Generating Sustainable Solutions for the Urban Transportation Considering Multiple User Classes

Çağla Doğru, Orhan Feyzioğlu

Abstract—**Sustainability of transportation has become one of the most significant issues in the world due to the increasing global warming concerns. There has been a growing interest in improving the performance of the transportation systems using sustainability concepts. In this study, we use some social and environmental measures to assess the sustainability of transportation, such as accessibility of zones and equal distribution of the accessibility, accidents, emissions and noise generated by vehicles. Our main aim is to achieve a sustainable traffic assignment. To carry out our purpose, we develop a bi-level traffic assignment model. The lower level of this model consists of the stochastic user equilibrium with multinomial logit discrete choice and multiple user classes. At the upper level, we identify user class based toll prices while optimizing social and environmental objectives. As the two objectives are conflicting, we aim to generate a set of Pareto optimal solutions. Overall problem is solved with an adapted genetic algorithm, namely Non-Dominated Sorting Genetic Algorithm. During the course of the algorithm, the lower level problem is solved many times by means of Self-Regulated Averaging method. The developed method is applied to a known instance from the literature, and solutions are elaborated.**

Keywords—**Sustainable traffic assignment, bi-level programming, stochastic user equilibrium, non-dominated sorting genetic algorithm, self-regulated averaging method**

I. Introduction

Transportation has important and long lasting social, environmental, and economic impacts, thus, it is a significant dimension of urban sustainability. Therefore, there are some attempts which are related to urban transportation sustainability development. Some studies implement sustainable transportation indicators to compare sustainability through different world cities [1]. To achieve more sustainable urban transportation in the cities, we need some pillars which are "effective governance of land use and transportation", "fair, efficient, stable funding", "strategic infrastructure investments", and "attention to neighborhood design" [2].

Planning for sustainable transportation systems has become one of the most important subjects in many studies, conferences, and debates. To determine the right policies for sustainable transportation is a significant issue for policy makers and planners, because the identified accurate policies will contribute to the sustainability of urban transportation effectively. However, it is difficult to acquire a consensus for generating the right mix of policy measures. Sometimes, policy makers and planners can face with the problem of finding a suitable approach for sustainability development. These times, it can be efficient to use scenario approaches to obtain right policies and plans for sustainability development of transportation systems [3].

Sustainable transportation systems are the requirement of modern times. There has been a considerable increase in the number of transportation activities in recent years. This increase causes environmental costs such as air pollution, noise, etc. which reduce quality of people life. This means that we have to consider the sustainability of transportation as an important issue for people's health [4].

The features of sustainable transportation are safe, comfortable and efficient in terms of economic and energy consumption and minimization of the environmental pollution. Carbon emissions into the atmosphere contribute to the environmental pollution in terms of quality decrease of life [5]. If we try to reduce carbon emissions with some restrictions, we can decrease the environmental pollution. Furthermore, if we balance the transportation costs between the user classes, transportation can become more economic. In addition to these, if road accidents are decreased, we have safer transportation than before. To realize all of these within the scope of sustainability development of transportation will increase the quality of human life. With the consideration of these, we can easily say that sustainable transportation is important for the life quality.

The pace of life in the 21st Century continues to increase dramatically, and as a result of this, it can be said that mobility is now one of the most significant characteristics of societies. This means that more and more cars and, unfortunately, more and more pollution [6]. This pollution can be air or noise pollution. If we establish sustainable transport systems, we can reduce these pollutions. If we reduce these pollutions, there will not be any need to decrease mobility.

We first provide in the next a brief literature survey to introduce some studies related to our study. Then, a multi-objective multi-user bi-level traffic assignment model together with the method developed to solve it optimally is explained in details. The efficiency of the modeling approach is demonstrated with an illustrative example. Finally, the last section contains some concluding remarks and perspectives.

Cagla Dogru is with the Department of Industrial Engineering, Galatasaray University, Ciragan Caddesi No:36 Ortakoy 34357 Istanbul, Turkey (e-mail: cagladogru@gmail.com).

Orhan Feyzioglu is with the Department of Industrial Engineering, Galatasaray University, Ciragan Caddesi No:36 Ortakoy 34357 Istanbul, Turkey (phone: +90-212-227-4480; fax: +90-212-259-5557; e-mail: ofeyzioglu@gsu.edu.tr).

