Introducing Transportation-Related Carbon Footprint Considerations in Optimal Urban Road Infrastructure Management

Loukas Dimitriou, Antonios Kaltsounis, and Antony Stathopoulos

***Abstract*—**Environmental considerations are gaining importance in civil infrastructure design and management. In particular the transportation sector of urban civil infrastructure is regarded a major determinant of life quality and environmental sustainability. Its development and operation plans involve the employment of multiple policies, and demand multiple objectives to be met. In this paper, a policy-driven approach is presented for providing optimal investment and management plans for future network developments, by taking into account air quality criteria and in particular the carbon footprint related to vehicle emissions. Optimal network design and pricing decisions are tested in order that multiple conflicting social, economic and environmental targets to be simultaneously optimized. Under this framework, social dilemmas are revealed, while quantitative results can support decisions related to the sustainable urban development. The methodological approach presented here is based on a formulation of multi-objective, non-convex, multi-level, vector optimization programming problem. The problem's formulation nature leads to solution sets that are composing Pareto Fronts (PF). PFs, are estimated by suitably hybridized evolutionary algorithms. Insights are provided by applying the proposed framework into a part of a realistic network, for alternative problem setups.

***Keywords*—**Sustainable Urban Development, Carbon-footprint, Optimal Transportation Planning, Vector Optimization.

I. Introduction

FOLLOWING the standard paradigm of the optimal design of future transportation infrastructure development plans, investments are allocated based on criteria expressing the prudence of public and private authorities for the performance of the designed system. The performance criteria used in most of such studies, endeavor to optimize economic (or economic related) metrics of the relative investments. Nevertheless, contemporary society's requirements are moving towards a sustainable development pattern, especially since -for some time now- environmental conditions have been identified that determine the attractiveness of cities thus their possible future opportunities and potential [1]. Concentrating in metropolitan areas, the development plans are focusing to ameliorate negative externalities of the requirements for increased mobility, a phenomenon closely related to urban welfare growth.

One of the most evident negative environmental externality of urban transportation is air pollution. Since traffic emissions are closely related to congestion, a net of policies and initiatives should be suitably combined to remedy negativities, spanning to multimodal infrastructure provision, road pricing and/or other traffic management strategies. The importance of emissions management within the European Union is reflected to the emergence of control initiatives such as the European Emissions Trading Scheme (EU ETS) [2], [3].

The theoretical foundations of optimal traffic networks design and management strategies are mainly based on classical and neoclassical economic ideas. Nevertheless, the implementation of such ideas have come against problems emerging when only monetary costs are considered in development plans, as well as to complexity of identifying optimal management plans in realistic networks, as they have been revealed in various paradoxes exposed in investigations of investment and pricing strategies. One such example is the paradox of the increment of the total social cost (as reflected by total travel time) by the provision of additional transportation infrastructure and the similar case of the increase of congestion-related traffic emissions in certain cases of reducing travel times by capacity improvements [4]. Also, the paradox of the increase of traffic emissions when reducing total travel time shifting from user-optimal towards system-optimal traffic network conditions through network pricing [5], demonstrates the complex and conflicting nature of alternative network design and management strategies. The difficulty of identifying optimal strategies is significantly increased when considering the determination of joint choices for a set of available alternative policies, or when dealing with multiple interrelations as those arising in urban networks.

This paper aims to provide a comprehensive framework for

Loukas Dimitriou is with the Laboratory of Railways and Transport, Dept. of Transportation Planning and Engineering, School of Civil Engineering, National Technical University of Athens, 5, Iroon Polytechniou Str., 15773, Athens, Greece (corresponding author to provide phone: +30 210 772 1370; fax: +30 210 7721287; e-mail: lucdimit@central.ntua.gr).

Antonios Kaltsounis, is a Lecturer at the Road Works Laboratory, Dept. of Transportation Planning and Engineering, School of Civil Engineering, National Technical University of Athens, 5, Iroon Polytechniou Str., 15773, Athens, Greece (author: +30 210 772 1477; fax: +30 210 7721327; e-mail: akaltsounis@transport.ntua.gr).

Antony Stathopoulos is Professor and Head of Laboratory of Railways and Transport, Dept. of Transportation Planning and Engineering, School of Civil Engineering, National Technical University of Athens, 5, Iroon Polytechniou Str., 15773, Athens, Greece (corresponding author to provide phone: +30 210 772 1288; fax: +30 210 7721287; e-mail: a.stath@transport.ntua.gr).

identifying optimal network strategies, encompassing joint decisions of both network development (investments) and management policies (pricing) for a realistic case of an urban highway, as well as in exposing the social dilemmas that are formed in such circumstances. Moreover, instead of determining a unique optimal strategy, a non-linear, non-convex, multi-level, multi-objective optimization problem is formulated incorporating conflicting (economical, social, and environmental) network objectives, able to provide a Pareto-Optimal set of policies. The solution algorithm for addressing the above described optimization problem is based on hybrid game-theoretic evolutionary tactics implemented in genetic algorithms. The proposed formulation and solution approach is able to capture optimal tradeoffs among contradicting objectives, providing valuable information for meta-analysis aiming to a final network management plan.

In the next section, the description of the problem of the multi-objective sustainable joint network design and pricing problem will be provided. Then the formulation of the problem as a multi-level optimization problem is presented, while the description of the solution evolutionary algorithm follows. Results from the implementation of the proposed framework on a part of a realistic network from the city of Athens, Greece will be provided, while the final section concludes.

