4 | 3 | 17110.52372 | 4 | 4 |
| 4 | 5 | 17782.7941 | 2 | 2 |
| 4 | 11 | 4908.82673 | 6 | 6 |
| 5 | 4 | 17782.7941 | 2 | 2 |
| 5 | 6 | 4947.995469 | 4 | 4 |
| 5 | 9 | 10000 | 5 | 5 |
| 6 | 2 | 4958.180928 | 5 | 5 |
| 6 | 5 | 4947.995469 | 4 | 4 |
| 6 | 8 | 4898.587646 | 2 | 2 |
| 7 | 8 | 7841.81131 | 3 | 3 |
| 7 | 18 | 23403.47319 | 2 | 2 |
| 8 | 6 | 4898.587646 | 2 | 2 |
| 8 | 7 | 7841.81131 | 3 | 3 |
| 8 | 9 | 5050.193156 | 10 | 10 |
| 8 | 16 | 5045.822583 | 5 | 5 |
| 9 | 5 | 10000 | 5 | 5 |
| 9 | 8 | 5050.193156 | 10 | 10 |
| 9 | 10 | 13915.78842 | 3 | 3 |
| 10 | 9 | 13915.78842 | 3 | 3 |
| 10 | 11 | 10000 | 5 | 5 |
| 10 | 15 | 13512.00155 | 6 | 6 |
| 10 | 16 | 4854.917717 | 4 | 4 |
| 10 | 17 | 4993.510694 | 8 | 8 |
| 11 | 4 | 4908.82673 | 6 | 6 |
| 11 | 10 | 10000 | 5 | 5 |
| 11 | 12 | 4908.82673 | 6 | 6 |

| | | | | |
|---|---|---|---|---|
| 11 | 14 | 4876.508287 | 4 | 4 |
| 12 | 3 | 23403.47319 | 4 | 4 |
| 12 | 11 | 4908.82673 | 6 | 6 |
| 12 | 13 | 25900.20064 | 3 | 3 |
| 13 | 12 | 25900.20064 | 3 | 3 |
| 13 | 24 | 5091.256152 | 4 | 4 |
| 14 | 11 | 4876.508287 | 4 | 4 |
| 14 | 15 | 5127.526119 | 5 | 5 |
| 14 | 23 | 4924.790605 | 4 | 4 |
| 15 | 10 | 13512.00155 | 6 | 6 |
| 15 | 14 | 5127.526119 | 5 | 5 |
| 15 | 19 | 14564.75315 | 3 | 3 |
| 15 | 22 | 9599.180565 | 3 | 3 |
| 16 | 8 | 5045.822583 | 5 | 5 |
| 16 | 10 | 4854.917717 | 4 | 4 |
| 16 | 17 | 5229.910063 | 2 | 2 |
| 16 | 18 | 19679.89671 | 3 | 3 |
| 17 | 10 | 4993.510694 | 8 | 8 |
| 17 | 16 | 5229.910063 | 2 | 2 |
| 17 | 19 | 4823.950831 | 2 | 2 |
| 18 | 7 | 23403.47319 | 2 | 2 |
| 18 | 16 | 19679.89671 | 3 | 3 |
| 18 | 20 | 23403.47319 | 4 | 4 |
| 19 | 15 | 14564.75315 | 3 | 3 |
| 19 | 17 | 4823.950831 | 2 | 2 |
| 19 | 20 | 5002.607563 | 4 | 4 |
| 20 | 18 | 23403.47319 | 4 | 4 |
| 20 | 19 | 5002.607563 | 4 | 4 |
| 20 | 21 | 5059.91234 | 6 | 6 |
| 20 | 22 | 5075.697193 | 5 | 5 |
| 21 | 20 | 5059.91234 | 6 | 6 |
| 21 | 22 | 5229.910063 | 2 | 2 |
| 21 | 24 | 4885.357564 | 3 | 3 |
| 22 | 15 | 9599.180565 | 3 | 3 |
| 22 | 20 | 5075.697193 | 5 | 5 |
| 22 | 21 | 5229.910063 | 2 | 2 |
| 22 | 23 | 5000 | 4 | 4 |
| 23 | 14 | 4924.790605 | 4 | 4 |
| 23 | 22 | 5000 | 4 | 4 |
| 23 | 24 | 5078.508436 | 2 | 2 |
| 24 | 13 | 5091.256152 | 4 | 4 |
| 24 | 21 | 4885.357564 | 3 | 3 |
| 24 | 23 | 5078.508436 | 2 | 2 |

**Table B.2**: Sioux Falls Network Travel Demands

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 100 | 100 | 500 | 200 | 300 | 500 | 800 | 500 | 1300 | 500 | 200 | 500 | 300 | 500 | 500 | 400 | 100 | 300 | 300 | 100 | 400 | 300 | 100 |
| 2 | 100 | 0 | 100 | 200 | 100 | 400 | 200 | 400 | 200 | 600 | 200 | 100 | 300 | 100 | 100 | 400 | 200 | 0 | 100 | 100 | 0 | 100 | 0 | 0 |
| 3 | 100 | 100 | 0 | 200 | 100 | 300 | 100 | 200 | 100 | 300 | 300 | 200 | 100 | 100 | 100 | 200 | 100 | 0 | 0 | 0 | 0 | 100 | 100 | 0 |
| 4 | 500 | 200 | 200 | 0 | 500 | 400 | 400 | 700 | 700 | 1200 | 1400 | 600 | 600 | 500 | 500 | 800 | 500 | 100 | 200 | 300 | 200 | 400 | 500 | 200 |
| 5 | 200 | 100 | 100 | 500 | 0 | 200 | 200 | 500 | 800 | 1000 | 500 | 200 | 200 | 100 | 200 | 500 | 200 | 0 | 100 | 100 | 100 | 200 | 100 | 0 |
| 6 | 300 | 400 | 300 | 400 | 200 | 0 | 400 | 800 | 400 | 800 | 400 | 200 | 200 | 100 | 200 | 900 | 500 | 100 | 200 | 300 | 100 | 200 | 100 | 100 |
| 7 | 500 | 200 | 100 | 400 | 200 | 400 | 0 | 1000 | 600 | 1900 | 500 | 700 | 400 | 200 | 500 | 1400 | 1000 | 200 | 400 | 500 | 200 | 500 | 200 | 100 |
| 8 | 800 | 400 | 200 | 700 | 500 | 800 | 1000 | 0 | 800 | 1600 | 800 | 600 | 600 | 400 | 600 | 2200 | 1400 | 300 | 700 | 900 | 400 | 500 | 300 | 200 |
| 9 | 500 | 200 | 100 | 700 | 800 | 400 | 600 | 800 | 0 | 2800 | 1400 | 600 | 600 | 600 | 900 | 1400 | 900 | 200 | 400 | 600 | 300 | 700 | 500 | 200 |
| 10 | 1300 | 600 | 300 | 1200 | 1000 | 800 | 1900 | 1600 | 2800 | 0 | 4000 | 2000 | 1900 | 2100 | 4000 | 4400 | 3900 | 700 | 1800 | 2500 | 1200 | 2600 | 1800 | 800 |
| 11 | 500 | 200 | 300 | 1500 | 500 | 400 | 500 | 800 | 1400 | 3900 | 0 | 1400 | 1000 | 1600 | 1400 | 1400 | 1000 | 100 | 400 | 600 | 400 | 1100 | 1300 | 600 |
| 12 | 200 | 100 | 200 | 600 | 200 | 200 | 700 | 600 | 600 | 2000 | 1400 | 0 | 1300 | 700 | 700 | 700 | 600 | 200 | 300 | 400 | 300 | 700 | 700 | 500 |
| 13 | 500 | 300 | 100 | 600 | 200 | 200 | 400 | 600 | 600 | 1900 | 1000 | 1300 | 0 | 600 | 700 | 600 | 500 | 100 | 300 | 600 | 600 | 1300 | 800 | 800 |
| 14 | 300 | 100 | 100 | 500 | 100 | 100 | 200 | 400 | 600 | 2100 | 1600 | 700 | 600 | 0 | 1300 | 700 | 700 | 100 | 300 | 500 | 400 | 1200 | 1100 | 400 |
| 15 | 500 | 100 | 100 | 500 | 200 | 200 | 500 | 600 | 1000 | 4000 | 1400 | 700 | 700 | 1300 | 0 | 1200 | 1500 | 200 | 800 | 1100 | 800 | 2600 | 1000 | 400 |
| 16 | 500 | 400 | 200 | 800 | 500 | 900 | 1400 | 2200 | 1400 | 4400 | 1400 | 700 | 600 | 700 | 1200 | 0 | 2800 | 500 | 1300 | 1600 | 600 | 1200 | 500 | 300 |
| 17 | 400 | 200 | 100 | 500 | 200 | 500 | 1000 | 1400 | 900 | 3900 | 1000 | 600 | 500 | 700 | 1500 | 2800 | 0 | 600 | 1700 | 1700 | 600 | 1700 | 600 | 300 |
| 18 | 100 | 0 | 0 | 100 | 0 | 100 | 200 | 300 | 200 | 700 | 200 | 200 | 100 | 100 | 200 | 500 | 600 | 0 | 300 | 400 | 100 | 300 | 100 | 0 |
| 19 | 300 | 100 | 0 | 200 | 100 | 200 | 400 | 700 | 400 | 1800 | 400 | 300 | 300 | 300 | 800 | 1300 | 1700 | 300 | 0 | 1200 | 400 | 1200 | 300 | 100 |
| 20 | 300 | 100 | 0 | 300 | 100 | 300 | 500 | 900 | 600 | 2500 | 600 | 500 | 600 | 500 | 1100 | 1600 | 1700 | 400 | 1200 | 0 | 1200 | 2400 | 700 | 400 |
| 21 | 100 | 0 | 0 | 200 | 100 | 100 | 200 | 400 | 300 | 1200 | 400 | 300 | 600 | 400 | 800 | 600 | 600 | 100 | 400 | 1200 | 0 | 1800 | 700 | 500 |
| 22 | 400 | 100 | 100 | 400 | 200 | 200 | 500 | 500 | 700 | 2600 | 1100 | 700 | 1300 | 1200 | 2600 | 1200 | 1700 | 300 | 1200 | 2400 | 1800 | 0 | 2100 | 1100 |
| 23 | 300 | 0 | 100 | 500 | 100 | 100 | 200 | 300 | 500 | 1800 | 1300 | 700 | 800 | 1100 | 1000 | 500 | 600 | 100 | 300 | 700 | 700 | 2100 | 0 | 700 |
| 24 | 100 | 0 | 0 | 200 | 0 | 100 | 100 | 200 | 200 | 800 | 600 | 500 | 700 | 400 | 400 | 300 | 300 | 0 | 100 | 400 | 500 | 1100 | 700 | 0 |