This work has been partially supported by the Scientific and Technological Research Council of Turkey (TUBITAK) grant 109M137 and by Galatasaray University Research Fund.

II. Literature Survey

Every transportation system plays a major role for the sustainability of the planet. The transportation systems must be sustained in order to continue to afford to all people access to the social, environmental, and economic opportunities which are necessary for the quality of life. While great developments have been made to many transportation systems, there are also a lot of problems in the sustainability of these systems [7]. In the literature, there are some studies which find solutions to these problems with some models and algorithms for the sustainability of transportation systems.

Traffic assignment models are sorted according to users' behaviors for route choice. These models can be deterministic user equilibrium (UE), stochastic user equilibrium (SUE), and system optimum (SO) [8]. In UE, all drivers have complete and perfect information regarding network conditions, and behave rationally. In SUE, drivers' perception variations for travel times or costs are taken account [9]. At SO, the drivers have to cooperate with each other in order to minimize the overall travel costs [10]. Thus, it is difficult to implement this last model.

SUE traffic assignment models can be used for transportation network designs. In the literature, there some models and solution algorithms for SUE traffic assignment. For example, expected value model, chance-constrained model, and dependent-chance stochastic models in bi-level programming framework can be used for designing transportation networks with demand uncertainty. To solve these stochastic network design problem models, traffic assignment algorithm, genetic algorithm, and Monte-Carlo simulations can be used [11].

Bi-level programming approach can be used for SUE traffic assignment problems. Bi-level programming models are constituted with two levels which are upper and lower levels of the model. In the transport network analysis, there can be some problems which are trip matrix estimation and traffic signal optimization on congested road networks. These two problems can be formulated with bi-level programming approach as the second-level programming problem for SUE traffic assignment [12].

Bi-level programming model with uncertain demand can be used for the multi-period network design problem of comprehensive transport. The upper level of the problem maximizes the consumer surplus of all demand scenarios with budget constraint. The lower level problem maximizes the consumer surplus of every demand scenario with the consideration of the network investment decisions of the upper level problem. The lower level problem also takes into account the collaborations of transportation modes, traffic load balancing and capacity constraints [13]. As we see in this problem, if we would like to establish a complex model, bi-level programming is a convenient approach for this. The transportation network design problems need comprehensive models to acquire optimal solutions. Thus, the bi-level programming is an appropriate approach for these problems.

To select sustainable transportation systems, multi-criteria decision making approach can be used under partial or incomplete information (uncertainty). In this approach, fuzzy TOPSIS can be used for sustainability assessment and selecting the best alternative among transportation systems. This approach includes three steps. In the first step, the criterion for sustainability assessment of transportation is identified. In the second step, experts give linguistic ratings to the potential alternatives against the selected criterion. Finally, in the third step, sensitivity analysis is used to determine the effect of criterion weights on the decision making process [4]. Multi-criteria decision making approach is a consistent and comprehensive approach for the analysis of urban transportation problems. With the contribution of this approach, we can generate and design strategies for sustainable transportation in sustainable cities. This approach can consist of socioeconomic, environmental, and technological concepts which include the development, integration, and demonstration of tools and methodologies to improve assessment of sustainability [14].

Generally, in traditional traffic assignment problems, only a single objective is taken account. However, the concept of traffic assignment is a significant procedure for transportation planning and thus all needs have to be considered. Because of this reason, we have to use multi objectives to do the transportation planning more comprehensive. If we formulate an effective multi objective model for traffic assignment problems, we can obtain optimal flow patterns from this model. The objectives can be related to total travel time, air pollution, travel distance, etc [15]. Moreover, these objectives can be classified such as social, environmental, economic, and institutional objectives.

In the traffic assignment models, we can use more than one user class. The classes are separated according to their characteristics. "Multiple user classes" concept is used in some traffic assignment models in the literature. It can be used in link transmission model for dynamic transportation network loading. In this model, triangular fundamental diagrams for each user class are considered [16]. Moreover, a novel reliability-based SUE traffic assignment model for transportation networks includes multiple user classes. In this model, each class of users has a different safety margin for on-time arrival in response to the stochastic travel times which increase with the demand variations. Users' perception errors on travel times are also taken account in this model [17].