II. Problem Statement

Environmental prudence about the performance of urban networks has been mainly investigated in works related to network pricing strategies [6], while a comprehensive investigation of alternative pricing strategies can be found in [5]. Less attention has been paid to the case of optimal network investments allocation (usually described as Network Design Problems) with respect to the emission performance. Nagurney [7] has pointed out several valuable insights regarding the effects of capacity improvements in total network emissions. Nevertheless, no analysis has been made for the more realistic situation for the optimal strategies determination by considering joint network design and pricing decisions aiming to take into account the environmental (in terms of emissions) effects, as well as to case that the network users themselves are taking a series of network decisions (e.g. residential or work location selection).

The problem of the simultaneous determination of optimal design and pricing strategies for urban networks, despite its considerable policy implications, has received little attention ([8]-[14]). Most of these studies actually refer to simplified networks, using assumptions that considerably depart from realistic situations.

Here a number of extensions are introduced for taking into account the emissions produced in the network with respect to alternative planning strategies, revealing the multiple social choice issues raised in such urban planning cases. At first, a multi-objective problem is formulated for identifying optimal tradeoffs among conflicting social, economic and environmental objectives. The formulation aims to model a multi-level Stackelberg game among a single network authority (responsible for the investments decisions and pricing policies) and the network users. Also, at the level of network users, a joint model of trip (re-)distribution and stochastic traffic assignment has been utilized for capturing residential/work location selection and route choices non-cooperative game among multi-class network users, triggered by the network operational schema. The formulation will be presented in the following section.

III. Expanding the Network Design and Pricing Game to Incorporate Environmental Considerations

The processes of road network design and pricing (with or without emission reduction considerations) are typically considered as two-stage Stackelberg games with perfect information among alternative players. These games recognize the principal players, which are the system designer/operator (here termed the network authority) and the system's users, and they can be generally solved as bi-level programming problems. Such type of formulation is commonly met in the literature when considering separately the Network Design Problem - NDP [15] and the Toll Design Problem - TDP [16]. At the upper level, the system operator (the 'leader'), taking into account a number of constraints, integrates within the design and pricing tactics the non-cooperative responses of users of different classes (the 'followers').

In this paper, the 'leader' stands for the system authority (government) who controls location-specific development in network expansions and the level of toll rates imposed on highway access points. It is assumed that the set (number and location) of highway links has already been identified before the problem is formulated and solved. This assumption typically holds for a realistic network design process that takes place in an urban environment, as in our present case. Therefore, the problem seeks to estimate the spatially differentiated toll charges and/or the number of link lanes from the designer/operator's point of view, so that the tolled highway, which competes with toll-free alternative urban roads, will attract such a portion of multi-class users that optimizes network performance.

Since an attempt is made in this paper to deal with the situation where significant alterations on the network conditions are endeavored, the users' responses should involve the joint non-cooperative decisions of the residential/work location selection and route choice. This is considered as a significant addition to the exploration for optimal development plans since it captures the relationship among land use and transportation infrastructure, an element identified as of increased importance ([17] - [19]). Here, the case has been investigated as a network equilibrium problem where network users are competing for choosing (or been supplied with) residential/work locations with respect to network conditions as determined by route choices. Such complex network equilibrium circumstances of joint trip distribution and traffic assignment models have been proposed for capturing urban interactions by [20] and [21]. In these studies, the network users' responses have been investigated for the case of determination of optimal road tolls on urban highways aiming to maximize social welfare. Also, a bi-level formulation has been proposed for capturing network users' location decisions and transportation infrastructure [22]. Here the combined trip-distribution and traffic assignment problem is modeled by adopting an elastic demand route choice model. In particular, multiple user classes are engaged in a stochastic route choice process leading to network conditions termed as stochastic user equilibrium-(SUE) where the network performance determines the demand levels on all locations and for every origin-destination pair.

Formally, let's consider a network $G(N, A)$ composed of a set of N nodes and A links, which connect the origin zone r with destination zone s, and q_m^{rs} be the demand of the users of class m for the O-D pair r - s. In this context, each class m corresponds to a particular user group having an assumed common value of travel time (VOTT), which may reflect similar socio-economic and travel characteristics. As it is typically adopted in the literature, in the present study it is assumed that, for each user group, travelers share the same discrete VOTT probability distribution. It is noted that other user group definitions may be additionally adopted, according to the nature of each application, such as the operational characteristics (e.g. the type of vehicle, or other).

Also, consider the link travel time function $t_a(x_a)$ (in minutes) as being positive and monotonically increasing with traffic flow x_a for each link $a \in A$. Here, the complete form of the bi-level optimization framework, for the design and pricing of a private highway that constitutes part of the network is expressed in the upper-level problem as a vector optimization problem:

$$\min_{p,y} R = [R_1, R_2, R_3] = \\ = \left[\sum_{a \in A} E\{c_a(x_a)\, x_a\},\ \sum_{a \in \hat{A}} E\{V_a(y_a(w_a))\} - \sum_{a \in \hat{A}} E\{p_a f_a\},\ \sum_{a \in A} E\{e(x_a)\} \right] \quad (1)$$