# C FULL DATA FOR SUE MODELS

**Table C.1**: Pareto optimal front results for SUE-FD-TP

| TP Links | | | | | | | | Objectives | |
|---|---|---|---|---|---|---|---|---|---|
| 13 | 21 | 23 | 24 | 28 | 30 | 43 | 51 | Equity | Emission |
| 6.99 | 15.35 | 7.21 | 15.21 | 12.00 | 14.38 | 12.00 | 14.40 | 9.54% | 372.14 |
| 6.69 | 15.34 | 7.30 | 15.17 | 12.00 | 14.38 | 12.00 | 14.40 | 9.52% | 372.14 |
| 5.28 | 16.29 | 6.53 | 15.61 | 12.00 | 14.21 | 12.00 | 14.20 | 9.41% | 372.21 |
| 4.33 | 12.72 | 7.49 | 16.47 | 12.00 | 15.33 | 12.00 | 14.90 | 9.25% | 372.30 |
| 4.06 | 13.05 | 7.49 | 16.49 | 11.98 | 15.33 | 12.00 | 15.09 | 9.23% | 372.30 |
| 2.37 | 13.85 | 7.28 | 17.20 | 12.00 | 15.72 | 11.94 | 14.80 | 9.11% | 372.42 |
| 2.25 | 13.80 | 7.13 | 17.21 | 12.00 | 15.72 | 11.95 | 14.74 | 9.09% | 372.43 |
| 1.38 | 13.59 | 7.17 | 16.54 | 11.97 | 15.47 | 11.99 | 14.75 | 9.03% | 372.53 |
| 1.50 | 13.35 | 6.50 | 16.59 | 11.81 | 15.50 | 11.76 | 14.99 | 8.99% | 372.65 |
| 0.78 | 12.67 | 6.02 | 16.64 | 12.00 | 15.69 | 11.81 | 13.92 | 8.91% | 372.76 |
| 0.40 | 11.87 | 6.50 | 17.16 | 11.60 | 15.81 | 12.00 | 14.34 | 8.86% | 372.88 |
| 0.42 | 11.74 | 6.15 | 15.58 | 11.84 | 15.82 | 11.68 | 14.10 | 8.84% | 372.96 |
| 0.09 | 10.80 | 6.42 | 17.46 | 11.66 | 15.74 | 9.68 | 14.24 | 8.73% | 373.41 |
| 0.08 | 10.84 | 6.42 | 17.49 | 11.67 | 15.74 | 9.62 | 14.25 | 8.73% | 373.42 |
| 0.01 | 9.23 | 3.77 | 16.26 | 11.51 | 15.91 | 12.00 | 13.89 | 8.65% | 373.65 |
| 0.00 | 9.66 | 3.92 | 16.36 | 9.86 | 15.90 | 10.93 | 13.71 | 8.57% | 374.08 |
| 0.00 | 9.33 | 3.99 | 16.36 | 9.67 | 15.91 | 10.48 | 13.70 | 8.54% | 374.23 |
| 0.01 | 9.55 | 3.58 | 14.85 | 8.05 | 15.92 | 10.46 | 14.02 | 8.45% | 374.71 |
| 0.00 | 9.15 | 3.80 | 15.60 | 6.56 | 15.83 | 10.64 | 13.85 | 8.41% | 375.05 |
| 0.00 | 8.98 | 3.57 | 15.52 | 6.29 | 15.84 | 10.11 | 13.86 | 8.36% | 375.28 |
| 0.82 | 7.57 | 3.90 | 15.54 | 8.89 | 16.00 | 5.33 | 13.11 | 8.35% | 375.53 |
| 0.66 | 7.58 | 4.08 | 15.56 | 8.63 | 16.00 | 4.53 | 13.05 | 8.30% | 375.76 |
| 0.39 | 7.35 | 4.01 | 15.29 | 7.37 | 15.97 | 5.19 | 12.96 | 8.24% | 376.02 |
| 0.38 | 7.33 | 4.03 | 15.27 | 7.36 | 15.97 | 5.10 | 12.99 | 8.23% | 376.04 |
| 0.39 | 7.58 | 3.99 | 14.93 | 6.78 | 16.00 | 4.58 | 13.06 | 8.20% | 376.30 |
| 0.38 | 7.27 | 3.91 | 15.02 | 6.54 | 15.97 | 4.79 | 13.03 | 8.18% | 376.37 |
| 0.30 | 6.13 | 3.91 | 14.45 | 8.48 | 15.95 | 2.57 | 13.12 | 8.13% | 376.57 |
| 0.00 | 4.84 | 2.50 | 14.47 | 8.38 | 15.88 | 3.46 | 13.01 | 8.06% | 376.91 |
| 0.15 | 5.31 | 2.16 | 14.37 | 7.64 | 16.00 | 2.56 | 12.86 | 8.01% | 377.25 |
| 0.77 | 7.56 | 1.86 | 10.87 | 1.93 | 15.63 | 5.61 | 10.75 | 7.98% | 377.74 |
| 0.67 | 7.38 | 1.70 | 10.97 | 1.57 | 15.66 | 5.72 | 10.77 | 7.94% | 377.89 |
| 0.48 | 6.96 | 1.56 | 11.10 | 0.90 | 15.66 | 5.96 | 10.96 | 7.88% | 378.14 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0.12 | 6.74 | 1.60 | 11.34 | 0.55 | 15.78 | 5.78 | 10.39 | 7.83% | 378.34 |
| 0.09 | 5.34 | 1.28 | 11.98 | 1.23 | 16.00 | 4.63 | 9.41 | 7.79% | 378.57 |
| 0.03 | 3.62 | 2.73 | 13.15 | 1.75 | 15.97 | 2.92 | 12.08 | 7.72% | 378.90 |
| 0.30 | 2.91 | 2.62 | 13.09 | 1.47 | 15.96 | 2.73 | 11.94 | 7.71% | 379.13 |
| 0.32 | 3.10 | 2.94 | 13.17 | 0.85 | 15.99 | 2.41 | 11.81 | 7.69% | 379.26 |
| 0.35 | 3.23 | 2.39 | 12.50 | 0.35 | 15.99 | 2.66 | 11.85 | 7.65% | 379.46 |
| 0.34 | 4.24 | 0.08 | 10.33 | 0.29 | 15.99 | 1.86 | 11.03 | 7.57% | 380.02 |
| 0.37 | 4.31 | 0.00 | 10.26 | 0.47 | 15.99 | 1.39 | 11.06 | 7.56% | 380.08 |
| 0.22 | 3.83 | 0.34 | 9.70 | 0.00 | 16.00 | 1.07 | 11.12 | 7.51% | 380.44 |
| 0.21 | 3.44 | 0.29 | 8.63 | 0.15 | 16.00 | 0.86 | 11.29 | 7.48% | 380.68 |
| 0.00 | 1.86 | 1.89 | 5.05 | 0.35 | 15.87 | 1.16 | 11.82 | 7.43% | 381.30 |
| 0.00 | 1.90 | 2.28 | 3.68 | 0.12 | 15.97 | 0.42 | 11.83 | 7.37% | 381.76 |
| 0.02 | 1.80 | 1.98 | 2.29 | 0.04 | 15.97 | 0.49 | 11.61 | 7.35% | 382.13 |
| 0.00 | 1.99 | 0.26 | 2.58 | 0.00 | 15.96 | 1.16 | 12.15 | 7.32% | 382.28 |
| 0.00 | 1.99 | 0.22 | 2.00 | 0.00 | 15.96 | 0.46 | 12.13 | 7.29% | 382.58 |
| 0.01 | 0.35 | 0.35 | 2.01 | 0.00 | 15.99 | 0.19 | 12.01 | 7.28% | 382.95 |
| 0.00 | 0.00 | 0.00 | 1.35 | 0.00 | 15.98 | 0.00 | 11.98 | 7.26% | 383.29 |
| 0.00 | 0.00 | 0.00 | 0.11 | 0.00 | 16.00 | 0.00 | 12.14 | 7.25% | 383.60 |

