A COMPUTATIONAL MODEL OF ENVIRONMENTAL SUSTAINABILITY FOR MIXED TRAFFIC

Stella Papagianni, National Technical University of Athens, Iroon Polytechneiou 9, Zografou Campus, 15 780, Athens, Greece), email: stellap@mail.ntua.gr

Chrysa Papagianni, National Technical University of Athens, Iroon Polytechneiou 9, Zografou Campus, 15 780, Athens, Greece), email: chrisap@noc.ntua.gr

ABSTRACT

With the issue of environmental sustainability placed high up in the agenda of policy makers, there is a set of specific targets to meet including the decrease of air pollutants caused by vehicular traffic. The combined modal split and assignment problem for urban mixed traffic network is considered in conjunction with the minimization of vehicles emissions. The traveler's need to minimize travel time is considered in parallel with the environmental objective of cutting down on emissions and the results obtained by the joint optimization process could be further used to provide routing information and promote sustainable transport. Solutions, based on swarm intelligence and evolutionary computation, are applied to handle the multi-criteria multi-modal path finding problem in complex urban areas.

Keywords: green multimodal routing strategies; multi -objective optimization; swarm intelligence; evolutionary algorithms

1. INTRODUCTION

Transportation infrastructure development has been used in the past as a remedy to cope with the ever increasing need for transportation in the dynamic and challenging environment of modern cities. However, transportation policies oriented towards infrastructure development do not necessary address environmental sustainability issues. During the past decade on the infrastructure side, the complex networks of roads, railways, bridges, traffic lights and tolls have been coupled together with Intelligent Transport Systems (ITS). In order to provide for transportation needs in the future, the efficient orchestration and coordination of modern monitoring and management systems is crucial in order to tackle a wide range of objectives, including congestion as well as environmental pollution.

According to estimates from the European Commission, energy consumed by road transport in 2002 represents approximately 26% of the total energy consumption in the EU. Transport energy demand in 2030 has been projected to be 21% higher than in 2000 (Directorate General for Energy and Transport, 2006). Mobility has also been linked to the climate change problem with estimates that transport's share in greenhouse gas emissions (GHG) were already accounting for 28% of GHG emissions in 1998. Within this context, experts believe that road traffic generates 71% of emissions attributable to transport and expect an increase of 25% by 2050 if no action is taken (Directorate General for Energy and Transport, 2004) (Department for Transport, UK). For the aforementioned reasons, most cities adopt global traffic management services for assisting traffic planners and operators to mitigate congestion, reduce travel times and pollutant emissions.

With the issue of environmental sustainability placed high up in the agenda of policy makers, there is a set of specific objectives to meet including the decrease of air pollutants caused by vehicular traffic. Network managers, responsible for the operation of traffic control centers and global traffic management on behalf of city authorities, are preoccupied with policy targets like reducing vehicle emissions and energy consumption, as well as tackling congestion on multi-modal networks of metropolitan areas. Technological advances in recent years, including most prominently the deployment and implementation of ITS, are widely used for the enhanced management of traffic, through systems such as adaptive area-wide traffic control, real-time travel information, bus priority at traffic lights, smart card ticketing and car park management and guidance etc. The application of ITS in cities and regions can also provide network managers with an instrument suitable to influence travel behavior and promote non-motorized and eco-friendly modes. Furthermore, the provisioning of real-time information, via the deployment and application of such systems, can also aim to tackle vehicle emissions by presenting users with mode and route options that utilize network capacity with the objective to minimize GHG emissions.

Nonetheless, there is quite often a 'contradiction' between the environmental objectives described above and the objectives of travelers on multi-modal networks. The latter mainly seek to minimize their negative utility related to travel that includes travel time in price/cost of travelling, comfort etc. Especially for certain categories of trips such as work trips, parameters like the time spent commuting with regards to the VOT of groups of individuals becomes critical for the choice of the available modes and routes.