subject to

$$w_a \in \{0,1,\ldots,\ell\}, \qquad \forall\, a \in \hat{A} \quad (2)$$

$$p_{\min} \le p_a \le p_{\max}, \qquad \forall\, a \in \hat{A} \quad (3)$$

$$\sum_{a \in \hat{A}} \left(V_a\left(y_a\left(w_a\right)\right)\right) \le B, \qquad \forall\, a \in \hat{A} \quad (4)$$

$$x_a(p,y)/y_a \le L, \qquad \forall\, a \in \hat{A} \quad (5)$$

$$\sum_{rsm} D_{rsm}(S_m^{rs}) \ge k \sum_{rsm} D_{rsm}^0(S_m^{rs}) \quad (6)$$

while the SUE link flow conditions are estimated at the lower-level:

$$\min_{x,q} Z(x,q) = \sum_{rsakm} \mathrm{VOTT}_m\, \delta_{a,km}^{rs}\, t_a(x_a)\, x_a - \sum_{rsakm} \mathrm{VOTT}_m\, \delta_{a,km}^{rs} \int_0^{x_a} t_a(w)\mathrm{d}w + \\ \sum_{rsm} \mathrm{VOTT}_m\, D_{rsm}^{-1}(q_m^{rs})\, D_{rsm}\left(S_m^{rs}(x)\right) - \sum_{rsm} S_m^{rs}(x)\, D_{rsm}\left(S_m^{rs}(x)\right) + \\ \sum_{rsm} \int_0^{q_m^{rs}} \mathrm{VOTT}_m\, D_{rsm}^{-1}(q)\mathrm{d}q - \sum_{rsm} q_m^{rs}\, \mathrm{VOTT}_m\, D_{rsm}^{-1}(q_m^{rs}) \quad (7)$$

In the upper-level problem, R denotes the vector of objectives that aimed to be optimized by exploring the search space. Here the vector of the objective function is composed of 3 components. The first stands for the total network travel cost (as a sum of links cost $c_a(x_a)$ multiplied by link demand x_a), a metric able to capture the effectiveness of the investments and pricing strategies in providing better opportunities. The second component provides the economic performance of alternative strategies. This objective is a composite function of the investment (monetary) expenditures V_a for capacity provision of highway link $a \in \hat{A}$ minus the revenues collected by the toll (operational or enterprising benefits are omitted). Toll charges, p_a, are imposed only on the highway entry volumes f_a. At this entry-based toll pricing scheme, revenues depend on the selection of the entry point, and index a refers to the highway access (entry) link $a \in \hat{A} \subset A$ with capacity y_a, whose entry node is used by travelers to access the highway, where $\hat{A}$ is the set of highway links.

Finally, the third component stands for the aggregate network CO_2 emission, produced in all network links reflecting the carbon footprint of network operation. Although other pollutants may be used as being representative of the car use [5], here CO_2 has been preferred for reasons explained in the introductory section. Under this assumption, CO_2 emissions (in g/km) of each vehicle traversing a network's link are estimated based on the following formula:

$$e_\alpha(x_a) = \omega_1 + \omega_2 / s(x_a) + \omega_3 s(x_a)^2 \quad (8)$$

where $s(x_a)$ is the average speed (in km/h) of link *a* that is estimated subject to the link loading x_a and $\omega_1,\ldots,\omega_3$, scalars.

Moving to the constraints set, scalar w_a is an integer decision variable which determines the number of lane additions in link $a \in \hat{A}$, up to a physical threshold ℓ, as shown in relationship (2). The scalars $p_{\min}$ and $p_{\max}$ in relationship (3) denote the minimum and maximum allowable toll charges, which are controlled by some authority (e.g. police, mobility center, etc). The budgetary restrictions are represented in inequality (4), where B is the total available highway construction budget.

Relationship (5) introduces the regulatory control of the authority on the minimum required level of service (mobility target) in the set of constraints, where L is the maximum allowable flow-to-capacity (x_a / y_a) ratio for each highway link $a \in \widehat{A}$. This operational target is used to ensure a desired balance between infrastructure supply and highway utilization rate that enhances mobility, in terms of reducing travel times between the various O-D pairs, after the new network configuration. It should be noted here that the simultaneous consideration of budget and level-of-service requirements in the set of constraints may result in an unfeasible solution. This possibility stresses the need for careful selection of the bound of each problem constraint.

Finally, due to the nature of the problem of the joint design and pricing problem with elastic demand, an additional welfare constraint is added in inequality (6), related to the total social welfare and equity conditions. Namely, the minimization of total travel time could be obtained by setting an infinite (or extremely high) toll rate and thus the reduction of total travel time could be attributed to residential/work location decisions outside the study area. Thus, this constraint assures that total demand will not decrease below a set rate k.

In the lower-level problem, Z expresses the objective function of network users of different classes m, in terms of their value of travel time (VOTT$_{\mathrm{m}}$), who seek to minimize their perceived generalized travel cost by making medium/long term joint residential/work location and route choices. This procedure is formulated as an un-constrained minimization problem expressed in equation (7).