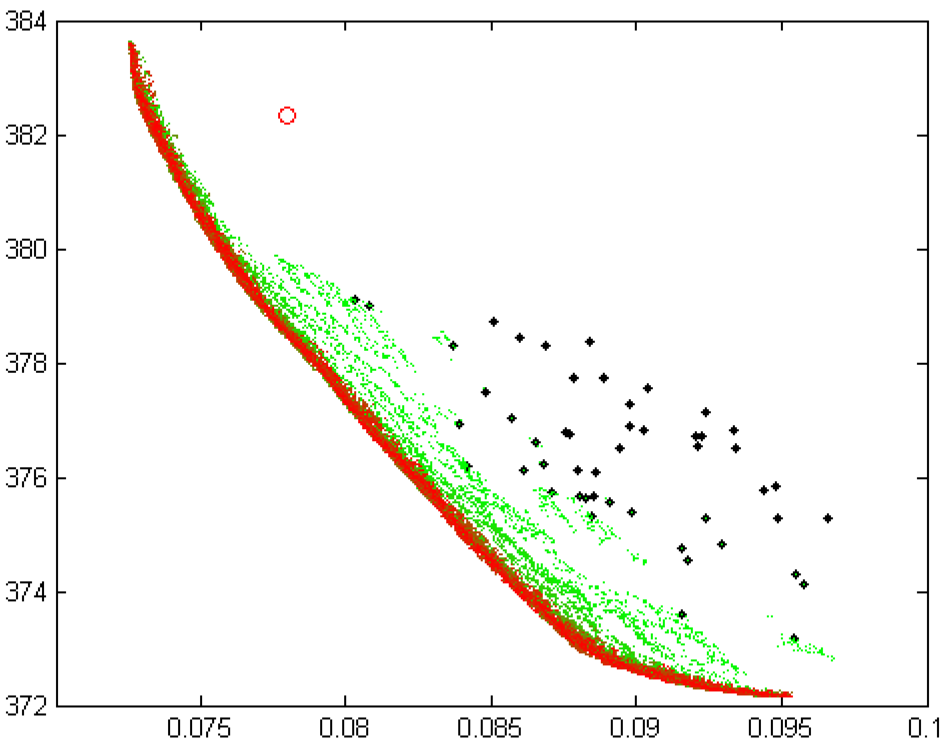


**Figure C.1**: Pareto optimal front for SUE-FD-TP

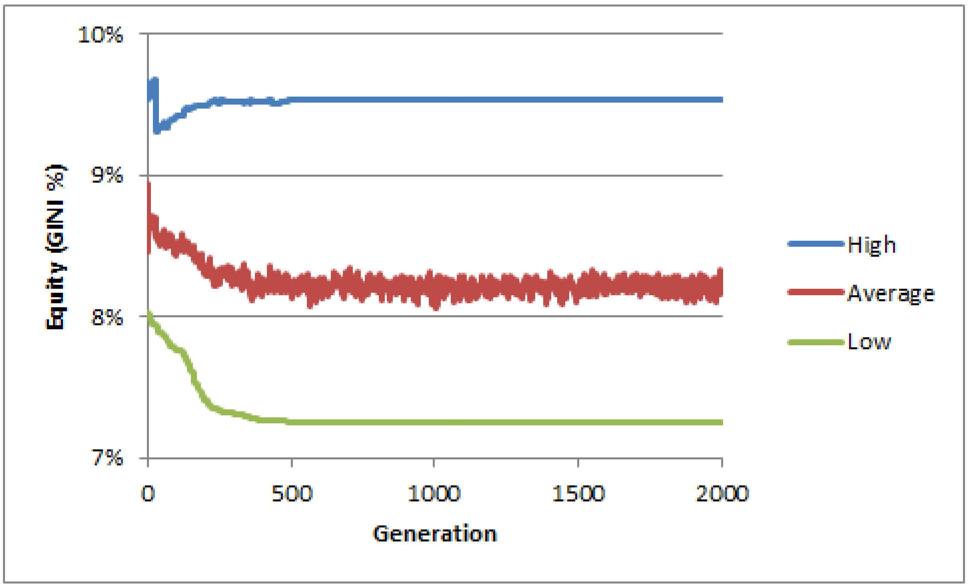


**Figure C.2**: Equity over generations of NSGA-II for SUE-FD-TP

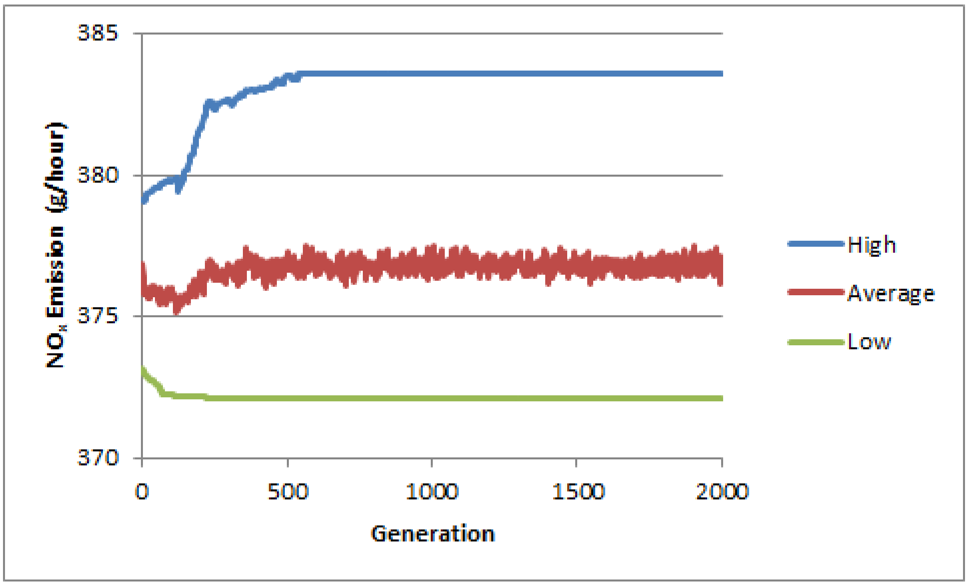


**Figure C.3**: Emission over generations of NSGA-II for SUE-FD-TP

**Table C.2**: Pareto optimal front results for SUE-FD-CE

| CE Links | | | | | | | | Objectives | |
|---|---|---|---|---|---|---|---|---|---|
| 25 | 26 | 29 | 34 | 40 | 48 | 66 | 75 | Equity | Emission |
| 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.51% | 364.03 |
| 0.00 | 2.59 | 2.43 | 2.44 | 2.44 | 0.00 | 1.62 | 2.44 | 6.28% | 371.44 |
| 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.51% | 364.03 |
| 1.29 | 6.94 | 2.43 | 2.44 | 2.44 | 1.41 | 2.37 | 2.38 | 6.76% | 367.06 |
| 1.30 | 6.92 | 2.43 | 2.44 | 2.42 | 1.34 | 2.39 | 2.42 | 6.74% | 367.15 |
| 1.40 | 6.96 | 2.43 | 2.43 | 2.44 | 1.67 | 2.27 | 2.42 | 6.83% | 366.63 |
| 0.78 | 6.74 | 2.43 | 2.44 | 2.44 | 0.89 | 2.44 | 2.44 | 6.60% | 368.12 |
| 0.02 | 5.75 | 2.42 | 2.44 | 2.44 | 0.59 | 2.40 | 2.42 | 6.50% | 369.16 |
| 0.55 | 6.93 | 2.43 | 2.44 | 2.44 | 1.27 | 2.33 | 2.38 | 6.71% | 367.57 |
| 0.81 | 6.96 | 2.37 | 2.41 | 2.44 | 0.99 | 2.44 | 2.44 | 6.63% | 367.97 |
| 4.00 | 6.96 | 2.41 | 2.42 | 2.44 | 2.30 | 2.44 | 2.44 | 7.21% | 364.87 |
| 0.05 | 3.47 | 2.41 | 2.44 | 2.44 | 0.20 | 2.33 | 2.43 | 6.35% | 370.47 |
| 4.38 | 6.96 | 2.41 | 2.42 | 2.44 | 2.31 | 2.43 | 2.44 | 7.24% | 364.76 |
| 1.37 | 6.96 | 2.43 | 2.43 | 2.44 | 1.80 | 2.32 | 2.42 | 6.86% | 366.42 |
| 0.52 | 2.99 | 2.43 | 2.44 | 2.44 | 0.02 | 1.60 | 2.44 | 6.31% | 371.10 |
| 0.38 | 2.95 | 2.41 | 2.44 | 2.44 | 0.08 | 2.32 | 2.44 | 6.33% | 370.74 |
| 0.58 | 6.71 | 2.43 | 2.44 | 2.44 | 0.82 | 2.41 | 2.44 | 6.58% | 368.32 |
| 5.19 | 6.87 | 2.43 | 2.44 | 2.44 | 2.41 | 2.43 | 2.44 | 7.35% | 364.42 |
| 4.76 | 6.96 | 2.43 | 2.44 | 2.44 | 2.40 | 2.44 | 2.44 | 7.30% | 364.52 |
| 0.33 | 4.29 | 2.43 | 2.44 | 2.44 | 0.61 | 2.34 | 2.44 | 6.48% | 369.34 |
| 0.89 | 6.96 | 2.43 | 2.44 | 2.43 | 1.07 | 2.33 | 2.44 | 6.65% | 367.77 |
| 1.75 | 6.96 | 2.43 | 2.44 | 2.44 | 1.97 | 2.29 | 2.43 | 6.92% | 366.04 |
| 3.18 | 6.88 | 2.43 | 2.43 | 2.44 | 2.43 | 2.44 | 2.44 | 7.17% | 364.92 |
| 0.52 | 3.28 | 2.43 | 2.44 | 2.44 | 0.09 | 1.63 | 2.44 | 6.33% | 370.87 |
| 1.74 | 6.92 | 2.42 | 2.37 | 2.44 | 2.11 | 2.33 | 2.40 | 6.97% | 365.91 |
| 0.54 | 4.13 | 2.43 | 2.44 | 2.44 | 0.52 | 2.34 | 2.44 | 6.46% | 369.46 |
| 0.54 | 6.39 | 2.43 | 2.44 | 2.42 | 0.57 | 2.37 | 2.44 | 6.52% | 368.91 |
| 2.73 | 6.87 | 2.43 | 2.43 | 2.44 | 2.43 | 2.44 | 2.44 | 7.13% | 365.06 |
| 2.73 | 6.85 | 2.43 | 2.43 | 2.44 | 2.31 | 2.44 | 2.44 | 7.10% | 365.21 |
| 1.87 | 6.96 | 2.43 | 2.43 | 2.44 | 1.84 | 2.31 | 2.41 | 6.90% | 366.19 |
| 6.79 | 6.96 | 2.43 | 2.44 | 2.44 | 2.37 | 2.44 | 2.44 | 7.48% | 364.13 |
| 4.23 | 6.95 | 2.41 | 2.42 | 2.44 | 2.43 | 2.44 | 2.44 | 7.26% | 364.65 |
| 0.40 | 2.91 | 2.38 | 2.43 | 2.44 | 0.00 | 1.68 | 2.44 | 6.30% | 371.24 |
| 0.59 | 4.12 | 2.43 | 2.44 | 2.44 | 0.29 | 2.35 | 2.44 | 6.40% | 369.90 |
| 1.79 | 6.95 | 2.43 | 2.44 | 2.44 | 2.20 | 2.29 | 2.43 | 6.99% | 365.71 |
| 0.75 | 4.05 | 2.43 | 2.44 | 2.43 | 0.41 | 2.34 | 2.44 | 6.44% | 369.62 |
| 1.79 | 6.83 | 2.43 | 2.41 | 2.44 | 2.36 | 2.26 | 2.44 | 7.03% | 365.55 |
| 0.71 | 4.01 | 2.43 | 2.44 | 2.44 | 0.34 | 2.34 | 2.44 | 6.42% | 369.78 |
| 1.39 | 6.96 | 2.43 | 2.43 | 2.44 | 1.68 | 2.28 | 2.42 | 6.83% | 366.61 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 6.35 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.45% | 364.14 |
| 0.75 | 6.34 | 2.43 | 2.44 | 2.42 | 0.68 | 2.37 | 2.44 | 6.54% | 368.61 |
| 1.76 | 6.92 | 2.42 | 2.36 | 2.44 | 2.05 | 2.33 | 2.40 | 6.95% | 365.98 |
| 4.45 | 6.87 | 2.43 | 2.44 | 2.44 | 2.43 | 2.43 | 2.44 | 7.28% | 364.58 |
| 0.53 | 6.72 | 2.43 | 2.44 | 2.44 | 0.78 | 2.41 | 2.44 | 6.57% | 368.43 |
| 0.86 | 6.96 | 2.43 | 2.44 | 2.43 | 1.13 | 2.33 | 2.44 | 6.67% | 367.67 |
| 0.27 | 3.41 | 2.43 | 2.44 | 2.44 | 0.26 | 2.32 | 2.44 | 6.37% | 370.26 |
| 0.24 | 3.34 | 2.43 | 2.44 | 2.44 | 0.24 | 2.33 | 2.44 | 6.37% | 370.33 |
| 1.79 | 6.96 | 2.43 | 2.44 | 2.44 | 2.20 | 2.30 | 2.43 | 6.99% | 365.71 |
| 0.58 | 6.35 | 2.43 | 2.44 | 2.42 | 0.63 | 2.37 | 2.44 | 6.53% | 368.78 |
| 0.00 | 2.86 | 2.43 | 2.44 | 2.44 | 0.00 | 1.59 | 2.44 | 6.29% | 371.38 |