In most cases where the objective is to meet specific policy targets, a suitable approach would seek to find a 'compromising' solution between 'conflicting' objectives, i. e. minimising simultaneously vehicle emissions and individuals' travel time. In an operational context, by utilizing various devices, personalized travel planners for example, network managers can disseminate pre-trip information to travelers in order to provide them with modal and routing alternatives that take into consideration environmental objectives or real-time information so as to increase the capacity of the transportation network. Nonetheless, the impact that such information might have on the actual travel patterns of individuals on the multi-modal network cannot be accurately foreseen, as pro-environmental behavior and awareness varies significantly among travelers. The implementation of a pollution charging scheme for car users constitutes a policy instrument to address the matter.

Following the advances of bi-level programming approaches in addressing complicated traffic problems, Si et al. (2008b) developed a decision-making support model, where the problem of system performance optimization is treated in the upper level and the combined mode choice and assignment are represented in the lower level. The objective of their work is the definition of the appropriate policy variables i.e. the pricing of private cars and buses, in order to minimize congestion as well as personal travel cost. The above multi-criterion system optimization model for the urban multimodal traffic network was extended to include, further to congestion, factors such as environmental pollution and energy consumption, in the upper level of the optimization process (Si et al., 2011). In the work of Kim et al. (2009), the optimal freight system assignment and trade-off between freight costs and CO_2 emissions are identified and estimated by utilizing a multi-objective optimization problem. Although CO_2 emissions might be treated as a component of the external cost, it is argued that there are no conversion factors well-established and accepted to convert emissions to monetary terms. Thus the multi-objective optimization approach was considered more appropriate to address the problem.

Following the same incentive, the problem at hand, that is minimizing vehicle emissions in a multimodal transportation network, is formulated as a multi-objective optimization problem. We utilize a combined mode choice and assignment model for the urban mixed traffic network in order to consider simultaneously traveler's mode and route choice. The treatment of equilibrium is extended to mode choice modeling, to ensure that the travel times implied in the costs used to run the (user equilibrium) model are consistent with those generated during the assignment (Ortúzar & Willumsen, 2011). Interferences between different modes are taken into consideration by utilizing functions for link impedance developed by Si et al. (2008a, 2008b).

In the proposed multi-objective formulation, achieving user equilibrium for the urban mixed traffic network and minimizing vehicle emissions are considered as distinct objectives. Since the aforementioned goals are contradicting, there is set of congruent solutions, known as Pareto-optimal (Engelbrecht, 2006). Pareto-optimal solutions are non-dominated solutions in the sense that there are no other superior feasible solutions given the particular search space and set of objectives. In order to solve the problem, appropriate swarm intelligence and evolutionary computation approaches have been adopted.

In recent literature, metaheuristics have been increasingly utilized in the context of transportation research. Specifically evolutionary and swarm intelligence algorithms have been adopted for solving single or multi-objective formulations of transport network design problems. Yang et al. (2007) applied Ant Colony Optimization coupled with an evolutionary optimization mechanism to the NP-hard Urban Bus Network Design problem. Vitins et al. (2008) utilized the Ant Colony Optimization in order to address the Network Design Problem and evaluate in a time-efficient manner bundles of possible transport infrastructure projects taking into consideration the interdependencies between them. The same problem of the interdependent relationship of infrastructure projects was modeled as a variation of the multi-objective 0-1 knapsack problem by Gaytán et al. (2009) and NSGA–II algorithm was adopted for retrieving the Pareto front. Chevrier et al. (2011) addressed Demand Responsive Transport as a multi-objective optimization problem, with objectives related to operational costs, environmental sustainability and quality of service applying NSGA-II, Strength Pareto Evolutionary Algorithm 2 (SPEA-2) and Indicator based Evolutionary Algorithm (IBEA). Unnikrishnan et al. (2012) formulated the Continuous Network Design Problem that arises when users have access to information while traveling and make en-route routing decisions, as a bi-level mathematical programming network design, while two meta-heuristics (a Quantum-Inspired Genetic Algorithm and a Genetic Algorithm) were used to solve the problem. In a similar fashion, for the multi-objective optimization problem at hand, a Multi-objective Particle Swarm Optimization (MOPSO) (Coello, 2004) algorithm is applied and its efficiency is evaluated against a commonly used multi-objective Genetic Algorithm (NSGA-II) (Deb, 2002). To the extent of our knowledge, the application of PSO in the context of transportation research is limited.