Formally, the binary parameter $\delta_{a,km}^{rs}$ takes the value 1, if link a is part of the path k of the feasible path set K^{rs} followed by users of group m between r - s, or 0 otherwise. Assuming that the demand function D_{rsm} is non-negative and strictly decreasing with respect to the cost of paths between r - s, then $q_m^{rs} = D_{rsm}(S_m^{rs})$ and $S_m^{rs} = D_{rsm}^{-1}(q_m^{rs})$, where D_{rsm}^{-1} is the inverse demand function and S_m^{rs} is the perceived travel cost function. The latter is expressed in relation to the expected value E of the total path travel cost C_{km}^{rs}, as follows:

$$S_m^{rs}(x) = E\left[\min_{k \in K^{rs}} \left\{C_{km}^{rs}\right\} \middle| \, C^{rs}(x)\right], \tag{9}$$

$$\text{with } \frac{\partial S_m^{rs}(C^{rs})}{\partial C_{km}^{rs}} = P_{km}^{rs}, \tag{10}$$

where P_{km}^{rs} denotes the probability that users of class m select path k between r - s pair. Then, the measure of probability P_{km}^{rs} depends on the following utility function:

$$U_{km}^{rs} = -\theta\, C_{km}^{rs} + \varepsilon_{km}^{rs} \tag{11}$$

where U_{km}^{rs} expresses the utility of users of class m selecting path k between r - s pair, θ is the path cost perception parameter and ε_{km}^{rs} is a random error term, independent and identically distributed (iid) for all routes, which is assumed here to follow a Gumbel distribution, yielding a logit model formulation. The path travel cost C_{km}^{rs} is expressed in monetary terms, as a composite function of the value of travel time and toll charge:

$$C_{km}^{rs} = \sum_{a \in A} \mathrm{VOTT}_m\, \delta_{a,km}^{rs}\, t(x_a) + \sum_{a \in \bar{A}} \delta_{a,km}^{rs}\, p_a \tag{12}$$

The adoption of the stochastic user equilibrium (SUE) assumption implies that the resulting equilibrium flows correspond to the most probable (expected) flow pattern. The effect of this stochasticity on the performance of the upper-level problem is represented through the expected value operator in the vector of objectives presented in equation (1).

The estimation of the demand responses related to residential/work location selection with respect to path travel cost is based on the following relationship:

$$D_{rsm}^{(n)} = D_{rsm}^{0} \exp(uC_{rs}), \ \forall\, r, s, m \tag{13}$$

where D_{rsm}^{0} refers to the potential demand (or the demand at zero cost) expressing the maximum desire for travel of users of class m for the r - s pair and u is a scaling parameter that controls the users willingness to alter their residential location.

The solution of the lower-level unconstrained combined trip-distribution and assignment problem can be obtained by a recursive estimation of the demand levels in the network conditions resulting from the route choice process. Changes in the demand level are estimated by an algorithm based on the method of successive averages (MSA) [23]. In the following section a hybrid evolutionary algorithm is presented that is able to provide an estimation of the Pareto Front for the above multi-objective optimization problem.

IV. An Evolutionary Approach to the Multi-Objective Network Design and Pricing Problem

When dealing with multi-objective optimization problems, where the problem is consisted of conflicting objectives, optimality conditions correspond to a compromise among them. This compromise can be determined in advance, forming a desirable combination among the conflicting objectives, by providing a suitable parametric composite function, using scaling parameters for each objective. The determination of the set of optimal tradeoffs among conflicting objectives composes the so-called Pareto Front (PF). PF can be approximated usually by altering the scaling parameters among the objectives and estimating the optimum of the unique composite function [24]. This method is computationally intensive since it requires extensive runs in order to identify new points of the PF.

Here, an evolutionary mechanism able to directly provide a

PF approximation, introduced by [25] will be utilized. In this hybrid genetic algorithm (GA) it is suggested an elitist GA, a distance-based Pareto genetic algorithm (DPGA), which attempts to emphasize the progress towards the Pareto-optimal front and the diversity along the obtained front by using a fitness measure. Following the notation used in [29], the algorithm maintains two populations: one standard GA population P_t where genetic operations are performed, and another elite population E_t containing all non-dominated solutions found thus far.

The initial population P_0 of size N is created at random. The first population member is assigned a positive random fitness F_1 (chosen arbitrarily) and is automatically added to the elite set E_0. Thereafter, each solution is assigned a fitness based on its distance from the elite set, $E_t = \{e^{(k)} : k = 1,2,\ldots,K\}$, where K is a number of solutions in the elite set. Each elite solution $e^{(k)}$ has M function values, or $e^{(k)} = (e_1^{(k)}, e_2^{(k)}, ..., e_M^{(k)})^T$. The distance of a solution x from the elite set is calculated as follows:

$$d^{(k)}(x) = \sqrt{\sum_{m=1}^{M} \left(\frac{e_m^{(k)} - f_m(x)}{e_m^{(k)}} \right)^2} \tag{14}$$

For the solution x, the minimum $d^{(k)}(x)$ of all k=1,2,…K is found as follows:

$$d^{\min} = \min_{k=1}^{K} d^{(k)}(x) \tag{15}$$

and an index k^* for the minimum distance is also recorded. Thereafter, if the solution x is a non-dominated solution with respect to the existing elite set, it is accepted in the elite set and its fitness is calculated by adding the fitness of the elite member with minimum distance from it and its distance from the minimum member:

$$F(x) = F(e^{(k^*)}) + d^{\min} \tag{16}$$

The elite set is updated by deleting all elite solutions dominated by x, if any. On the other hand, if the solution x is dominated by any elite solution, it is not accepted in the elite set and its fitness is calculated as follows:

$$F(x) = \max\left[0, (F(e^{(k^*)}) - d^{\min})\right] \tag{17}$$

In this way, as population members are evaluated for their fitness, the elite set is constantly updated. At the end of the generation (when all N population members are evaluated), the maximum fitness F_{max} among the existing elite solutions is calculated and all existing elite solutions are assigned a fitness equal to F_{max}. At the end of a generation, selection, crossover and mutation operators are used to create a new population.