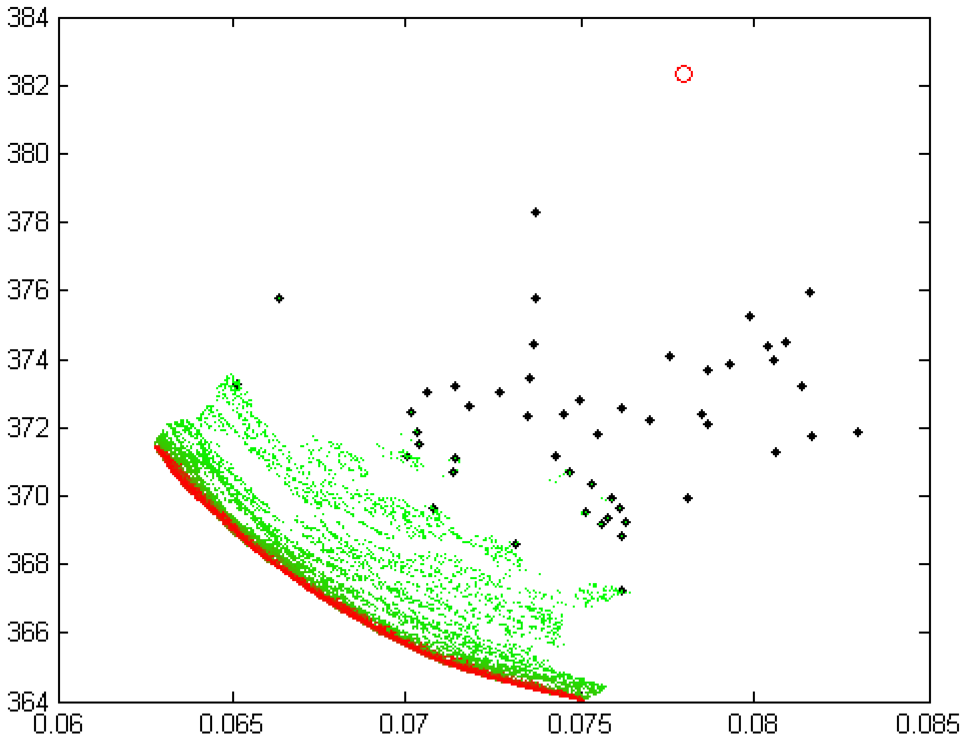


**Figure C.4**: Pareto optimal front for SUE-FD-CE

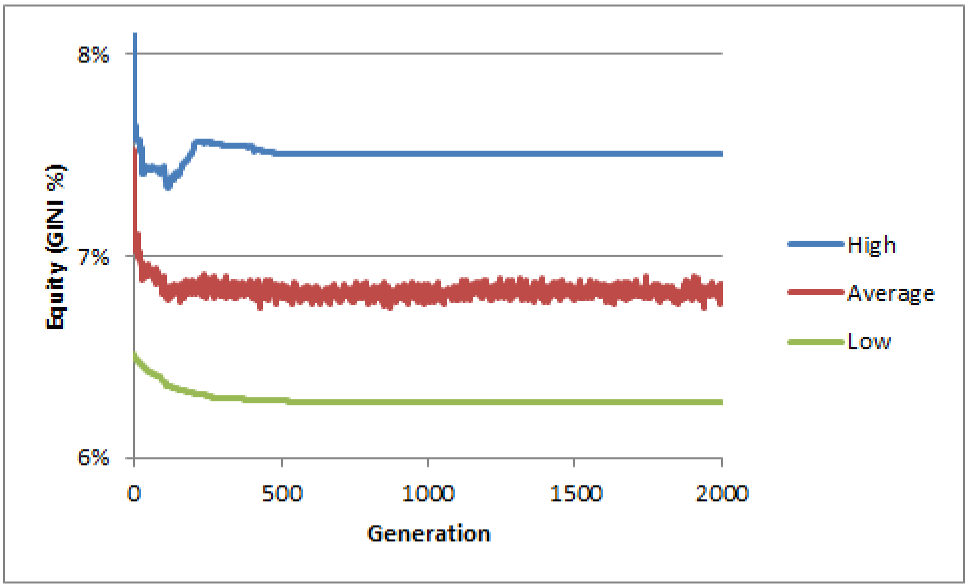


**Figure C.5**: Equity over generations of NSGA-II for SUE-FD-CE

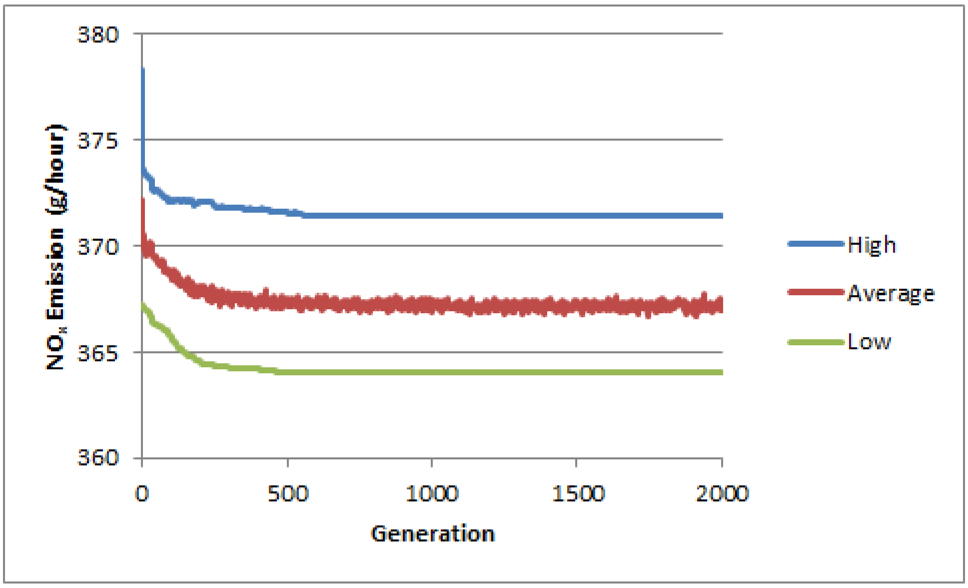


**Figure C.6**: Emission over generations of NSGA-II for SUE-FD-CE

**Table C.3**: Pareto optimal front results for SUE-FD-TPCE

| TP Links | | | | | | | | CE Links | | | | | | | | Objectives | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13 | 21 | 23 | 24 | 28 | 30 | 43 | 51 | 25 | 26 | 29 | 34 | 40 | 48 | 66 | 75 | Equity | Emission |
| 3.19 | 10.34 | 3.33 | 10.26 | 12.00 | 13.33 | 12.00 | 13.30 | 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 9.36% | 358.34 |
| 3.06 | 10.26 | 3.37 | 10.26 | 11.99 | 13.58 | 11.81 | 13.57 | 6.88 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 9.33% | 358.36 |
| 3.20 | 9.63 | 3.34 | 9.73 | 10.88 | 13.13 | 11.39 | 12.99 | 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.28 | 2.44 | 2.44 | 9.24% | 358.50 |
| 1.74 | 9.80 | 1.61 | 9.48 | 10.88 | 13.15 | 12.00 | 13.08 | 6.96 | 6.88 | 2.42 | 2.44 | 2.43 | 2.42 | 2.42 | 2.41 | 9.05% | 358.52 |
| 1.81 | 9.56 | 2.04 | 9.02 | 9.58 | 13.52 | 11.53 | 13.74 | 6.31 | 6.94 | 2.41 | 2.44 | 2.44 | 2.42 | 2.41 | 2.44 | 8.89% | 358.77 |
| 1.75 | 9.32 | 1.84 | 9.28 | 7.93 | 13.10 | 10.98 | 13.64 | 6.02 | 6.77 | 2.35 | 2.43 | 2.44 | 2.34 | 2.42 | 2.44 | 8.67% | 359.23 |
| 0.15 | 5.73 | 1.12 | 8.76 | 8.94 | 10.74 | 9.72 | 6.80 | 6.74 | 6.84 | 2.43 | 2.44 | 2.44 | 2.24 | 2.40 | 2.43 | 8.58% | 359.43 |
| 0.20 | 5.55 | 1.19 | 8.63 | 8.68 | 10.78 | 8.68 | 7.93 | 6.80 | 6.60 | 2.43 | 2.44 | 2.44 | 2.17 | 2.43 | 2.43 | 8.50% | 359.58 |
| 0.02 | 5.78 | 1.13 | 8.67 | 7.71 | 10.95 | 8.78 | 8.17 | 6.88 | 6.03 | 2.43 | 2.44 | 2.44 | 2.19 | 2.40 | 2.43 | 8.39% | 359.79 |
| 0.01 | 5.51 | 1.11 | 8.78 | 7.02 | 10.95 | 8.96 | 8.07 | 6.96 | 6.19 | 2.43 | 2.43 | 2.44 | 2.15 | 2.41 | 2.43 | 8.33% | 359.93 |
| 0.12 | 5.69 | 1.24 | 9.09 | 6.50 | 10.23 | 8.44 | 10.01 | 5.50 | 6.85 | 2.43 | 2.44 | 2.44 | 2.41 | 2.42 | 2.44 | 8.19% | 359.96 |
| 0.00 | 6.47 | 0.86 | 9.93 | 5.86 | 10.06 | 6.35 | 9.58 | 5.25 | 6.91 | 2.43 | 2.41 | 2.43 | 2.43 | 2.44 | 2.44 | 8.01% | 360.52 |
| 0.01 | 6.51 | 0.86 | 9.94 | 5.80 | 10.01 | 6.07 | 9.72 | 5.27 | 6.91 | 2.43 | 2.41 | 2.43 | 2.41 | 2.44 | 2.44 | 7.99% | 360.60 |
| 0.00 | 6.23 | 1.21 | 7.56 | 6.97 | 10.18 | 6.53 | 7.38 | 3.32 | 6.11 | 2.29 | 2.39 | 2.38 | 2.30 | 2.44 | 2.44 | 7.94% | 360.98 |
| 0.06 | 6.04 | 1.28 | 7.85 | 5.89 | 10.29 | 6.03 | 7.24 | 2.98 | 6.57 | 2.39 | 2.37 | 2.37 | 2.25 | 2.37 | 2.41 | 7.79% | 361.35 |
| 0.06 | 6.12 | 1.29 | 8.02 | 5.61 | 10.28 | 5.84 | 7.47 | 2.78 | 6.59 | 2.39 | 2.38 | 2.38 | 2.25 | 2.38 | 2.40 | 7.73% | 361.51 |
| 0.00 | 6.61 | 0.96 | 5.43 | 3.44 | 11.07 | 7.92 | 8.16 | 2.74 | 6.22 | 2.40 | 2.42 | 2.31 | 2.41 | 2.38 | 2.44 | 7.60% | 361.76 |
| 0.01 | 6.13 | 0.99 | 5.67 | 2.72 | 11.23 | 8.09 | 8.13 | 2.55 | 6.23 | 2.40 | 2.41 | 2.32 | 2.36 | 2.38 | 2.44 | 7.50% | 362.09 |
| 0.00 | 6.07 | 0.97 | 5.73 | 2.61 | 11.23 | 8.11 | 8.10 | 2.47 | 6.20 | 2.43 | 2.34 | 2.29 | 2.38 | 2.42 | 2.44 | 7.49% | 362.15 |
| 0.00 | 5.02 | 0.86 | 4.61 | 0.91 | 10.77 | 9.54 | 8.74 | 2.00 | 6.92 | 2.39 | 2.39 | 2.44 | 2.43 | 2.39 | 2.42 | 7.34% | 362.63 |
| 0.00 | 5.03 | 0.87 | 4.43 | 0.91 | 10.78 | 9.64 | 8.94 | 1.87 | 6.96 | 2.42 | 2.39 | 2.44 | 2.43 | 2.39 | 2.43 | 7.33% | 362.65 |
| 0.01 | 4.70 | 0.96 | 4.97 | 0.76 | 10.40 | 8.24 | 8.77 | 1.69 | 6.56 | 2.40 | 2.39 | 2.43 | 2.43 | 2.39 | 2.42 | 7.24% | 362.93 |
| 0.10 | 4.13 | 1.25 | 7.22 | 2.14 | 10.50 | 1.83 | 7.07 | 2.99 | 6.87 | 2.43 | 2.44 | 2.40 | 2.22 | 2.38 | 2.44 | 7.13% | 363.47 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.11 | 4.09 | 1.23 | 7.25 | 2.14 | 10.51 | 1.83 | 7.12 | 2.85 | 6.73 | 2.43 | 2.44 | 2.40 | 2.20 | 2.43 | 2.44 | 7.11% | 363.55 |
| 0.17 | 3.84 | 1.26 | 7.29 | 1.81 | 10.57 | 1.06 | 6.98 | 2.47 | 6.85 | 2.43 | 2.44 | 2.40 | 2.18 | 2.35 | 2.44 | 6.99% | 364.07 |
| 0.17 | 3.80 | 1.24 | 7.26 | 1.77 | 10.56 | 1.06 | 6.98 | 2.47 | 6.85 | 2.43 | 2.44 | 2.40 | 2.18 | 2.35 | 2.44 | 6.99% | 364.09 |
| 0.24 | 3.33 | 1.61 | 6.50 | 1.12 | 10.69 | 1.61 | 6.90 | 1.78 | 6.74 | 2.42 | 2.44 | 2.39 | 2.17 | 2.33 | 2.44 | 6.89% | 364.40 |
| 0.00 | 3.18 | 1.35 | 6.14 | 1.15 | 10.76 | 1.08 | 6.96 | 1.14 | 6.76 | 2.42 | 2.44 | 2.44 | 2.16 | 2.44 | 2.44 | 6.75% | 364.79 |
| 0.08 | 2.69 | 1.35 | 6.50 | 0.00 | 10.90 | 0.99 | 6.82 | 1.97 | 6.68 | 2.36 | 2.35 | 2.44 | 1.90 | 2.38 | 2.44 | 6.66% | 365.48 |
| 0.12 | 2.96 | 1.38 | 6.73 | 0.00 | 10.68 | 0.90 | 7.06 | 1.80 | 6.44 | 2.30 | 2.35 | 2.44 | 1.76 | 2.44 | 2.44 | 6.62% | 365.77 |
| 0.11 | 2.91 | 1.39 | 6.44 | 0.00 | 10.68 | 0.80 | 7.25 | 1.87 | 6.61 | 2.30 | 2.35 | 2.44 | 1.65 | 2.43 | 2.44 | 6.59% | 365.93 |
| 0.25 | 3.60 | 1.38 | 6.35 | 0.48 | 12.51 | 0.80 | 8.55 | 0.29 | 6.96 | 2.41 | 2.44 | 2.34 | 1.83 | 2.27 | 2.44 | 6.46% | 366.36 |
| 0.22 | 3.70 | 1.38 | 6.25 | 0.61 | 12.52 | 0.00 | 8.47 | 0.24 | 6.54 | 2.41 | 2.44 | 2.33 | 1.86 | 2.28 | 2.44 | 6.42% | 366.61 |
| 0.01 | 3.42 | 1.40 | 6.05 | 0.03 | 12.52 | 0.12 | 9.19 | 0.37 | 6.68 | 2.43 | 2.35 | 2.44 | 1.88 | 2.21 | 2.36 | 6.34% | 366.89 |
| 0.00 | 3.36 | 1.39 | 6.04 | 0.00 | 12.59 | 0.00 | 9.14 | 0.27 | 6.75 | 2.43 | 2.43 | 2.44 | 1.79 | 2.26 | 2.44 | 6.29% | 367.02 |
| 0.00 | 2.53 | 1.68 | 6.76 | 0.13 | 14.45 | 0.45 | 8.77 | 0.06 | 6.04 | 2.43 | 2.44 | 2.43 | 1.76 | 2.25 | 2.43 | 6.28% | 367.61 |
| 0.00 | 2.67 | 1.63 | 6.73 | 0.00 | 14.74 | 0.00 | 8.73 | 0.10 | 6.02 | 2.43 | 2.44 | 2.43 | 1.79 | 2.26 | 2.43 | 6.23% | 367.86 |
| 0.05 | 3.83 | 0.00 | 4.87 | 0.02 | 10.76 | 1.22 | 10.81 | 0.29 | 3.74 | 2.43 | 2.43 | 2.25 | 1.26 | 1.67 | 2.44 | 6.20% | 368.35 |
| 0.05 | 3.87 | 0.02 | 4.76 | 0.00 | 10.76 | 0.98 | 10.76 | 0.21 | 3.64 | 2.43 | 2.43 | 2.26 | 1.22 | 1.76 | 2.44 | 6.17% | 368.51 |
| 0.03 | 5.08 | 0.00 | 4.27 | 0.48 | 10.48 | 0.51 | 12.07 | 0.50 | 2.56 | 2.43 | 2.23 | 2.41 | 0.72 | 1.83 | 2.44 | 6.10% | 369.49 |
| 0.20 | 4.59 | 0.06 | 4.35 | 0.21 | 10.49 | 0.00 | 12.32 | 0.44 | 2.81 | 2.43 | 2.18 | 2.44 | 0.68 | 1.82 | 2.44 | 6.04% | 369.87 |
| 0.13 | 4.36 | 0.10 | 4.46 | 0.28 | 10.15 | 0.31 | 12.33 | 0.00 | 2.68 | 2.43 | 2.18 | 2.44 | 0.57 | 1.82 | 2.44 | 6.03% | 370.08 |
| 0.03 | 4.11 | 0.10 | 4.94 | 0.00 | 11.24 | 0.25 | 11.91 | 0.43 | 1.11 | 2.37 | 2.44 | 2.42 | 0.44 | 1.67 | 2.41 | 5.95% | 371.02 |
| 0.09 | 3.15 | 0.02 | 5.06 | 0.00 | 11.11 | 0.00 | 12.62 | 0.21 | 1.65 | 2.36 | 2.44 | 2.44 | 0.56 | 1.45 | 2.44 | 5.90% | 371.15 |
| 0.00 | 3.49 | 0.03 | 4.93 | 0.00 | 10.89 | 0.25 | 12.32 | 0.00 | 0.60 | 2.39 | 2.44 | 2.44 | 0.30 | 1.39 | 2.44 | 5.87% | 371.84 |
| 0.00 | 3.49 | 0.01 | 4.97 | 0.00 | 10.91 | 0.24 | 12.37 | 0.00 | 0.45 | 2.39 | 2.44 | 2.44 | 0.27 | 1.44 | 2.44 | 5.87% | 371.94 |
| 0.00 | 2.94 | 0.01 | 5.38 | 0.00 | 11.13 | 0.00 | 12.59 | 0.00 | 0.37 | 2.39 | 2.44 | 2.44 | 0.00 | 1.40 | 2.44 | 5.81% | 372.73 |
| 0.00 | 2.73 | 0.01 | 5.33 | 0.00 | 11.15 | 0.00 | 12.56 | 0.00 | 0.36 | 2.41 | 2.44 | 2.44 | 0.00 | 1.40 | 2.44 | 5.81% | 372.75 |
| 0.00 | 0.21 | 0.00 | 1.88 | 0.00 | 11.59 | 0.00 | 15.32 | 0.00 | 0.90 | 1.94 | 2.44 | 2.44 | 0.00 | 1.58 | 2.44 | 5.81% | 374.80 |
| 0.00 | 0.00 | 0.00 | 1.71 | 0.00 | 11.61 | 0.00 | 15.24 | 0.00 | 0.86 | 1.96 | 2.44 | 2.44 | 0.00 | 1.58 | 2.44 | 5.81% | 374.85 |