The remainder of the study is organized as follows. In section 2, the multi-modal network design model is formulated, taking into consideration problem specific objectives related to environmental sustainability and efficient user transportation. Moreover a brief description of the adopted multi-objective optimization approaches (MOPSO/NSGA-II) is provided Following, in section 3, problem specific parameters are cited along with computational results and evaluation of the design methodology via an appropriate numerical example. In section 4, conclusions and future research steps are summarized.

2. MULTI-MODAL ROUTING PROBLEM DEFINITION

2.1 Problem Definition and Mathematical Formulation

A multi-modal transportation network is considered, where individuals can choose between emission-accountable (e.g. car, bus) and emission free modes (e.g. bike, electric mini bus). Travelers between a specific Origin-Destination (O-D) pair have access to all available modes, whereas mixed-mode movements are not considered in the context of this study. Mode choice and assignment are treated simultaneously by using a combined model. Environmental sustainability issues are addressed by minimizing emission from vehicular traffic. On the other hand, users arrange their traveling on the network so as to minimize individual costs. The proposed methodology seeks to find the optimal solution between the conflicting environmental objective and the interests of individuals (travel cost) on the multi-modal transportation network.

The transport network is modeled as a set A of available roads (links) and a set M of available modes that are further classified as emission-free or as modes accountable for GHG emissions. The distance for every link $\alpha \in A$ is denoted as L_α. The set of available modes M is comprised from $|K|$ emission-accountable modes (e.g. car, bus) and $|L|$ emission free modes (e.g. bike, electric mini bus) where $K \cup L = M$. Moreover total demand between every O-D pair $w \in W$ is denoted as q^w. Users' preferences are not taken into account in the optimization process. A simple vehicle emission model is adopted (Si et al., 2011), where only HC, CO and NO*x* pollutants are included in the emissions objective.

The multi objective formulation of the problem is stated as following:

Objectives:

$$\min \quad Z = \sum_{k=0}^{|K|-1} \sum_{\forall a \in A} \int_0^{x_a^k} t_a^k(\omega) d\omega + \sum_{l=0}^{|L|-1} \sum_{\forall a \in A} \int_0^{x_a^l} t_a^l(\omega) d\omega + \sum_{k=0}^{|K|-1} \sum_{\forall w \in W} \int_0^{q_k^w} g_k^w(\omega) d\omega + \sum_{l=0}^{|L|-1} \sum_{\forall w \in W} \int_0^{q_l^w} g_l^w(\omega) d\omega \qquad (1)$$

$$\min \quad \mathrm{E} = \sum_{\forall \alpha \in \mathrm{A}} \sum_{k=0}^{|K|-1} x_a^k \left[P_{\alpha,CO}^k + P_{\alpha,HC}^k + P_{\alpha,NO_x}^k \right] \tag{2}$$

Objective (1) addresses the combined mode choice and assignment problem for Wardrop's first principle while objective (2) denotes the minimization of HC, CO and NO*x* pollutants. The target is to find the appropriate set of $(\mathbf{x},\mathbf{q}) \in \Omega$ where x and q are vectors of traffic flow and O-D demand respectively. The search space Ω is constrained for the urban mixed traffic network as following:

$$\sum_{\forall k \in K} q_k^w = q_K^w \tag{3}$$

$$\sum_{\forall l \in L} q_l^w = q_L^w \tag{4}$$

$$\sum_{\forall k \in K} q_k^w + \sum_{\forall l \in L} q_l^w = q^w \tag{5}$$

$$\sum_{\forall n} f_m^{w,n} = q_m^w \tag{6}$$

$$x_a^m = \sum_{\forall w} \sum_{\forall n} f_m^{w,n} \delta_\alpha^{w,n} \tag{7}$$