It is interesting to note that a non-dominated solution lying a large distance away from the existing elite set gets a large (better) fitness. This helps in two ways. First, if the new solution dominates a few members of the elite set, the fitness assignment procedure helps in emphasizing solutions closer to the Pareto-optimal set. A distant solution here means a solution distant from the existing elite set but closer to the Pareto-optimal front. Assigning a large fitness to such a solution helps to progress towards the Pareto-optimal front. On the other hand, if the new solution lies in the same non-dominated front along with the elite solutions, the fitness assignment procedure helps in maintaining diversity among them. A distant solution here means an isolated solution on the same front. Assigning a large fitness to an isolated solution helps to maintain diversity among obtained non-dominated solutions. This novel evolutionary approach has not been used before for addressing the joint network design and pricing problem with environmental considerations.

V. Computational Results and Discussion

A. Experimental Setup of the Study

The proposed modeling framework is implemented in a suitably selected part of the urban road network of Athens, Greece, that is composed of primary and secondary roads, which are linked with a closed orbital tolled urban highway, called Attiki Odos. The network (see Figure 1) covers a densely populated region along the highway, where heavy daily traffic volume is observed. It is composed of 54 (internal and connecting) links servicing the demand represented by a representative 10×10 O-D matrix. The physical and operating characteristics of the internal links of the network under study, has been previously used in [26] and [28], while the same assumptions regarding the construction costs (normalized for a representative design hour) are valid here too.

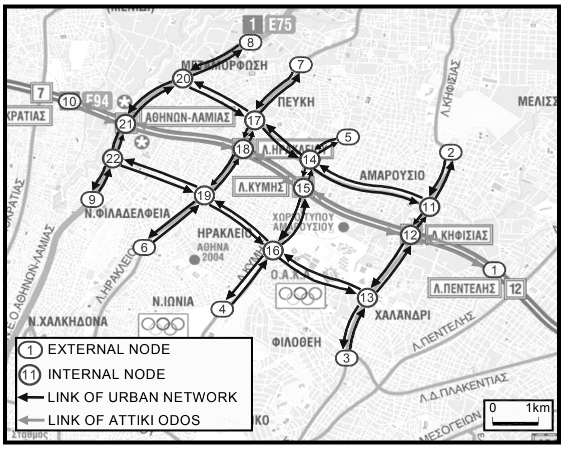

Figure 1. Map of the study area, and configuration and coding of the urban network and tolled highway

Based on the socio-economic and travel characteristics of the case study area, two distinctive VOTT user classes are identified. The first class *I*, in which an hourly $VOTT_I$ = 4.0 € is assigned, representing primary commuters with un-elastic trips, and refers to the 80% of the traveling population, while the second class *II* has an hourly $VOTT_{II}$ = 1.5 €, representing discretionary trips or more elastic trips, and refers to the 20% of the same population.

The minimum and maximum toll levels are set equal to $p_{\min} = 0$ € and $p_{\max} = 7$ €. The optimal toll and capacity choices are examined for highway sections 21↔18,↔15↔12 based on the demand pattern of the design hour. In order to calculate the travel time t_a on link a, the well-known Bureau of Public Roads (BPR) formulation is used, as follows:

$$t_a(x_a) = t_a^0\left(1+\mu\left(\frac{x_a}{G_a}\right)^{\beta}\right),\ \forall\, a \in A \tag{18}$$

where t_a^0 is the link travel time at free-flow conditions, μ and β are parameters referring to local operating conditions (in this study, μ = 0.15 and β = 4) and G_a is the maximum traffic capacity of link a.

Concerning the demand elasticity, a relatively large value $u = -0.1$ is used, standing for an increased willingness of users to drastically respond to network design and pricing strategies. In order to get more insight of the effect that demand elasticity has on system performance, Figure 2 shows convergence diagram of the MSA algorithm that provides the SUE conditions for the case of just traffic assignment (with inelastic demand) and joint location selection and traffic assignment case. As can be observed, at the joint network model total travel cost is less than in the inelastic case attributed –almost- solely to residential/work re-allocation activity which ultimately leads to a better (in terms of total travel cost/time) utilization of the urban space. It is evident that for realistic studies the assumptions used concerning demand elasticities, actually control the model efficiency in terms of forecasting efficiency of alternative policies performance.

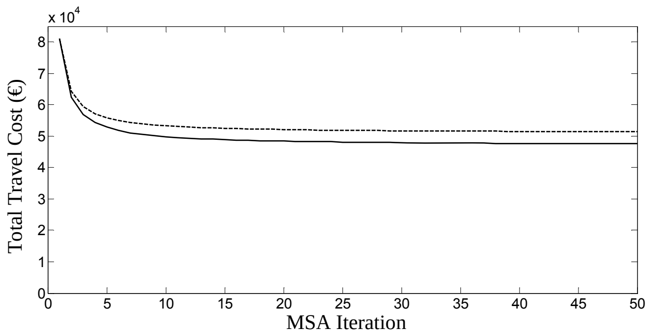

Figure 2. Convergence diagram to SUE conditions for two cases: (a) route choice model (dashed line) and (b) the joint location selection and route choice model (solid line).