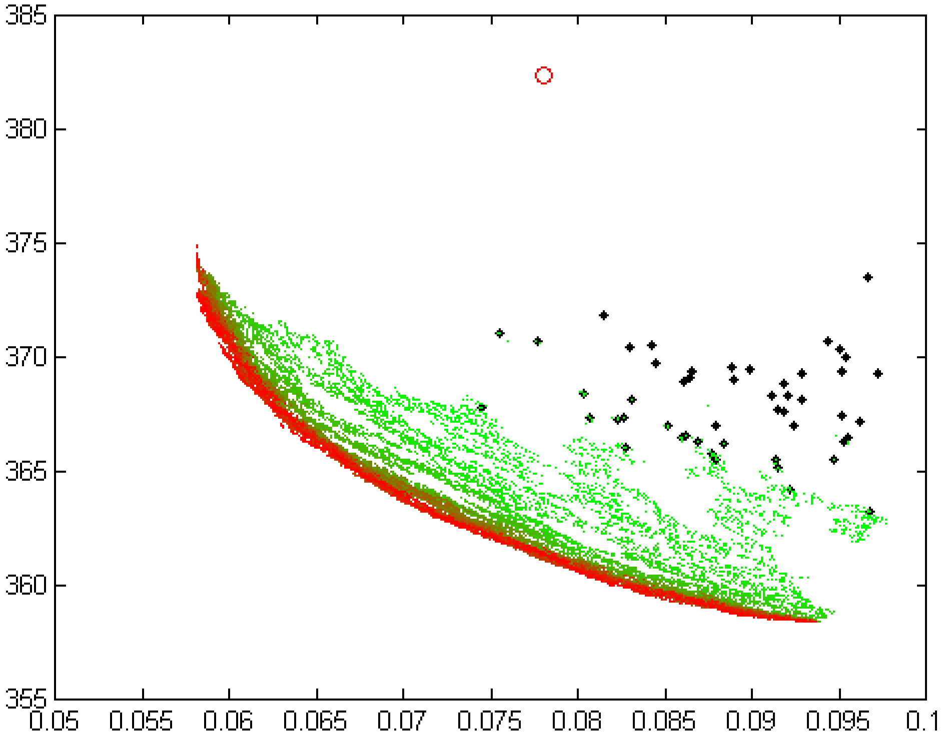


**Figure C.7**: Pareto optimal front for SUE-FD-TPCE

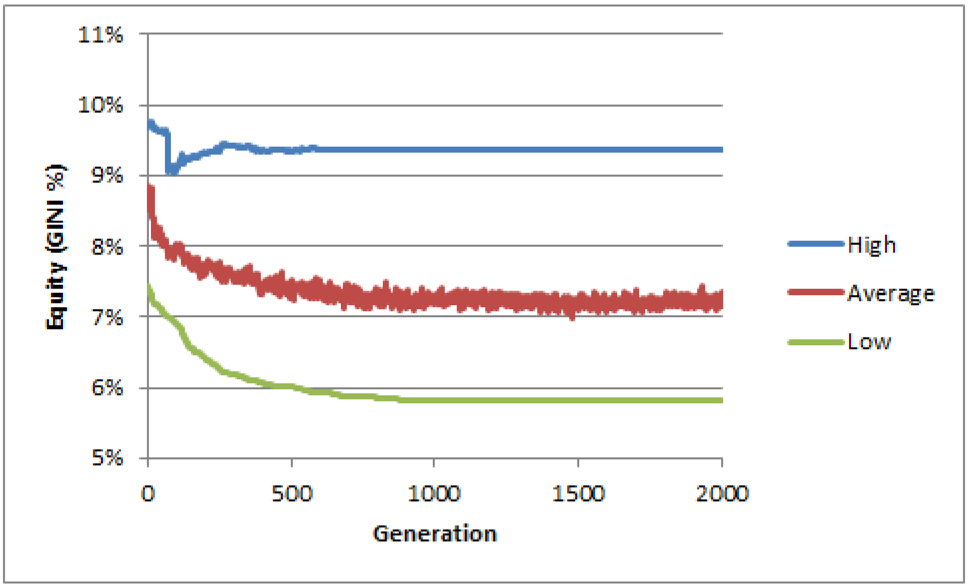


**Figure C.8**: Equity over generations of NSGA-II for SUE-FD-TPCE

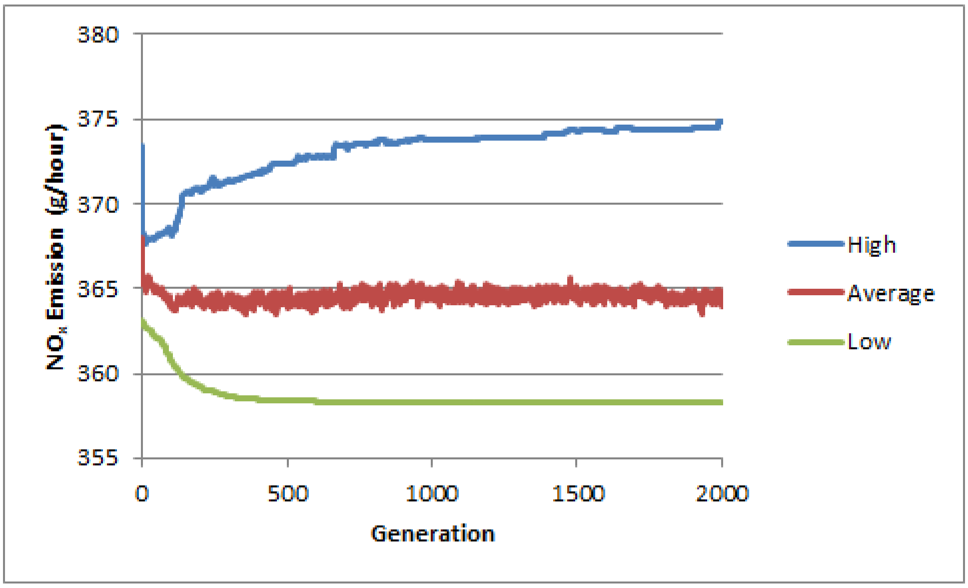


**Figure C.9**: Emission over generations of NSGA-II for SUE-FD-TPCE

**Table C.4**: Pareto optimal front results for SUE-ED-TP

| TP Links | | | | | | | | Objectives | |
|---|---|---|---|---|---|---|---|---|---|
| 13 | 21 | 23 | 24 | 28 | 30 | 43 | 51 | Equity | Emission |
| 4.46 | 14.48 | 4.55 | 14.25 | 12.00 | 14.17 | 12.00 | 14.19 | 9.09% | 346.18 |
| 3.66 | 13.77 | 4.39 | 13.63 | 11.91 | 13.91 | 11.89 | 13.87 | 8.99% | 346.24 |
| 3.64 | 13.15 | 4.34 | 14.15 | 11.91 | 13.93 | 11.85 | 13.88 | 8.97% | 346.26 |
| 2.78 | 12.94 | 4.23 | 14.85 | 12.00 | 14.83 | 12.00 | 14.26 | 8.87% | 346.26 |
| 2.70 | 13.46 | 4.41 | 13.92 | 11.31 | 14.80 | 12.00 | 14.18 | 8.85% | 346.38 |
| 1.57 | 13.60 | 3.74 | 16.65 | 12.00 | 15.16 | 12.00 | 14.59 | 8.76% | 346.39 |
| 1.19 | 11.99 | 3.70 | 15.84 | 11.93 | 15.02 | 11.85 | 15.00 | 8.67% | 346.51 |
| 1.25 | 11.86 | 3.66 | 15.55 | 11.77 | 15.00 | 11.25 | 15.04 | 8.64% | 346.64 |
| 0.13 | 13.06 | 3.19 | 14.29 | 11.93 | 15.96 | 11.54 | 14.76 | 8.54% | 346.70 |
| 0.12 | 13.16 | 3.06 | 14.29 | 11.48 | 15.96 | 11.21 | 14.85 | 8.49% | 346.87 |
| 0.12 | 10.77 | 3.16 | 13.40 | 11.17 | 15.87 | 12.00 | 14.64 | 8.45% | 346.98 |
| 0.12 | 10.99 | 3.14 | 13.21 | 10.98 | 15.87 | 11.78 | 14.65 | 8.43% | 347.04 |
| 0.12 | 10.27 | 3.30 | 12.66 | 10.52 | 15.86 | 11.86 | 14.52 | 8.39% | 347.21 |
| 0.09 | 10.81 | 2.44 | 12.59 | 10.93 | 16.00 | 10.62 | 14.73 | 8.34% | 347.39 |
| 0.09 | 7.78 | 3.07 | 15.48 | 9.66 | 15.82 | 11.95 | 14.27 | 8.28% | 347.66 |
| 0.09 | 7.65 | 3.03 | 15.23 | 8.90 | 15.82 | 11.54 | 14.30 | 8.21% | 347.93 |
| 0.09 | 7.76 | 3.05 | 15.36 | 8.56 | 15.82 | 11.37 | 14.23 | 8.19% | 348.02 |
| 0.00 | 8.14 | 2.86 | 14.35 | 9.38 | 15.63 | 9.18 | 15.19 | 8.14% | 348.20 |
| 0.05 | 7.85 | 2.79 | 14.68 | 8.97 | 15.79 | 8.74 | 15.04 | 8.09% | 348.42 |
| 0.03 | 7.18 | 2.68 | 14.63 | 9.02 | 15.82 | 7.96 | 14.76 | 8.04% | 348.66 |
| 0.01 | 7.37 | 2.56 | 14.62 | 8.46 | 15.82 | 7.58 | 14.66 | 8.00% | 348.87 |
| 0.00 | 6.80 | 3.33 | 11.18 | 3.81 | 15.82 | 11.79 | 13.85 | 7.90% | 349.53 |
| 0.00 | 7.32 | 3.10 | 11.31 | 3.55 | 15.79 | 10.42 | 13.84 | 7.85% | 349.71 |
| 0.06 | 6.57 | 2.52 | 12.01 | 4.90 | 15.71 | 6.47 | 10.49 | 7.80% | 349.97 |
| 0.06 | 6.54 | 2.53 | 11.73 | 4.46 | 15.70 | 6.59 | 10.38 | 7.78% | 350.09 |
| 0.39 | 6.59 | 2.43 | 10.74 | 4.19 | 15.62 | 4.97 | 11.43 | 7.72% | 350.54 |
| 0.39 | 6.77 | 2.44 | 10.91 | 3.94 | 15.64 | 4.86 | 11.62 | 7.70% | 350.62 |
| 0.03 | 6.09 | 2.68 | 11.59 | 4.06 | 15.62 | 3.81 | 11.59 | 7.63% | 350.89 |
| 0.01 | 6.06 | 2.63 | 11.58 | 4.17 | 15.64 | 3.40 | 11.58 | 7.62% | 350.96 |
| 0.07 | 5.75 | 2.40 | 10.72 | 3.98 | 15.57 | 2.86 | 11.34 | 7.57% | 351.24 |
| 0.00 | 5.67 | 1.46 | 8.03 | 2.28 | 15.74 | 5.70 | 10.51 | 7.51% | 351.59 |
| 0.00 | 5.29 | 1.44 | 7.83 | 1.92 | 15.74 | 5.53 | 10.52 | 7.47% | 351.83 |
| 0.00 | 5.53 | 1.36 | 7.91 | 1.52 | 15.74 | 5.25 | 10.50 | 7.44% | 351.97 |
| 0.01 | 5.40 | 1.68 | 8.33 | 1.19 | 15.74 | 4.20 | 11.11 | 7.39% | 352.24 |
| 0.01 | 5.43 | 1.57 | 8.17 | 0.68 | 15.74 | 3.80 | 11.17 | 7.34% | 352.53 |
| 0.02 | 5.14 | 1.63 | 8.09 | 0.05 | 15.73 | 4.23 | 11.29 | 7.31% | 352.70 |
| 0.01 | 5.50 | 0.58 | 7.83 | 1.42 | 15.70 | 1.43 | 10.80 | 7.28% | 353.02 |
| 0.05 | 5.45 | 0.29 | 7.66 | 0.31 | 15.71 | 0.96 | 10.38 | 7.20% | 353.54 |
| 0.00 | 5.72 | 0.29 | 7.70 | 0.14 | 15.71 | 0.92 | 10.60 | 7.18% | 353.59 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0.00 | 4.23 | 0.38 | 6.54 | 0.66 | 15.75 | 1.60 | 11.70 | 7.16% | 353.82 |
| 0.00 | 2.75 | 0.28 | 5.44 | 0.32 | 15.75 | 1.50 | 11.31 | 7.08% | 354.44 |
| 0.00 | 2.11 | 0.42 | 5.00 | 0.22 | 15.92 | 1.76 | 11.47 | 7.05% | 354.69 |
| 0.01 | 2.37 | 0.12 | 4.66 | 0.22 | 16.00 | 0.45 | 11.60 | 6.99% | 355.14 |
| 0.00 | 2.79 | 0.18 | 2.43 | 0.00 | 15.98 | 0.37 | 11.80 | 6.94% | 355.70 |
| 0.02 | 0.88 | 0.24 | 2.74 | 0.14 | 16.00 | 0.60 | 12.30 | 6.92% | 356.06 |
| 0.02 | 0.99 | 0.32 | 2.38 | 0.00 | 15.99 | 0.35 | 12.49 | 6.90% | 356.25 |
| 0.02 | 1.11 | 0.18 | 2.39 | 0.01 | 16.00 | 0.05 | 12.45 | 6.88% | 356.32 |
| 0.02 | 0.31 | 0.04 | 1.17 | 0.00 | 16.00 | 0.15 | 12.51 | 6.87% | 356.88 |
| 0.00 | 0.01 | 0.02 | 0.29 | 0.00 | 16.00 | 0.26 | 12.68 | 6.87% | 357.22 |
| 0.00 | 0.00 | 0.00 | 0.25 | 0.00 | 16.00 | 0.00 | 12.67 | 6.86% | 357.32 |