This study differs from the previous ones by considering: (1) sustainability related objectives within a multi-objective optimization framework; (2) a bi-level model where traffic authority adjusts toll prices to achieve sustainability objectives at the upper level while users aim to decrease their perceived travel time to their destination at the lower level; and (3) behaviors of different traffic network users. Moreover, a solution method is developed to solve the problem efficiently. These features are explained in the next sections.

III. Mathematical Programming Model

Let us denote $G(N, A)$ the directed graph with N as the set of nodes and A is the set of links. Then, $x_{a,u}$ is the flow of class $u \in U$ users on link $a \in A$, $x_a = \sum_{u \in U} x_{a,u}$ is the total link flow on link $a \in A$, and $t_a(x_a)$ is the total flow-dependent travel cost for link $a \in A$,. We also define q_u^{rs} as the trip demand of class $u \in U$ users for origin-destination (OD) pair (r, s), $f_{k,u}^{rs}$ as the path flow and $c_{k,u}^{rs}$ as the path travel cost on path $k \in K^{rs}$ respectively where K^{rs} is the set of paths for pair (r, s). The relationship between path flow and demand can be described as $q_u^{rs} = \sum_k f_{k,u}^{rs}$ for each $u \in U$ and OD pair (r, s). We can now describe the problems that we involve at the upper and lower levels of our bi-level traffic assignment problem.

A. Upper Level Problem

At the upper level, we aim to identify the toll prices that best serve sustainability objectives. The functional forms of these objectives are given as follows:

Accessibility and Equity:
$g^{AE}(x) = w_1 \frac{A^{\max} - A}{A^{\max} - A^{\min}} + w_2 \frac{E^{\max} - E}{E^{\max} - E^{\min}}$. Here the total accessibility is calculated as $A = \sum_s A_s(x)$ where A_s is the accessibility of node $s \in N$. The accessibility of node s can be found as $A_s = \sum_{r \in N/s} q^{rs}/\bar{c}^{rs}$ where $q^{rs} = \sum_u q_u^{rs}$ and $\bar{c}^{rs}$ is the minimum actual travel cost for OD pair (r, s). The equity of the accessibility is calculated based on the well-known Gini coefficient such as $\left(\sum_{s \in N} \sum_{s' \in N} |A_s(x) - A_{s'}(x)|\right) / 2n^2 \bar{A}$ where n is the number of destinations and $\bar{A}$ is the mean accessibility of these destinations. Finally, note that w_1 and w_2 as simple weights with $w_1, w_2 \in [0, 1]$ and $w_1 + w_2 = 1$ [18].

Road Accidents:
$g^{ACC}(x) = \frac{B - B^{\min}}{B^{\max} - B^{\min}}$, where $B = \sum_{a \in A} KT^{0.45} v_a(x_a)$ with K as a constant, T as the number of trips per day and $v_a(x_a)$ as the average speed (km/h) on link a [19].

Vehicle Emissions:
$g^{EM}(x) = \frac{C - C^{\min}}{C^{\max} - C^{\min}}$. Here the total network emission (g) is obtained as $C = \sum_{a \in A} e(v_a(x_a)) l_a x_a$ where $e(v_a(x_a))$ is the vehicle emission (g/km) and l_a is the length (km) of link a [19].

Vehicle Noise:
$g^{NO}(x) = \frac{D - D^{\min}}{D^{\max} - D^{\min}}$ where $D = \max_{a \in A} N_a(x_a, v_a(x_a))$ and N_a is the noise (dbA) generated by vehicles travelling on link a as a function of vehicle flow x_a and average vehicle speed $v_a(x_a)$ [20].

Based on these definitions, the social and environmental objectives can be formulated as

$$\min g^{SOC} = w_{AE} \times g^{AE}(x) + w_{ACC} \times g^{ACC}(x) \quad (1)$$

and

$$\min g^{ENV} = w_{EM} \times g^{EM}(x) + w_{NO} \times g^{NO}(x) \quad (2)$$

respectively. The weights w_{AE}, w_{ACC}, w_{EM} and w_{NO} are set according to the traffic authority priorities.