The variable $f_m^{w,n}$ denotes travel demand for motor mode m on route n between O-D pair w and $\delta_\alpha^{w,n}$ is a decision variable; if road α is on the route n for O-D pair w then $\delta_\alpha^{w,n} = 1$.
Equation (3) provides traffic demand for emission-accountable modes and equation (4) for emission-free modes. Equation (5) defines that traffic demand for OD pair $w \in W$ is split between all available modes and (6) defines how traffic per mode is split between different routes n. The last equation denotes the traffic flow per mode $m \in M$ for road a.
The link impedance functions t_a^m are estimated according to Si et al. (2008b) so as to simulate a mixed traffic system.
The general cost functions for traffic modes $g_k^w(\mathbf{q})$ and $g_l^w(\mathbf{q})$ are defined according to Si et al (2011) as follows, in order to transfer the above mode-split and assignment problem into a logit model:

$$g_k^w(\mathbf{q}) = \frac{1}{\theta} \ln(\mathbf{q}) + \kappa M_k^w - \psi E_k^w, \forall k, w \tag{8}$$

$$g_l^w(\mathbf{q}) = \frac{1}{\theta} \ln(\mathbf{q}) - \psi E_l^w, \forall l, w \tag{9}$$

$$\mathbf{q} = [q_1^1, ..., q_1^w, ..., q_m^1, ..., q_m^w]^T \tag{10}$$

where M_k^w is the potential fee of mode k between O-D pair w and E_k^w the convenience and comfort of mode k and l between O-D pair w.
The emissions of HC, CO and NO*x* of emission-accountable modes k on road a, denoted as $P_{\alpha,CO}^k, P_{\alpha,HC}^k$ and P_{α,NO_x}^k respectively and are given by the following equations (Si, 2011):

$$P_{\alpha,CO}^{k} = a_{1}^{k}\left(\frac{L_a}{t_a^k}\right)^{\beta_1^k} \tag{11}$$

$$P_{\alpha,HC}^{k} = a_{2}^{k}\left(\frac{L_a}{t_a^k}\right)^{\beta_2^k} \tag{12}$$

$$P_{\alpha,NO_x}^{k} = a_{3}^{k}\left(\frac{L_a}{t_a^k}\right)^{\beta_3^k} + \frac{b^k L_a}{t_a^k} + c^k \tag{13}$$

$v_a^k = L_a / t_a^k$ denotes the average speed of mode k on road a and $\alpha_y^k, \beta_y^k, b^k, c^k$ are regression parameters corresponding to the various modes.

2.2 Pareto Front

The main goal of multi-objective optimization algorithms is to find an appropriate set of solutions that balance trade-offs among the various objectives of the multi-objective optimization problem in the most efficient way. Widespread approaches consist of (Engelbrecht, 2006) (i) weighted aggregation techniques where the fitness function is a weighted sum of the respective objective functions, (ii) criteria based methods where different objectives are evaluated in different stages of the optimization process and (iii) techniques based on Pareto dominance. Pareto-based techniques maintain a set of non-dominated solutions. Pareto-optimal solutions, when plotted in objective space, are collectively known as the Pareto front.
Given the multi-objective formulation presented in the previous section, the next step consists of the adoption of the appropriate technique for generating a set of Pareto solutions. A set of multi-objective meta-heuristics have been considered; a multi-objective version of the PSO algorithm which was introduced by Kennedy and Eberhart (1995) and a multi-objective GA were adopted for this purpose. Specifically MOPSO algorithm proposed by Coello et al. (2004) and NSGA-II by Deb et al. (2002) are utilized in the particular study. The adopted algorithms and their adaptation to identify Pareto solutions with attractive properties for the decision maker are the topics of discussion in this section.

2.2.1 MOPSO algorithm

The MOPSO algorithm was introduced by Coello et al (Coello, 2004). It is inspired from Multi-Objective Evolutionary Algorithms; therefore an external fixed repository similar to the adaptive grid of PAES (Knowles, 2000) is used in which every particle deposits its flight experiences after each flight cycle. The updates to the repository are performed considering a geographically-based system defined in terms of the objective function values of each particle. The search space is divided in hypercubes that are appointed a fitness value based on the containing number of particles as a form of fitness sharing. Roulette-wheel is applied to select the hypercube from which a leader for a particle of the swarm will be selected randomly. Following the calculation of the particles' new positions, reflective boundary