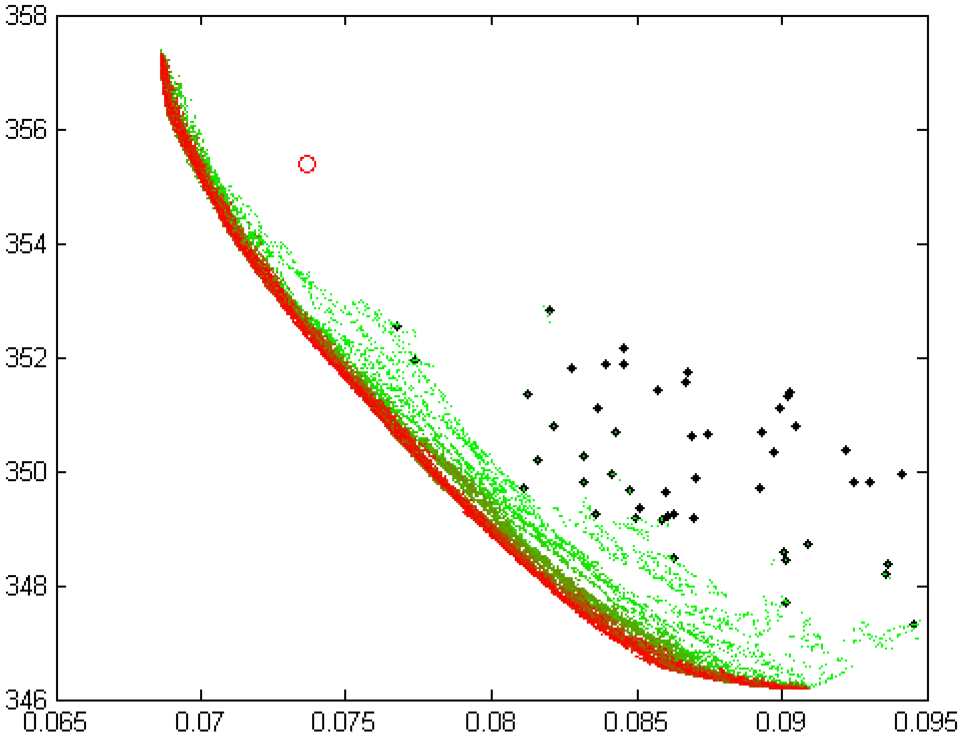


**Figure C.10**: Pareto optimal front for SUE-ED-TP

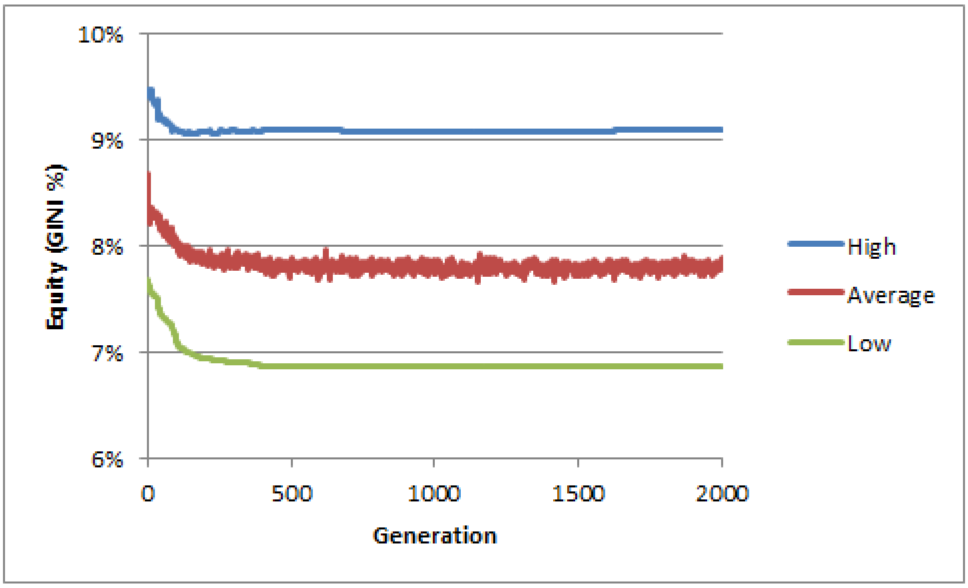


**Figure C.11**: Equity over generations of NSGA-II for SUE-ED-TP

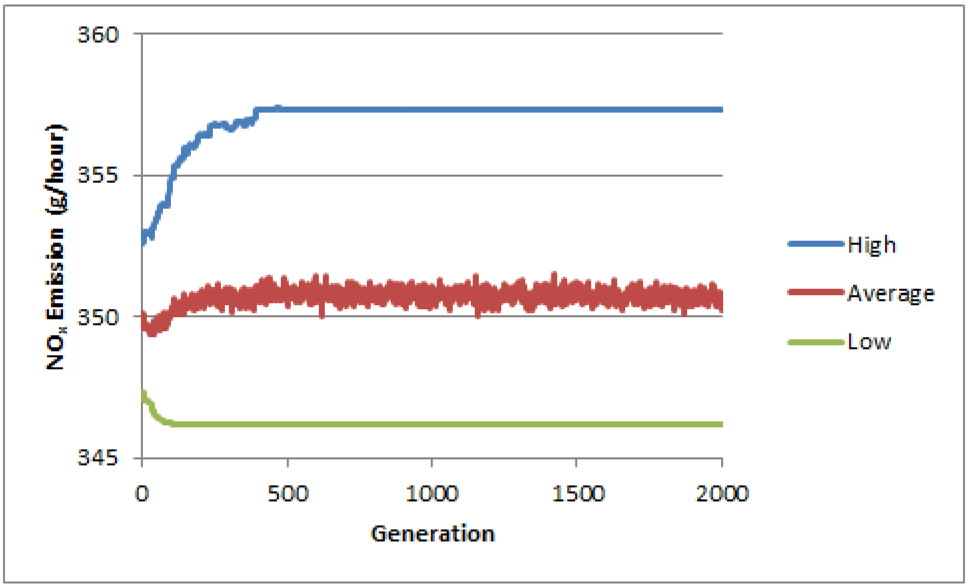


**Figure C.12**: Emission over generations of NSGA-II for SUE-ED-TP

**Table C.5**: Pareto optimal front results for SUE-ED-CE

| CE Links | | | | | | | | Objectives | |
|---|---|---|---|---|---|---|---|---|---|
| 25 | 26 | 29 | 34 | 40 | 48 | 66 | 75 | Equity | Emission |
| 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.27% | 341.06 |
| 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.27% | 341.06 |
| 6.96 | 6.96 | 2.43 | 2.44 | 2.44 | 2.41 | 2.43 | 2.44 | 7.26% | 341.08 |
| 6.31 | 6.96 | 2.43 | 2.44 | 2.44 | 2.43 | 2.43 | 2.44 | 7.22% | 341.15 |
| 6.18 | 6.96 | 2.43 | 2.43 | 2.44 | 2.43 | 2.43 | 2.44 | 7.21% | 341.17 |
| 5.82 | 6.90 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.18% | 341.23 |
| 5.50 | 6.93 | 2.43 | 2.43 | 2.44 | 2.43 | 2.43 | 2.44 | 7.15% | 341.28 |
| 5.22 | 6.94 | 2.42 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.13% | 341.33 |
| 4.73 | 6.94 | 2.42 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.09% | 341.42 |
| 4.52 | 6.94 | 2.43 | 2.44 | 2.44 | 2.43 | 2.44 | 2.44 | 7.07% | 341.46 |
| 4.69 | 6.93 | 2.42 | 2.44 | 2.44 | 2.31 | 2.44 | 2.44 | 7.06% | 341.55 |
| 4.38 | 6.73 | 2.43 | 2.43 | 2.44 | 2.31 | 2.41 | 2.44 | 7.03% | 341.64 |
| 4.24 | 6.96 | 2.42 | 2.43 | 2.44 | 2.26 | 2.34 | 2.44 | 7.01% | 341.72 |
| 3.22 | 6.94 | 2.43 | 2.43 | 2.43 | 2.43 | 2.34 | 2.44 | 6.96% | 341.77 |
| 3.21 | 6.96 | 2.43 | 2.43 | 2.43 | 2.40 | 2.34 | 2.44 | 6.95% | 341.80 |
| 2.75 | 6.94 | 2.43 | 2.43 | 2.43 | 2.43 | 2.33 | 2.44 | 6.92% | 341.88 |
| 2.60 | 6.94 | 2.43 | 2.43 | 2.43 | 2.43 | 2.33 | 2.44 | 6.91% | 341.92 |
| 1.93 | 6.84 | 2.43 | 2.42 | 2.44 | 2.43 | 2.42 | 2.44 | 6.86% | 342.08 |
| 1.92 | 6.86 | 2.43 | 2.42 | 2.44 | 2.38 | 2.42 | 2.44 | 6.85% | 342.12 |
| 1.68 | 6.96 | 2.42 | 2.44 | 2.44 | 2.30 | 2.43 | 2.44 | 6.81% | 342.25 |
| 1.93 | 6.71 | 2.43 | 2.43 | 2.44 | 2.14 | 2.44 | 2.44 | 6.79% | 342.38 |
| 1.10 | 6.42 | 2.43 | 2.43 | 2.44 | 2.15 | 2.44 | 2.44 | 6.74% | 342.64 |
| 1.67 | 6.54 | 2.43 | 2.43 | 2.44 | 1.89 | 2.42 | 2.44 | 6.71% | 342.77 |
| 1.53 | 6.57 | 2.43 | 2.43 | 2.44 | 1.85 | 2.42 | 2.44 | 6.69% | 342.84 |
| 0.95 | 6.92 | 2.43 | 2.44 | 2.42 | 1.88 | 2.44 | 2.44 | 6.67% | 342.92 |
| 0.92 | 6.92 | 2.42 | 2.43 | 2.43 | 1.65 | 2.43 | 2.44 | 6.61% | 343.21 |
| 0.94 | 6.67 | 2.42 | 2.43 | 2.44 | 1.55 | 2.42 | 2.44 | 6.58% | 343.36 |
| 0.22 | 6.96 | 2.42 | 2.43 | 2.43 | 1.43 | 2.43 | 2.44 | 6.53% | 343.68 |
| 0.70 | 6.58 | 2.43 | 2.44 | 2.43 | 1.22 | 2.23 | 2.39 | 6.50% | 343.95 |
| 0.74 | 6.42 | 2.43 | 2.41 | 2.44 | 1.11 | 2.44 | 2.40 | 6.47% | 344.06 |
| 0.53 | 6.31 | 2.43 | 2.34 | 2.44 | 1.04 | 2.41 | 2.38 | 6.45% | 344.27 |
| 0.50 | 6.34 | 2.43 | 2.34 | 2.44 | 1.00 | 2.41 | 2.38 | 6.44% | 344.33 |
| 0.52 | 6.28 | 2.42 | 2.43 | 2.44 | 0.89 | 2.42 | 2.44 | 6.41% | 344.44 |
| 0.52 | 6.28 | 2.42 | 2.44 | 2.44 | 0.89 | 2.42 | 2.44 | 6.40% | 344.44 |
| 0.00 | 6.38 | 2.42 | 2.44 | 2.44 | 0.79 | 2.39 | 2.44 | 6.38% | 344.72 |
| 0.32 | 5.67 | 2.42 | 2.44 | 2.44 | 0.74 | 2.40 | 2.44 | 6.35% | 344.80 |
| 0.40 | 5.53 | 2.42 | 2.44 | 2.44 | 0.50 | 2.41 | 2.44 | 6.32% | 345.17 |
| 0.09 | 4.68 | 2.43 | 2.40 | 2.43 | 0.60 | 2.25 | 2.44 | 6.30% | 345.30 |
| 0.00 | 4.40 | 2.43 | 2.40 | 2.43 | 0.54 | 2.28 | 2.44 | 6.28% | 345.45 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0.10 | 3.50 | 2.43 | 2.37 | 2.44 | 0.46 | 2.38 | 2.44 | 6.26% | 345.71 |
| 0.13 | 3.69 | 2.43 | 2.37 | 2.44 | 0.42 | 2.37 | 2.44 | 6.25% | 345.74 |
| 0.23 | 3.23 | 2.43 | 2.37 | 2.44 | 0.33 | 2.41 | 2.44 | 6.24% | 345.93 |
| 0.24 | 3.23 | 2.43 | 2.37 | 2.44 | 0.29 | 2.41 | 2.44 | 6.23% | 345.99 |
| 0.23 | 2.99 | 2.43 | 2.37 | 2.44 | 0.24 | 2.41 | 2.44 | 6.22% | 346.12 |
| 0.30 | 2.89 | 2.43 | 2.41 | 2.44 | 0.23 | 1.76 | 2.44 | 6.20% | 346.35 |
| 0.22 | 3.34 | 2.43 | 2.41 | 2.44 | 0.08 | 1.69 | 2.44 | 6.19% | 346.54 |
| 0.08 | 3.36 | 2.43 | 2.41 | 2.38 | 0.00 | 1.71 | 2.44 | 6.18% | 346.74 |
| 0.00 | 1.87 | 2.43 | 2.43 | 2.43 | 0.11 | 1.80 | 2.43 | 6.17% | 346.86 |
| 0.00 | 1.90 | 2.43 | 2.43 | 2.43 | 0.00 | 1.84 | 2.43 | 6.15% | 347.02 |
| 0.00 | 1.71 | 2.43 | 2.44 | 2.44 | 0.00 | 1.38 | 2.44 | 6.13% | 347.21 |