Additionally, the constant k that reflects the total demand allowable to change residential location outside the study area (Equation (8)) is set equal to 0.6, while term L is taken to be 0.95. Finally, the emissions are calculated by function (8) using $\omega_1 = 72.73$, $\omega_2 = 33.98 \cdot 10^2$ and $\omega_3 = 23.26 \cdot 10^{-3}$. These values were derived by modifying the NETCEN database's basic formula [29] in order to adapt to the driving pattern and reflect the fleet composition and age distribution of vehicles in the study area. This function estimates EURO II car CO_2 emissions in g/km. In Figure 3, the emissions curve is presented for a stretch of one km, for alternative average link speeds.

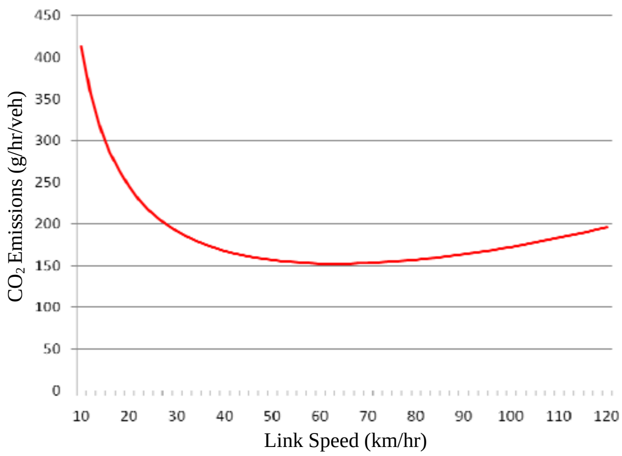

Figure 3. CO_2 Emissions vs. link average speed

Finally, the configuration of the three-objectives vector optimization problem is presented in Table 1.

Table 1. Selection of the evolutionary characteristics of the Genetic Algorithm

Genetic Operation	Characteristic
Population	200 Individuals
Pareto Front (max)	100 Individuals
Initialization	Random
Selection	Tournament selection among 3 candidates
Crossover	80% (n-point)
Mutation	5%
Elitism	10%
Stopping criteria	Max. 300 generations

In the next section, numerical results for two representative cases are presented and analyzed, in order to gain some insight on the ability of the proposed network design and pricing framework to provide Pareto optimal strategies for the above described part of the realistic network of Attiki Odos.

B. *Numerical results*

Next the framework is applied to the complete objective vector as described in equation (1). The results are presented in Figure 4. Although for computational time purposes the population of the GA used here is relatively small (200 individuals) producing 100 estimates the PF, it is possible to derive the complex relationship among these three conflicting objectives, a relationship that is not evident without conducting such an analysis (Figure 5).

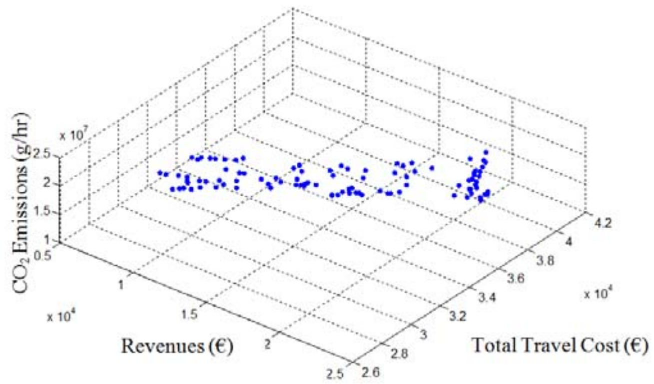

Figure 4. Pareto Front decomposition for the three-objectives vector optimization

It can be observed that despite the complexity of the search space, the proposed framework is efficient in providing a wide range of alternative optimal solutions, which can be used for further investigation related to social choice issues and sustainable network development policy initiatives.

The combination of the value of each variable (lane additions and toll rate) that forms the PF is also presented in Figure 5. In this figure the value of each variable is presented in color coding (ranging from 0-7) that forms the surface estimate of the PF, presented in Figure 4. As it can be identified, the first 6 variables (the left part of the surface) is composed of only three colors since it corresponds to a discrete variable (lane additions), while the rest of the surface (the right part) is composed of a multicolor set since it corresponds to continuous variables (toll rates). From this diagram it can be observed the complexity of the search space as well as the capability of the proposed framework to provide with a wide range of alternative optimal solutions, which can be used for further investigation related to the network development of policy measures including these of sustainability.

Moreover, this diagram actually reveals the multiple dilemmas that an authority could came across when dealing with design and management of urban road infrastructure. Namely, the selection of the most appropriate solution of those composing the PF is a subject of social choice endeavor. The final selection of the point from the PF, although optimal in some sense (objective) it is not without cost for the others.