B. Lower Level Problem

At the lower level, we are considering SUE assignment. Let us define $\Delta = (\ldots, \Delta^{rs}, \ldots) = (\delta_{ij})$ as the link-path incidence matrix where $\delta_{ij} = 1$ if path j traverses link i and $\delta_{ij} = 0$ otherwise. It is then possible to relate link flows and path flows as $x = \Delta f$. Similarly, the relationship between link-cost and path-cost is given as $c = \Delta^T (t + \bar{t})$ where $\bar{t}$ denotes toll price vector. The flow of class u users on path k is determined by $f_{k,u}^{rs} = q_u^{rs} P_{k,u}^{rs}$ where $P_{k,u}^{rs}$ is the probability that a class u user traverses through path $k \in K^{rs}$. We assume that the random term of discrete route choice satisfies Gumbel distribution, hence the route choice probability can be described as a multinomial logit, or

$$P_{k,u}^{rs} = \frac{e^{-\theta_u c_{k,u}^{rs}}}{\sum_l e^{-\theta_u c_{l,u}^{rs}}}. \quad (3)$$

Here $\theta > 0$ indicates the familiarity degree of a class u driver to traffic conditions. This parameter is set such that drivers with more equipped cars have larger θ. Sheffi and Powell (1982) proposed the following unconstrained convex minimization model for SUE problem:

$$\min z(x) = -\sum_{rs} \sum_u q_u^{rs} S_u^{rs}[c^{rs}] + \sum_{a \in A} x_a t_a(x_a) - \sum_{a \in A} \int_0^{x_a} t_a(w) dw \quad (4)$$

where

$$S_u^{rs}[c_u^{rs}] = E\left[\min_{k \in K^{rs}} \left\{c_{k,u}^{rs}\right\} | c_u^{rs}\right], \text{ and } \frac{\partial S_u^{rs}(c_u^{rs})}{\partial c_{k,u}^{rs}} \quad (5)$$

define the expected perceived travel cost for OD pair (r, s) and user type u which is relevant to the entire path set between r and s.

IV. Solution Method

To solve the proposed bi-objective bi-level optimization model, we adapted the well-known Non-dominated Sorting Genetic Algorithm (NSGA-II) which is proven to be very efficient for multi-objective problems [21]. At each iteration of this algorithm, SUE model in (4) must be solved for each individual of the current solution population. To realize this, we make use of the Self-Regulated Averaging (SRA) method due to [22] and the Bell's second algorithm to solve logit-based stochastic network loading problem [23]. The details about these algorithms are provided in the next.

A. SRA Algorithm

The solution of the minimization problem in (4) can be found by simultaneously solving the set of equations $\nabla z(x_u) = 0$ for each $u \in U$. This gradient is given as

$$\nabla z(x_u) = \nabla_{x_u} t(x_u) \left[x_u - \sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u)\right] \quad (6)$$

for all $u \in U$. When the travel cost function is separable, $\nabla_{x_u} t(x_u)$ is a diagonal positive definite matrix. With this property, it is possible to express the set of equations such as

$$\nabla z(x_u) = 0 \Leftrightarrow x_u - \sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u) = 0 \quad (7)$$

for all $u \in U$. If we denote $y_u(x_u) = \sum_{rs} q_u^{rs} \Delta^{rs} P_u^{rs}(x_u)$ then the solution of the minimization problem can be found by solving $x_u - y_u(x_u) = 0$ for each $u \in U$ simultaneously. It can be shown that $y_u(x_u) - x_u$ is a descent direction. With this property, it becomes possible to solve the equation system iteratively. A recently proposed algorithm, namely SRA method [22], exactly achieves this. The general description of the adapted SRA is given as follows:

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

The operation $F(x)$ in this algorithm corresponds to stochastic network loading. Here we use Bell's second algorithm for solving logit-based stochastic transportation network loading problem [23].

SRA method depends on the consideration that the step size must be larger to give more aggressive search of the solution space when the current iteration's solutions converge, but, it must be smaller when the solutions diverge. The step size series $\{\alpha_k\}$ in SRA method satisfies the conditions of $\sum_k \alpha_k = \infty$ and $\lim_{k\to\infty} \alpha_k = 0$. Because of this, it ensures the convergence for SUE problems. In SRA method, $\{\alpha_k\}$ is a monotonically decreasing positive series. However, it maintains a more reasonable decreasing speed. Particularly, when iterates are close to the optimal solution, the step sizes decline slowly to avoid a slow convergence speed [22].