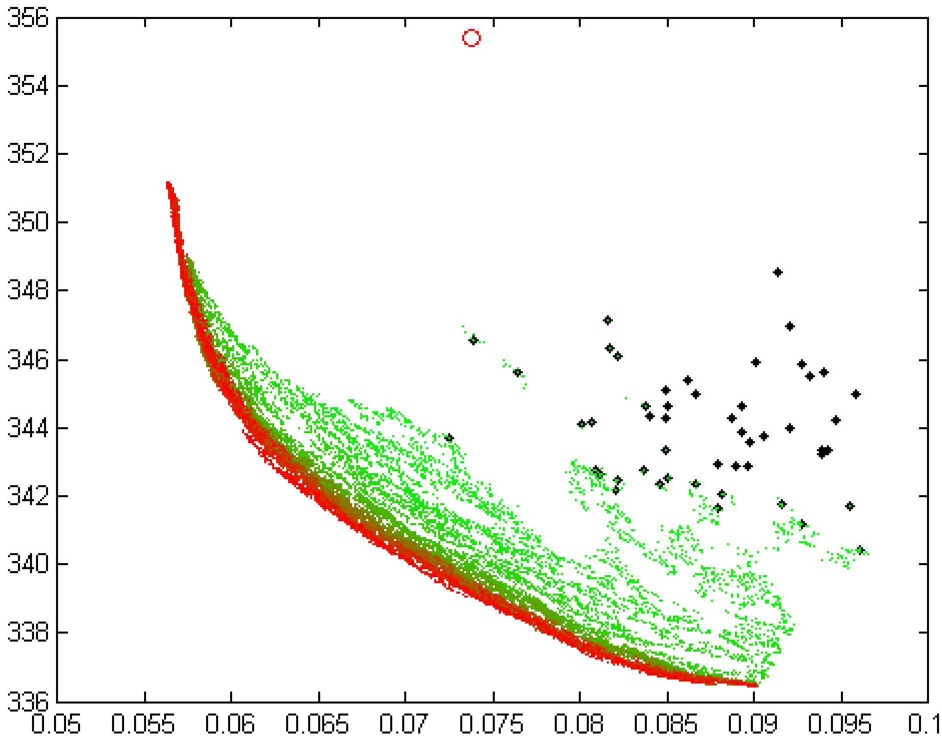


**Figure C.13**: Pareto optimal front for SUE-ED-TPCE

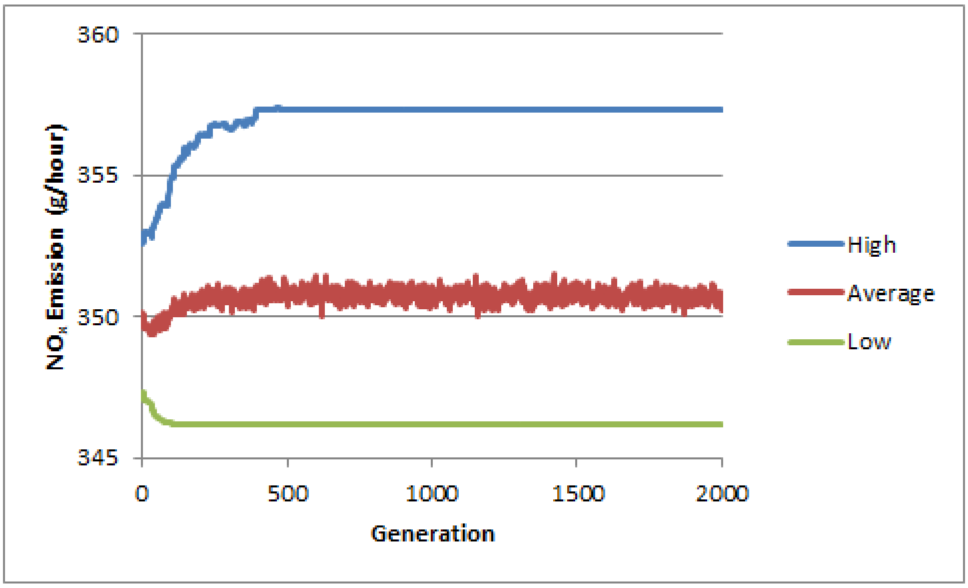


**Figure C.14**: Equity over generations of NSGA-II for SUE-ED-CE

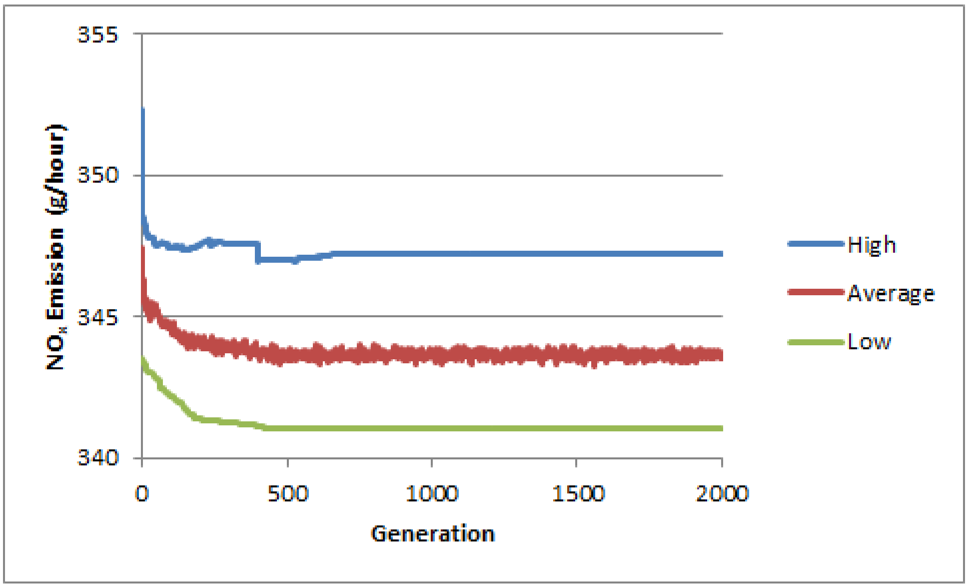


**Figure C.15**: Emission over generations of NSGA-II for SUE-ED-CE

**Table C.6**: Pareto optimal front results for SUE-ED-TPCE

| TP Links | | | | | | | | CE Links | | | | | | | | Objectives | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13 | 21 | 23 | 24 | 28 | 30 | 43 | 51 | 25 | 26 | 29 | 34 | 40 | 48 | 66 | 75 | Equity | Emission |
| 1.25 | 10.30 | 1.42 | 10.27 | 12.00 | 13.20 | 12.00 | 13.25 | 6.96 | 6.96 | 2.43 | 1.99 | 1.99 | 2.43 | 2.44 | 2.44 | 9.00% | 336.46 |
| 1.26 | 10.48 | 1.38 | 10.42 | 10.77 | 13.15 | 12.00 | 13.36 | 6.56 | 6.94 | 2.42 | 1.98 | 1.98 | 2.43 | 2.44 | 2.44 | 8.89% | 336.55 |
| 0.02 | 8.01 | 1.50 | 9.78 | 11.52 | 11.90 | 9.57 | 11.41 | 6.96 | 6.89 | 2.43 | 2.30 | 2.43 | 2.43 | 2.41 | 2.43 | 8.68% | 336.57 |
| 0.02 | 7.64 | 1.42 | 9.61 | 11.48 | 11.90 | 9.13 | 11.41 | 6.96 | 6.93 | 2.43 | 2.30 | 2.43 | 2.43 | 2.43 | 2.43 | 8.64% | 336.58 |
| 0.04 | 6.28 | 0.73 | 8.21 | 10.67 | 11.91 | 8.42 | 9.30 | 6.96 | 6.96 | 2.40 | 2.16 | 2.38 | 2.43 | 2.44 | 2.41 | 8.47% | 336.76 |
| 0.04 | 6.33 | 0.71 | 8.34 | 9.26 | 11.87 | 8.12 | 9.25 | 6.95 | 6.94 | 2.40 | 2.16 | 2.38 | 2.41 | 2.44 | 2.41 | 8.34% | 336.86 |
| 0.04 | 5.67 | 0.75 | 8.02 | 9.51 | 11.93 | 7.80 | 9.53 | 5.88 | 6.73 | 2.40 | 2.14 | 2.35 | 2.33 | 2.44 | 2.41 | 8.25% | 337.13 |
| 0.32 | 6.74 | 0.86 | 7.95 | 6.79 | 11.92 | 7.78 | 9.55 | 6.75 | 6.95 | 2.43 | 2.11 | 2.44 | 2.41 | 2.40 | 2.35 | 8.14% | 337.25 |
| 0.20 | 6.63 | 0.84 | 8.02 | 6.22 | 11.88 | 7.66 | 9.70 | 6.91 | 6.95 | 2.43 | 2.17 | 2.43 | 2.43 | 2.30 | 2.35 | 8.07% | 337.38 |
| 0.17 | 6.50 | 0.87 | 7.98 | 6.07 | 11.88 | 7.23 | 9.41 | 5.98 | 6.93 | 2.43 | 2.19 | 2.42 | 2.43 | 2.29 | 2.36 | 7.97% | 337.59 |
| 0.17 | 6.74 | 0.81 | 8.07 | 6.04 | 11.87 | 7.01 | 9.52 | 5.75 | 6.96 | 2.42 | 2.21 | 2.42 | 2.43 | 2.28 | 2.36 | 7.94% | 337.67 |
| 0.18 | 5.68 | 0.91 | 8.06 | 5.41 | 11.92 | 7.04 | 9.99 | 6.15 | 6.46 | 2.42 | 2.17 | 2.43 | 2.38 | 2.39 | 2.36 | 7.86% | 337.88 |
| 0.19 | 5.47 | 0.93 | 8.07 | 5.05 | 11.96 | 6.90 | 9.82 | 5.60 | 6.45 | 2.41 | 2.17 | 2.42 | 2.32 | 2.40 | 2.35 | 7.77% | 338.14 |
| 0.53 | 5.38 | 0.80 | 7.38 | 6.44 | 12.00 | 6.62 | 8.81 | 2.07 | 6.53 | 2.39 | 2.02 | 2.29 | 2.29 | 2.43 | 2.43 | 7.63% | 338.56 |
| 0.54 | 5.11 | 0.77 | 7.46 | 6.41 | 11.98 | 6.37 | 8.94 | 1.80 | 6.56 | 2.39 | 2.02 | 2.29 | 2.29 | 2.43 | 2.43 | 7.58% | 338.69 |
| 0.55 | 5.09 | 0.74 | 7.13 | 6.07 | 11.94 | 6.00 | 9.10 | 1.88 | 6.87 | 2.43 | 2.04 | 2.33 | 2.21 | 2.34 | 2.44 | 7.53% | 338.82 |
| 0.55 | 5.13 | 0.75 | 6.73 | 5.94 | 11.94 | 5.55 | 8.95 | 1.80 | 6.87 | 2.43 | 2.04 | 2.33 | 2.16 | 2.34 | 2.44 | 7.48% | 338.98 |
| 0.27 | 4.23 | 0.42 | 3.90 | 2.04 | 9.06 | 5.95 | 6.09 | 3.64 | 6.55 | 2.43 | 2.26 | 2.33 | 2.40 | 2.44 | 2.44 | 7.30% | 339.17 |
| 0.10 | 4.88 | 0.55 | 3.99 | 2.05 | 8.86 | 4.95 | 6.34 | 3.17 | 6.60 | 2.43 | 2.29 | 2.44 | 2.25 | 2.43 | 2.35 | 7.19% | 339.47 |
| 0.08 | 4.80 | 0.62 | 3.84 | 1.93 | 8.91 | 5.01 | 6.33 | 3.18 | 6.58 | 2.43 | 2.29 | 2.44 | 2.24 | 2.44 | 2.43 | 7.17% | 339.49 |
| 0.02 | 3.98 | 0.48 | 5.44 | 1.08 | 9.39 | 4.33 | 6.05 | 3.77 | 6.44 | 2.42 | 2.44 | 2.39 | 2.09 | 2.24 | 2.41 | 7.04% | 340.05 |
| 0.02 | 4.25 | 0.45 | 5.35 | 0.95 | 9.55 | 4.05 | 6.81 | 3.57 | 6.61 | 2.42 | 2.44 | 2.39 | 2.07 | 2.27 | 2.41 | 6.97% | 340.20 |
| 0.02 | 4.46 | 0.53 | 4.92 | 0.66 | 9.60 | 3.98 | 6.79 | 2.99 | 6.53 | 2.42 | 2.40 | 2.43 | 1.98 | 2.31 | 2.37 | 6.87% | 340.52 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.02 | 4.44 | 0.54 | 4.75 | 0.52 | 9.86 | 3.90 | 6.93 | 2.97 | 6.38 | 2.42 | 2.41 | 2.43 | 2.01 | 2.32 | 2.37 | 6.84% | 340.63 |
| 0.15 | 5.05 | 0.25 | 3.53 | 2.34 | 10.91 | 3.42 | 8.73 | 0.12 | 6.69 | 2.38 | 2.40 | 2.44 | 2.40 | 1.98 | 2.44 | 6.76% | 340.96 |
| 0.15 | 4.73 | 0.24 | 3.45 | 2.33 | 10.88 | 3.13 | 8.78 | 0.11 | 6.44 | 2.39 | 2.41 | 2.44 | 2.39 | 1.99 | 2.44 | 6.72% | 341.10 |
| 0.09 | 4.13 | 0.16 | 3.71 | 1.50 | 10.83 | 3.09 | 8.39 | 0.25 | 6.58 | 2.41 | 2.43 | 2.42 | 2.39 | 2.04 | 2.39 | 6.63% | 341.29 |
| 0.23 | 4.51 | 0.01 | 4.77 | 2.37 | 11.34 | 1.26 | 9.35 | 0.45 | 6.85 | 2.40 | 2.41 | 2.35 | 2.30 | 2.03 | 2.44 | 6.58% | 341.68 |
| 0.26 | 4.27 | 0.00 | 4.87 | 1.65 | 11.26 | 1.21 | 9.35 | 0.44 | 6.86 | 2.40 | 2.41 | 2.40 | 2.28 | 2.03 | 2.44 | 6.49% | 341.96 |
| 0.21 | 4.45 | 0.00 | 4.82 | 1.18 | 11.37 | 1.11 | 9.36 | 0.12 | 6.83 | 2.40 | 2.38 | 2.36 | 2.26 | 2.02 | 2.44 | 6.39% | 342.37 |
| 0.25 | 4.34 | 0.05 | 4.87 | 0.50 | 11.35 | 1.32 | 10.25 | 0.35 | 6.70 | 2.38 | 2.40 | 2.36 | 2.20 | 2.02 | 2.44 | 6.32% | 342.70 |
| 0.01 | 3.57 | 0.00 | 4.28 | 0.41 | 11.42 | 0.88 | 8.73 | 0.20 | 6.84 | 2.40 | 2.42 | 2.44 | 2.19 | 1.93 | 2.44 | 6.25% | 342.81 |
| 0.01 | 3.70 | 0.00 | 4.69 | 0.05 | 11.49 | 0.77 | 8.75 | 0.13 | 6.79 | 2.43 | 2.38 | 2.44 | 2.17 | 1.97 | 2.42 | 6.19% | 343.04 |
| 0.02 | 3.77 | 0.06 | 4.84 | 0.00 | 11.52 | 0.32 | 8.65 | 0.11 | 6.82 | 2.43 | 2.38 | 2.44 | 2.11 | 1.97 | 2.41 | 6.15% | 343.25 |
| 0.01 | 4.17 | 0.13 | 4.25 | 0.00 | 11.45 | 0.36 | 9.85 | 0.15 | 6.15 | 2.41 | 2.37 | 2.43 | 1.78 | 1.85 | 2.44 | 6.09% | 343.83 |
| 0.00 | 4.35 | 0.09 | 4.36 | 0.00 | 11.27 | 0.00 | 10.00 | 0.00 | 6.17 | 2.41 | 2.36 | 2.44 | 1.80 | 1.89 | 2.44 | 6.06% | 343.95 |
| 0.08 | 4.12 | 0.14 | 4.46 | 0.25 | 12.06 | 0.36 | 10.85 | 0.66 | 4.54 | 2.40 | 2.43 | 2.43 | 1.31 | 1.84 | 2.44 | 6.06% | 344.65 |
| 0.13 | 3.86 | 0.08 | 5.04 | 0.12 | 11.99 | 0.00 | 11.27 | 0.17 | 4.73 | 2.40 | 2.44 | 2.42 | 1.28 | 1.80 | 2.44 | 5.97% | 345.10 |
| 0.18 | 3.42 | 0.08 | 2.79 | 0.00 | 12.27 | 0.65 | 11.51 | 0.16 | 2.20 | 2.38 | 2.34 | 2.43 | 1.36 | 2.03 | 2.43 | 5.93% | 345.77 |
| 0.11 | 2.55 | 0.07 | 2.49 | 0.00 | 12.24 | 0.00 | 12.07 | 0.00 | 2.70 | 2.39 | 2.36 | 2.42 | 1.36 | 2.03 | 2.43 | 5.86% | 346.32 |
| 0.11 | 2.54 | 0.07 | 2.49 | 0.00 | 12.24 | 0.00 | 12.07 | 0.00 | 2.70 | 2.39 | 2.36 | 2.42 | 1.30 | 2.05 | 2.43 | 5.85% | 346.38 |
| 0.08 | 2.12 | 0.04 | 2.89 | 0.00 | 11.74 | 0.11 | 11.04 | 0.01 | 1.61 | 2.43 | 2.31 | 2.44 | 0.64 | 2.24 | 2.43 | 5.81% | 346.83 |
| 0.02 | 1.71 | 0.01 | 6.12 | 0.02 | 11.56 | 0.34 | 12.89 | 0.03 | 0.89 | 2.25 | 2.30 | 2.41 | 0.87 | 1.50 | 2.44 | 5.79% | 347.38 |
| 0.01 | 0.00 | 0.01 | 5.97 | 0.00 | 11.59 | 0.27 | 11.56 | 0.29 | 1.18 | 2.17 | 2.42 | 2.44 | 0.28 | 1.36 | 2.44 | 5.76% | 348.12 |
| 0.02 | 0.47 | 0.00 | 5.77 | 0.01 | 11.54 | 0.17 | 12.34 | 0.00 | 0.93 | 2.17 | 2.43 | 2.44 | 0.30 | 1.38 | 2.44 | 5.73% | 348.34 |
| 0.00 | 0.08 | 0.00 | 5.81 | 0.00 | 11.42 | 0.03 | 13.71 | 0.00 | 0.23 | 2.26 | 2.40 | 2.40 | 0.34 | 1.10 | 2.43 | 5.69% | 349.15 |
| 0.01 | 0.00 | 0.00 | 6.08 | 0.00 | 11.50 | 0.02 | 13.68 | 0.00 | 0.16 | 2.25 | 2.40 | 2.41 | 0.32 | 1.13 | 2.43 | 5.68% | 349.23 |
| 0.00 | 0.85 | 0.15 | 6.94 | 0.00 | 12.61 | 0.00 | 15.24 | 0.14 | 0.27 | 2.32 | 2.30 | 2.44 | 0.05 | 1.47 | 2.44 | 5.67% | 350.13 |
| 0.00 | 0.53 | 0.00 | 6.73 | 0.00 | 12.46 | 0.03 | 15.75 | 0.06 | 0.00 | 2.21 | 2.40 | 2.43 | 0.00 | 1.40 | 2.44 | 5.65% | 350.66 |
| 0.00 | 0.00 | 0.00 | 6.76 | 0.00 | 13.08 | 0.00 | 16.00 | 0.00 | 0.09 | 2.21 | 2.41 | 2.44 | 0.00 | 1.46 | 2.44 | 5.63% | 351.19 |