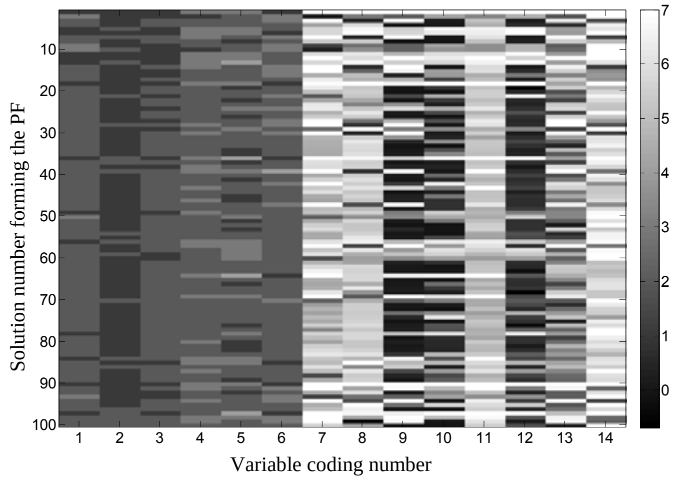

Figure 5. The combinations of solutions that are forming the PF, presented in a color code.

Using the framework described in Section 3, an additional experiment has been conducted: the investigation of the relationship of Total Travel Time Cost vs. CO_2 emissions. In this setup, it is possible to model the users' necessary reduction of their network Level of Service-LoS (in terms of travel time) that they should accept, for the benefit of a reduced carbon footprint.

In Figure 6, a relationship is provided, where the PF exhibits the relaxation on the LoS requirements that should be made in order to provide a transportation development compatible with sustainability policing. The increment of Total Travel Cost is achieved through a policy of not providing excess capacity to the highway or by imposing moderately low toll rates (increasing traffic flow and thus travel time), but it can be interpreted as a speed tap policy for environmental objectives. Such evidence can enhance the social understanding and awareness on transportation planning related policy issues, leading to more rational social choices.

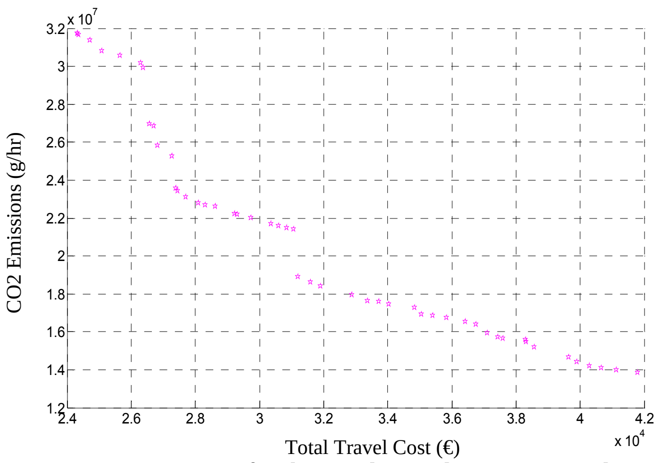

Figure 6. Pareto Front for the Total Travel Time vs. Total CO_2 Emissions model

VI. Conclusions and Outlook

This paper proposes an optimization framework able to support policy initiatives to the problem of designing and pricing of new urban transportation facilities such as urban highways by taking into account the management of carbon footprint. The framework is based on a game-theoretic vector multi-objective formulation of the joint decisions of investments and pricing of new urban highways, by taking into consideration the decisions of network multi-class users for location selection and route choice. The resulted multi-level optimization problem is solved by a novel evolutionary distance-based genetic algorithm, able to provide an approximation of the resulted Pareto Front for the conflicting objectives of invested capital returns, total social cost and the environmental performance.

The proposed framework has been applied to a properly selected part of a realistic network of Athens, Greece, where a closed urban highway is currently operating under a public-private-partnership concession. The results provide evidence on the ability of the proposed policy support framework to provide optimal tradeoffs among the conflicting objectives. Such results can significantly improve social awareness and thus acceptance of alternative transportation-related environmental-oriented strategies, leading to the commonly stated sustainable development policies.

As a work of outlook, the current problem setup is applied following the restricted (but representative) minimization case only for CO_2 emissions. A natural model extension would be to take into account a wider range of road traffic-related emissions, like particle matter (PM), NOx, and other primary pollutants. Also, a more elaborative location selection model can be used for capturing users' responses to alternative transportation development plans. Such extension could significantly amplify design inefficiencies of realistic transportation network.

References

[1] European Communities White Paper, European European transport policy for 2010: time to decide, 2001, (http://ec.europa.eu/transport/white_paper/documents/index_en.htm). Time of site access: 10/06/2008.

[2] Ellerman, A. D. and B.K. Buchner, The European Union Emissions Trading Scheme: Origins, Allocation, and Early Results, Review of Environmental Economics and Policy 2007 1(1), pp.66-87.

[3] Miclaus, P. G., R. Lupu, S.A. Dumitrescu, and A. Bobirca, Testing the Efficiency of the European Carbon Futures Market using Event-Study Methodology, International Journal of Energy and Environment, Issue 1, Volume 2, 2008, pp. 121-128.

[4] Nagurney, A., Congested urban transportation networks and emission paradoxes, Transportation Research Part D, Vol.5, 2000, pp.145-151.

[5] Yin, Y. and Lawphongpanich, S., Internalizing emission externality on road networks, Transportation Research Part D, Vol.11, 2006, pp.292-301.

[6] Yan, H. and Lam, W.H.K., Optimal road tolls under conditions of queueing and congestion, Transportation Research Part A, Vol.30, No.5, 1996, pp.319-332.

[7] Nagurney, A., Sustainable Transportation Networks, Edward Elgar Publishers, 2000.