conditions and position clipping (Mikki, 2005) is applied and their respective fitness functions are evaluated. In order to retain a non-dominated archive of solutions, taken into consideration constrained optimization, Pareto dominance is applied according to the following principles; if both solutions are feasible, non-dominance is directly applied. If one of the two solutions is only feasible, it is denoted as the dominant one. If both are infeasible, then the one with the lowest amount of constraint violation dominates. A special mutation operator that enriches the exploratory capabilities of the algorithm is also used in the initial version of the MOPSO algorithm.
In the adopted algorithm the actual differences from the aforementioned MOPSO, is that time varying inertia weight (Shi et al, 1999) and velocity clamping (Eberhart et al, 1996) are applied as well as a modified Gaussian mutation scheme (Papagianni et al, 2009). The same mutation operator is also adopted for the multi-objective GA.

2.2.2 NSGA-II Algorithm

The non-dominated sorting genetic algorithm II (NSGA-II) was introduced by Deb et al in 2002. The archiving strategy of NSGA-II consists of parent and child populations where the non-dominated solutions of the offspring population are compared with that of parent solution. With each generation, solutions from the current population are ranked based on constrained dominance to different classes of non-dominated solution sets. Two values are assigned to each individual; (i) the rank to which the solution belongs as a measure of the quality of the solution based on Pareto dominance and (ii) a crowing distance which estimates the size of the largest cuboid enclosing a solution without including any other population member and is a measure of the diversity of obtained solutions. The crowing distance metric is used to further refine the set of (constrained) non-dominated solutions, since among two non-dominated solutions the one with the best crowding distance is considered better than the other. In the proposed implementation, uniform crossover and modified Gaussian mutation (Papagianni et al, 2009) are used to generate new offspring, while rank selection is then used to select the population for the next generation with a predefined population size.

3. RESULTS

3.1 Experimentation Setup

For the aforementioned problem formulation, a simple numerical example is used to illustrate the effectiveness of the solution. The multimodal transport network used consists of nine nodes (Fig. 2). One O-D pair (1-9) is considered. One emission-free mode (bike) and two emission-accountable modes (private car and bus) are available on every link.

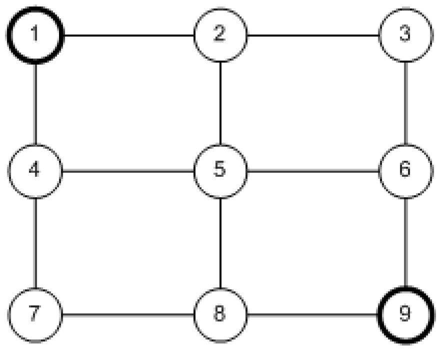

Figure 1 – Multimodal Transport network

The O-D travel cost functions are formulated by the logarithmic form given by Si et al (2011),as given in (8) and (9) with the corresponding parameters $\theta = 1$, $\kappa = 0{,}2$ and $\psi = 0.1$.

In order to estimate the fee M_k^w for mode car or bus, the value of time is assumed to be 7.5€/hr, the fare for a bus ticket across a route is 1.2€ and the average consumption per kilometer is 0.12€/km. The service level E_m^w for every mode was set according to Si et al (2008b).

Regarding the link impedance estimation, the free-flow travel time $t_a^{m(0)}(h)$ of mode m on road a, the capacity per mode $C_a^m(Ph^{-1})$ and length of the road $L_a(km)$ are provided by (Si et al., 2011). The link impedance functions, according to the same study, are stated as follows, for emission-accountable (i.e. car and bus) $k \in K$ and emission-free modes (i.e. bike):

$$t_a^k = t_a^{k(0)} \left[1 + a\left(\frac{v_a^K}{C_a^K} \right)^{\beta} \right] \left[1 + \gamma \left(\frac{x_a^{bike}}{C_a^{bike}} \right)^{\varphi} \right], \forall k, a \tag{14}$$

$$t_a^{bike} = t_a^{bike(0)} \left[1 + a\left(\frac{x_a^{bike}}{C_a^{bike}} \right)^{\beta} \right] \left[1 + \gamma \left(\frac{v_a^K}{C_a^K} \right)^{\varphi} \right], \forall a \tag{15}$$

where t_a^k is the travel time for emission-accountable mode $k \in K$ on road $a \in A$, and t_a^{bike} is the travel time for bike on road $a \in A$. The aforementioned equations are utilized in order to incorporate in the BPR functions the characteristics of different travel modes as well as the interferences among them, especially between motorized and non-motorized modes (Si et al., 2008a). Furthermore, equations (14) and (15) describe interferences in the case of a road with barriers between the two opposite directions and no barriers between motorized and non-motorized traffic.