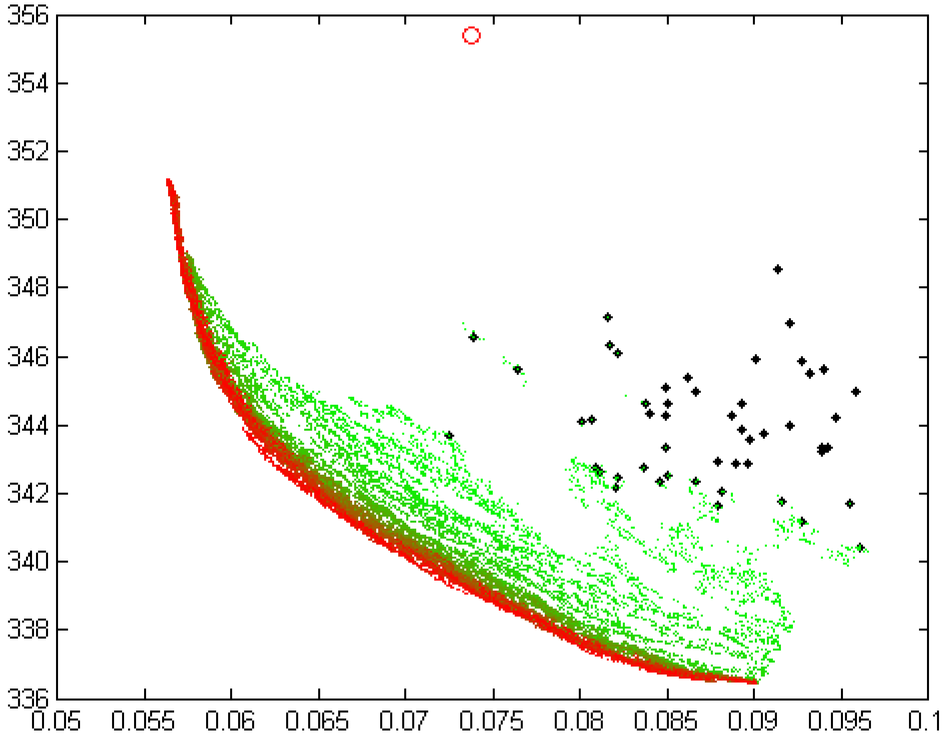


**Figure C.16**: Pareto optimal front for SUE-ED-TPCE

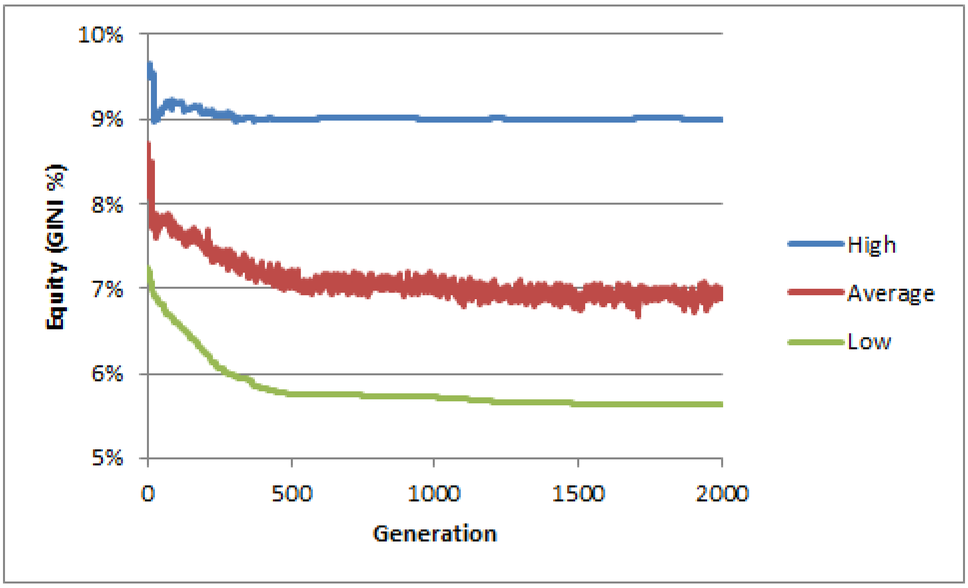


**Figure C.17**: Equity over generations of NSGA-II for SUE-ED-TPCE

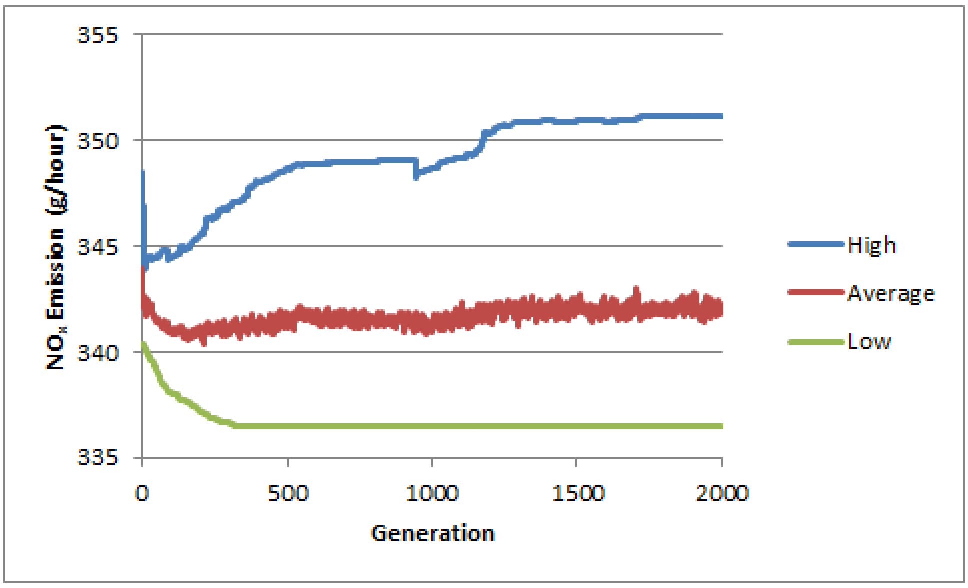


**Figure C.18**: Emission over generations of NSGA-II for SUE-ED-TPCE

## BIOGRAPHICAL SKETCH

Orhan İlker KOLAK was born in Istanbul on May 27, 1981. In 2005 he obtained the B.S. degree in Industrial Engineering from Galatasaray University. He received an M.S. degree in Industrial Engineering from the same university. Since 2006, he works as a research assistant in Industrial Engineering Department of Galatasaray University. His published work is as follows:

Kolak, O.İ., Feyzioğlu, O., Birbil, Ş.İ., Noyan, N. & Yalçındağ, S. (2013). Using emission functions in modeling environmentally sustainable traffic assignment policies. *Journal of Industrial and Management Optimization*, 9(2), 341–363.