B. NSGA-II Algorithm

In the literature, there are several multi-objective evolutionary algorithms (MOEA). Among them, we implemented NSGA-II algorithm since it is widely accepted as one of the best MOEA [21].

"Non-dominated sorting" is one of the main characteristics of the NSGA-II algorithm. A vector $u = (u_1, u_2, \dots, u_k)$ is said to dominate another vector, $v = (v_1, v_2, \dots, v_k)$ if and only if $u_i \leq v_i$ for all i and there exists an i such that $u_i < v_i$ [24]. Furthermore, another important concept is "crowding distance" for this algorithm. It measures the density of an individual through all the individuals in a particular front (rank).

The decision variables for the upper level problem are the toll prices. Each solution is represented by a vector of size $|\mathcal{A}'| \times |\mathcal{U}|$ where $\mathcal{A}'$ is the set of tolled arcs of the network. In other words, we choose to collect different toll prices for each user type. The general description of the adapted NSGA-II is given as follows [25]:

I. Generate the initial population by randomly choosing toll prices between predetermined lower and upper bounds.
II. Assess the objective functions. To realize this, first solve SUE model given toll prices for every individual of the population using SRA algorithm. Then, using optimal SUE flow values calculate the value of each objective function for every individual.
III. Assign the rank to every individual in the population on the basis of non-dominance.
IV. Classify the individuals in the population according to the ranks.
V. Find the crowding distance for every individual in the population.
VI. For each generation, we have to accomplish some tasks which are given below:
 a) Perform tournament selection to select the individuals randomly from the population.
 b) Produce offspring population by doing crossover and/or mutation based on the crossover and mutation probability.
 c) Generate intermediate population by integrating the populations of parents and offsprings.
 d) Carry out non-dominated sorting on the intermediate population.
 e) Choose the individuals from the intermediate population by depending on rank and crowding distance. The individuals in rank are classified in the increasing order of rank and added until the population size is reached. The final rank is included according to the individuals with least crowding distance.
 f) Replace the individuals in the population.

V. Illustrative Example

To demonstrate the efficiency of our approach, we have employed the nine node example from [26] which has data similar to large-scale traffic assignment problems. It has 18 links and all of the links have cost functions with the same structure:

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

where T_a and b_a are two constants denoting the free flow time on link a and the capacity of link a respectively. There are four OD-pairs: (1,3), (1,4), (2,3) and (2,4). The network is shown in Figure 1. The pair near link a is (T_a, b_a).

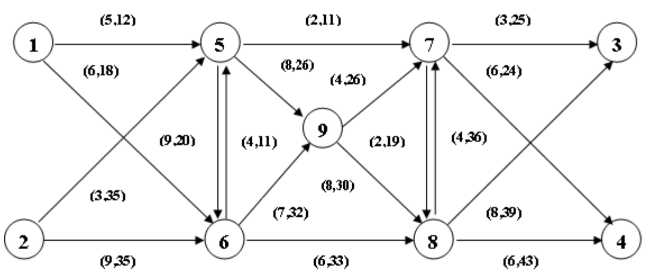

Fig. 1. The nine node network

Three types of users are investigated in this study with $\theta_1 = 0.01$, $\theta_2 = 0.10$ and $\theta_3 = 0.50$. In other words, type one users belong to the low income class with the least equipped cars while type three users belong to the high income class with the most equipped cars. The users travel demands are given in Table I.

ISBN: 978-988-19251-3-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

TABLE I
USER FLOWS ON NETWORK ARCS

OD	UT1	UT2	UT3
1-3	5	3	2
1-4	10	6	4
2-3	15	10	5
2-4	20	13	7

UTx = user type x

NSGA-II is run for a population size 50, tournament size 2, crossover rate 0.80, Pareto front population fraction 0.20 and maximum number of iteration 150. For the crossover operator, we first create a random binary vector. We then select the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child. For the mutation operator, we randomly generate directions that are adaptive with respect to the last successful or unsuccessful generation. A step length is then chosen along each direction so that linear constraints and bounds are satisfied. Finally, the minimum and maximum toll prices that can collected are set to 0 and 20 respectively, independent from the arc and user type selected.