Other parameters related to link impedance are $\beta = \varphi = 4$, $\alpha = 0.15$ and $\gamma = 0.1$. The passenger car unit flow of motor mode k on link a is given by $v_a^K = \sum_{\forall k \in K} v_a^k = \sum_{\forall k \in K} x_a^k \frac{U_k}{A_k}$ (Si et al., 2008b), where U_k is the PCU conversion coefficient of motor mode k and A_k is occupancy rate of mode k (Table 1). Regression parameters for the emission estimator functions (11) are also provided in Table 1.

Table 1 – Parameter selection

Mode	U_k	A_k	a_1^k	a_1^k	a_1^k	β_1^k	β_1^k	β_1^k	b^k	c^k
Car	1	4	68.72	1229.8	0.0002	−0.7760	−0.9314	2	0.0176	2.0514
Bus	1.5	20	102.89	901.49	0.0006	−0.7093	−0.8367	2	0.0556	5.2588

The total travel demand, q^w , is used to describe congestion level of the urban mixed traffic network. A simple scenario is considered with q^{1-9} =15000 Ph^{-1} .

3.2 Algorithms Parameter Selection

Swarm/population size was set to 200 while the number of iterations was set to 1000 for MOPSO and NSGA-II, to keep the same number of fitness function evaluations. The 200 particles of the swarm/population were initialized randomly on both cases.
Regarding MOPSO, standard parameter configuration $\{w=0.7298, c_1=c_2=1.49618\}$ was selected. Velocity clamping is usually applied at 10% - 20% of the dynamic range of each control parameter. In this case the upper limit was adopted. The modified Gaussian mutation scheme was employed with probability $p_{mut}=5\%$. Regarding the specifics of the MOPSO algorithm such as repository size and number of divisions for the adaptive grid the default values proposed by Coello et al (2004) were adopted.
For the GA, algorithmic parameters w are fine-tuned accordingly. In this sense, rank selection was utilized along with uniform crossover with probability $p_{cross}=90\%$ and modified Gaussian mutation with probability $p_{mut}=5\%$. Population is complemented (10%) with elitism.

3.3 Evaluation

The target is to compare the Pareto fronts that are obtained with the same number of fitness evaluations. The "known" Pareto Front (PF_{known}) is obtained, where $(PF_{known})=\bigcup_{i=1}^{i=10} PF_{known}^{i}$, and PF_{known}^{i} is the front acquired by each algorithm run (Van Veldhuizen, 1999). The results, obtained from the NSGA-II and the MOPSO optimization process, are depicted in Fig. 2.
Extreme left hand side values of the Pareto front with regards to the Objective (1), approximate the UE solution while at the same time provide an indicator of the estimated cost of emissions. Specifically, the Pareto solution {82351.59, 5.05} matches the UE solution. Table 2 shows the estimated equilibrium link flows and the corresponding travel times of traffic modes for q^{1-9} =15000 Ph^{-1}. In total approximately 54% of the traffic is routed via car, 40.5% by bus and 5.5% by bike.
As we move towards the right hand side of the front, selecting, a non-dominated solution that provides a better emission objective value, e.g. point {82775.96, 4, 6}, we observe that a 9% reduction of the emission objective results to 1% increase in the modal split and assignment objective that is translated to 3% reduction of traffic flow on car mode that is distributed by 2% to bus and 1% to bicycle. Changes up to 5% are observed regarding travel time on the various links. It is up to the network manager - based on the acceptable level of emissions, to

provide users with appropriate routing information that will navigate them in an eco-friendly way through the city.