[8] Keeler, T. E. and Small, K. A., Optimal peak-load pricing, investment and service levels on urban expressways, Journal of Political Economy, Vol.85, No.1, 1977, pp.1-25.

[9] Mills, G., Welfare and revenue divergence for a tolled link in a road network, Journal of Transport Economics and Policy, Vol.29, No.2, 1995, pp. 137-146.

[10] Viton, P. A., Private roads, Journal of Urban Economics, Vol.37, No.3, 1995, pp. 260-289.

[11] Verhoef, E. T. and Rouwendal, J. Pricing, capacity choice, and financing in transportation networks, Journal of Regional Science, Vol.44, No.3, 2004, pp.405-435.

[12] Yang, H. and Meng, Q., Highway pricing and capacity choice in a road network under a Build-Operate-Transfer scheme, Transportation Research Part A, Vol.34, No.3, 2000, pp.207–222.

[13] Chen, A., Subprasom, K. and Ji, Z., A simulation-based multi-objective genetic algorithm (SMOGA) for BOT network design problem, Optimization and Engineering, Vol.7, No.3, 2006, pp.225–247.

[14] Chen, A. and Subprasom, K., Analysis of regulation and policy of private toll roads in a build-operate-transfer scheme under demand uncertainty, Transportation Research Part A, Vol.41, No.6, 2007, pp.537-558.

[15] Ben-Ayed, O., Boyce, D. E. and Blair, C. E., A general bi-level programming formulation of the network design problem, Transportation Research Part B, Vol.22, No.4, 1998, pp.311–318.

[16] Yin, Y., Genetic-algorithms-based approach for bilevel programming models, Journal of Transportation Engineering, Vol.126, No.2, 2000, pp.115-120.

[17] Anjomani, A., Need for land-use forecasting improvements in intergrated transportation-land use planning, N. Mastorakis and M. Jha (Eds.), Proc. 2nd WSEAS International Conf. on Urban Planning and Transportation (UPT '09), 2009.

[18] De Lotto, R., Assessment of Development and Regeneration Urban Projects: Cultural and Operational Implications in Metropolization Context, International Journal of Energy and Environment, Issue 1, Volume 2, 2008, pp. 25-34.

[19] Roscia, M,. D. Zaninelli, and Gh. Lazaroiu, Sustainable Urban Model through Fuzzy Logic Weights, International Journal of Energy and Environment, Issue 1, Volume 2, 2008, pp. 66-72.

[20] Boyce, D.E. (1980). A framework for constructing network equilibrium models of urban location. Transportation Science, Vol. 14 (1), pp. 77-96.

[21] Boyce, D., and L.G. Mattsson (1999). Modeling residential location choice in relation to housing location and road tolls on congested urban highway networks. Transportation Research Part B 33, pp. 581-591

[22] Chang, J.S. and Mackett, R.L. (2006) A bi-level model of the relationship between transport and residential location. Transportation Research Part B Methodological, 40 (2). pp. 123-146.

[23] Zhao, Y. and Kockelman, K. M., On-line marginal-cost pricing across networks: Incorporating heterogeneous users and stochastic equilibria, Transportation Research Part B, Vol.40, No.5, 2006, pp.424–435.

[24] Yin, Y., Multiobjective bilevel optimization for transportation planning and management problems, Journal of Advanced Transportation, Vol.36, 2000, pp.93-105.

[25] Osyczka, A. and Kundu, S., A new method to solve generalized multicriteria optimization problems using the simple genetic algorithm, Structural and Multidisciplinary Optimization, Vol.10, No.2, 1995, pp.94-99.

[26] Deb, K., Multi-Objective Optimization Using Evolutionary Algorithms. J. Wiley & Sons, Ltd, 2001.

[27] Dimitriou, L., T. Tsekeris, and A. Stathopoulos, Joint Pricing and Design of Urban Highways with Spatial and User Group Heterogeneity, NETNOMICS, Economic Research and Electronic Networking, Springer US, Vol. 10, No.1, 2009, pp. 141-160.

[28] Dimitriou, L. and A. Stathopoulos, Emerging Social Dilemmas in Managing Transportation-Related Carbon Footprint in Optimal Infrastructure Development, N. Mastorakis and M. Jha (Eds.), Proc. 2nd WSEAS International Conf. on Urban Planning and Transportation (UPT '09), 2009.

[29] NETCEN, Vehicle Emission Factor Database (V02.8), January 2003.

Loukas Dimitriou Dipl.-Ing. is a Civil Engineer and Research Associate in the Laboratory of Railways and Transport of the Dept. of Transportation Planning and Engineering, School of Civil Engineering, NTUA. His research

interests include transportation planning, network economics and optimization, game-theoretic modeling in transportation, artificial intelligence and applied econometrics.

Antonios Kaltsounis Dipl.-Ing., Dr.-Ing (Berlin) is a Civil Engineer and Lecturer at the Road Works Laboratory, Dept. of Transportation Planning and Engineering, School of Civil Engineering, NTUA. He served in many positions in the public sector, related to planning of future transportation infrastructure development projects.

Antony Stathopoulos is Professor and Head of Laboratory of Railways and Transport of the Dept. of Transportation Planning and Engineering, School of Civil Engineering, NTUA. His research and teaching activities include transportation systems planning and engineering, traffic network analysis and Intelligent Transportation Systems. His has an extensive involvement in ITS research and an active role in demonstration programs.