Three different toll pricing schemes are investigated: (1) first best toll pricing (FBTP), (2) second best toll pricing (SBTP), and (3) no toll pricing (NOTP). In FBTP plan, it is assumed that all arcs can be tolled. As this can be difficult to realize in practice, only a subset of arcs is tolled in SBTP plan. In this study, only arcs (5,7), (6,8), (6,9) and (7,8) are included in this subset. For the first two pricing schemes, final results for 5 different runs of the NSGA-II are pooled and the final Pareto front is obtained after removing dominated solutions from this pool. The result of the last NOTP plan is found with a single execution of SRA and the calculation of the upper level objectives. These results are shown in Figure 2. It can be observed that toll pricing policy pays off in terms of sustainability objectives: NOTP solution is strictly dominated by all FBTP and SBTP solutions, and the closest solution to the NOTP solution is at least 16% better in both objectives. Moreover, FBTP plan produces solutions that all strictly dominate SBTP plan solutions. They are also much more diversified in the objective functions space, thus form much more interesting

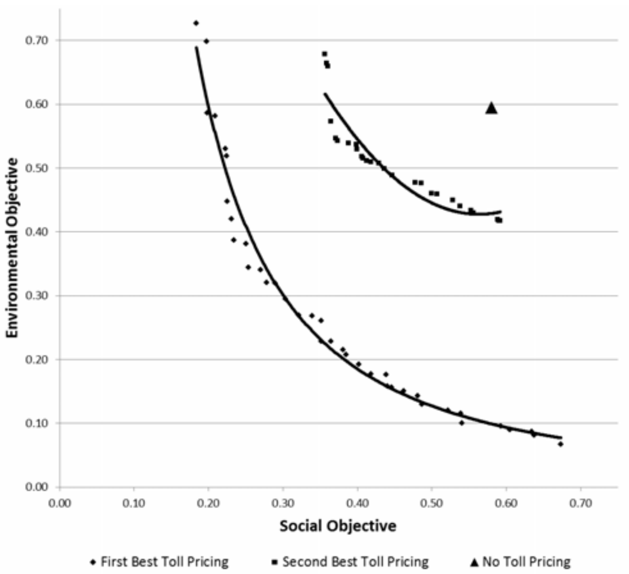

Fig. 2. Pareto optimal solutions depicted in the objective functions space

choices to the traffic authority. However, the inconvenience of pricing plans is that they lead to an increase in total time spent by the users on the network (in system optimum sense). Compared to SO total travel time at NOTP case, this increase resides in the interval 2.5%-5.5% for SBTP solutions while it resides in the interval 23%-28% for FBTP solutions. Therefore, we can claim that second best pricing is the most appropriate policy for sustainable traffic assignment.

Other insights can be gained by examining link flows. Here we only contrast NOTP plan flows with one of the Pareto optimal solutions of SBTP plan (see Table II). This solution is selected such that its distance to the origin at the objective functions space is minimal. Note that this distance is calculated by assigning equal weights to both environmental and social objectives. As the origin in this space corresponds to the ideal solution (yet impossible to attain), the closest Pareto optimal solution to the ideal solution can be considered as sustainable. It can be remarked from Table II that flow of user type 3 is significantly altered by the optimum toll prices. The change is much more less for user type 2 and almost insignificant (less than 1%) for user type 1. This implies that collecting toll from users that are more familiar with the road conditions help to achieve sustainability.

TABLE II
USER FLOWS ON NETWORK ARCS

	No Tolling			Second Best Tolling		
Arcs	UT1	UT2	UT3	UT1	UT2	UT3
1-5	7.97	3.95	1.66	7.98	4.23	5.30
1-6	7.03	5.05	4.34	7.02	4.77	0.70
2-5	19.05	13.28	9.00	19.23	14.97	11.96
2-6	15.94	9.72	3.00	15.77	8.03	0.04
5-7	7.47	7.56	9.40	8.01	11.77	1.45
5-9	15.06	8.82	1.27	15.29	6.70	15.81
5-6	40.02	0.87	0.00	39.61	0.74	0.00
6-5	35.52	0.01	0.00	35.70	0.02	0.00
6-8	10.06	8.40	6.84	11.01	12.18	0.70
6-9	17.40	7.22	0.49	15.69	1.35	0.04
7-3	10.90	9.10	6.41	11.07	9.25	6.86
7-4	15.86	10.28	4.50	16.06	10.20	6.21
7-8	66.59	0.20	0.00	61.04	0.19	0.00
8-3	9.10	3.90	0.59	8.93	3.75	0.14
8-4	14.14	8.72	6.50	13.94	8.79	4.79
8-7	70.47	3.11	0.01	65.76	3.67	0.01
9-7	15.41	8.90	1.51	14.40	4.21	11.62
9-8	17.05	7.13	0.25	16.58	3.84	4.24

UTx = user type x

VI. CONCLUSION AND FUTURE RESEARCH

There exist several sustainability related measures for rating urban transport systems and these measures are most of the time conflicting. Therefore, finding a single dominant solution that is the best performer regarding to all objectives is impossible. In this work, we aim at providing solutions that are sustainable for the traffic assignment if only environmental and social objectives are considered. To achieve this, we develop a bi-objective bi-level optimization model which includes user type based toll pricing policy and a solution method to solve this model. The efficiency of the model is demonstrated with an illustrative example and a descriptive analysis on the obtained results is provided.

This study has the potential of being a starting point for many future researches. We can only conceive of apparent ones. As for example, the economical dimension can be

ISBN: 978-988-19251-3-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

incorporated as a third objective. This objective may include several measures such as affordability or value-of-travel time. The number of environmental and social measure could be also increased. Instead of only focusing car traffic assignment, other stages of the transportation planning such as trip generation, trip distribution and/or modal split could be also included to the model. Only peak hour demand is investigated here. However, it is also possible to model in-day and day-to-day traffic by taking into account dynamic traffic assignment. All these enhancements will inherently enable the development of new sustainability performance metrics for urban transportation.

REFERENCES

[1] H. Haghshenasand and M. Vaziri, “Urban Sustainable Transportation Indicators for Global Comparison,” *Ecological Indicators*, vol. 15, no. 1, pp. 115-121, Apr. 2012.

[2] C. Kennedy, E. Miller, A. Shalaby, H. Maclean, and J. Coleman, “The Four Pillars of Sustainable Urban Transportation,” *Transport Reviews*, vol. 25, no. 4, pp. 393-414, Jul. 2005.

[3] Y. Shiftan, S. Kaplan, and S. Hakkert, “Scenario Building as a Tool for Planning a Sustainable Transportation System,” *Transportation Research Part D: Transport and Environment*, vol. 8, no. 5, pp. 323-342, Sep. 2003.

[4] A. Awasthi, S. S. Chauhan, and H. Omrani, “Application of Fuzzy TOPSIS in Evaluating Sustainable Transportation Systems,” *Expert Systems with Applications*, vol. 38, no. 10, pp. 12270-12280, Sep. 2011.

[5] M. R. M. Yazid, R. Ismail, and R. Atiq, “The Use of Non-Motorized for Sustainable Transportation in Malaysia”, in *The 2nd International Building Control Conference 2011*, pp. 125-134.

[6] U. Muntwyler and F. Koch, “Sustainable Transport? RE Supply Options and Resource Potential for Transportation,” *Refocus*, vol. 3, no. 4, pp. 34-37, Jul. 2002.

[7] B. C. Richardson, “Sustainable Transport: Analysis Frameworks,” *Journal of Transport Geography*, vol. 13, no. 1, pp. 29-39, Mar. 2005.

[8] J. N. Prashker and S. Bekhor, “Some Observations on Stochastic User Equilibrium and System Optimum of Traffic Assignment”, *Journal of Transport Geography*, vol. 34, no. 4, pp. 277-291, May. 2000.

[9] R. P. Batley and R. G. Clegg, “Driver Route and Departure Time Choices: The Evidence and the Models”, in *Universities Transport Study Group 33rd Annual Conference 2001*, p. 18.

[10] F. R. B. Cruz, T. Woensel, J. M. Smith, and K. Lieckens, “On the System Optimum of Traffic Assignment in M/G/c/c State-Dependent Queueing Networks”, *European Journal of Operational Research*, vol. 201, no. 1, pp. 183-193, Feb. 2010.

[11] A. Chen, J. Kim, S. Lee, and J. Choi, “Models and Algorithm for Stochastic Network Designs”, *Tsinghua Science and Technology*, vol. 14, no. 3, pp. 341-351, Jun. 2009.

[12] M. J. Maher, X. Zhang, and D. V. Vliet, “A Bi-level Programming Approach for Trip Matrix Estimation and Traffic Control Problems with Stochastic User Equilibrium Link Flows”, *Transportation Research Part B: Methodological*, vol. 35, no. 1, pp. 23-40, Jan. 2001.

[13] S. Qiang, W. Qingyun, and G. Yongling, “Multi-period Bi-level Programming Model for Regional Comprehensive Transport Network Design with Uncertain Demand”, *Journal of Transportation Systems Engineering and Information Technology*, vol. 11, no. 6, pp. 111-116, Dec. 2011.

[14] K. Fedra, “Sustainable Urban Transportation: A Model-based Approach”, *Cybernetics and Systems: An International Journal*, vol. 35, no. 5-6, pp. 455-485, Jul. 2004.

[15] G. H. Tzeng and C. H. Chen, “Multiobjective Decision Making for Traffic Assignment”, *IEEE Transactions on Engineering Management*, vol. 40, no. 2, pp. 180-187, May. 1993.

[16] E. S. Smits, M. Bliemer, and B. Arem, “Dynamic Network Loading of Multiple User-Classes with the Link Transmission Model”, in *2nd International Conference on Models and Technologies for Intelligent Transportation Systems 2011*, Leuven, Belgium.

[17] H. Shao, W. H. K. Lam, and M. L. Tam, “A Reliability-Based Stochastic Traffic Assignment Model for Network with Multiple User Classes under Uncertainty in Demand,” *Networks and Spatial Economics*, vol. 6, no. 3, pp. 173-204, Sep. 2006.

[18] B. Santos, A. Antunes, and E. J. Miller, “Integrating Equity Objectives in a Road Network Design Model”, *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2089, no. 1, pp. 35-42, Feb. 2009.

[19] S. P. Shepherd, “The Effect of Complex Models of Externalities on Estimated Optimal Tolls”, *Transportation*, vol. 35, no. 4, pp. 559–577, Jul. 2008.

[20] C. Steele, “A Critical Review of Some Traffic Noise Prediction Models”, *Applied Acoustics*, vol. 62, no. 3, pp. 271-287, Mar. 2001.

[21] M. Li, D. Lin, and S. Wang, Solving a Type of Biobjective Bilevel Programming Problem Using NSGA-II, *Computers and Mathematics with Applications*, vol. 59, no. 2, pp. 706-715, Jan. 2010.

[22] H. X. Liu, X. He, and B. He, “Method of Successive Weighted Averages (MSWA) and Self-Regulated Averages Schemes for Solving Stochastic User Equilibrium Problem”, *Networks and Spatial Economics*, vol. 9, no. 4, pp. 485-503, Dec. 2009.

[23] D. H. Lee, Q. Meng, and W. Deng, “Origin-Based Partial Linearization Method for the Stochastic User Equilibrium Traffic Assignment Problem,” *Journal of Transportation Engineering*, vol. 136, no. 1, pp. 52-60, Jan. 2010.

[24] C. A. Coello Coello, G. B. Lamont, and D. A. V. Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems*. Genetic Algorithms and Evolutionary Computation Book Series, 2007, Second Edition.

[25] R. Bhattacharya and S. Bandyopadhyay, “Solving Conflicting Bi-Objective Facility Location Problem by NSGA II Evolutionary Algorithm,” *International Journal of Advanced Manufacturing Technology*, vol. 51, no. 1-4, pp. 397-414, Apr. 2010.

[26] D. W. Hearn and M. V. Ramana, *Solving Congestion Toll Pricing Models*. New York: North-Holland, 1988, pp. 109-124.

ISBN: 978-988-19251-3-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)