As the true Pareto set is not known, the quality of the fronts $\left(PF_{known}\right)$ obtained by the two algorithms is compared through the coverage indicator or C-metric (Engelbrecht, 2006):

$$I_c(A,B) = \frac{\left\{\vec{b} \in B \mid \exists \vec{a} \in A : \vec{a} \prec \vec{b}\right\}}{|B|} \tag{15}$$

Coverage is a relative indicator measuring the fraction of solutions in front B that are dominated by at least one solution in front A. In the particular case study, since $I_c\left(PF_{known}^{NSGA-II}, PF_{known}^{MOPSO}\right) \approx 0.2\% < I_c\left(PF_{known}^{MOPSO}, PF_{known}^{NSGA-II}\right) \approx 33\%$, the set of non-dominated solutions in PF_{known}^{MOPSO} has a better convergence to the Pareto front.

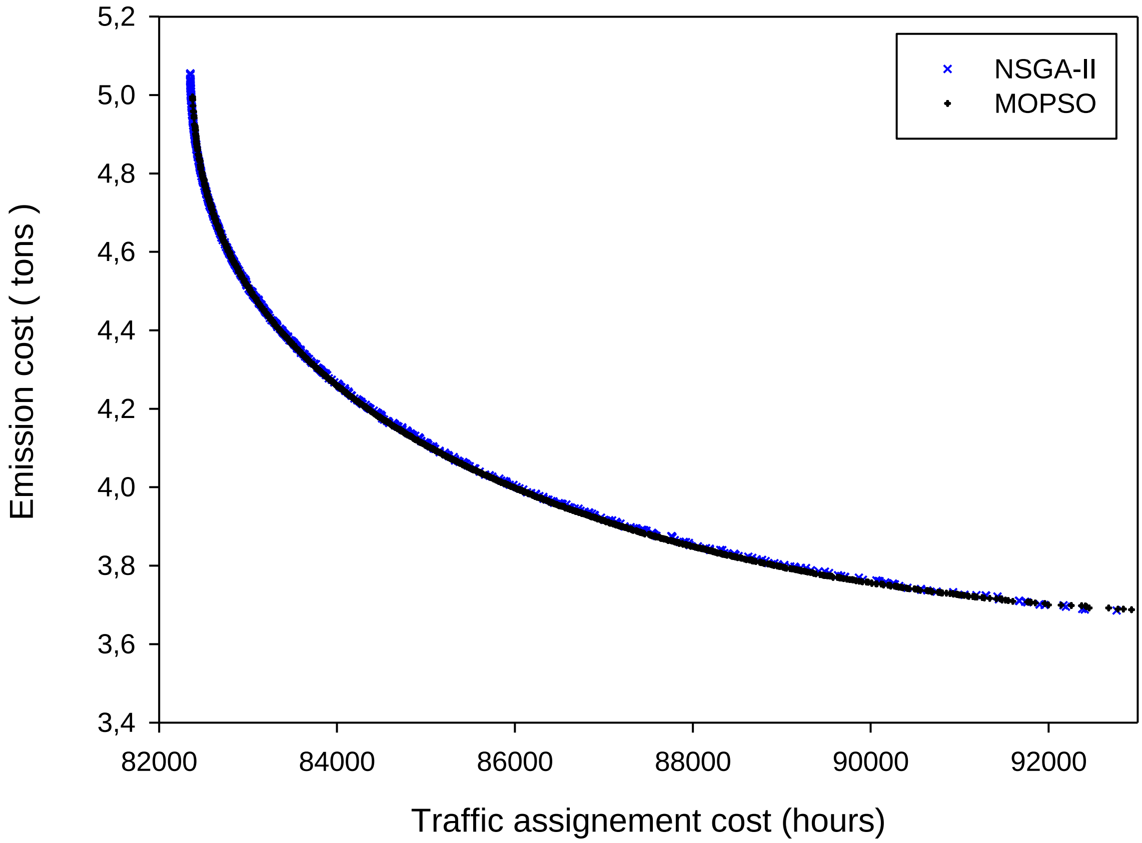

Figure 2 – Pareto front (NSGA-II, MOPSO)

Table 2 – Demand and travel time per link

Link	$x_a^{car}\left(Ph^{-1}\right)$	$x_a^{bus}\left(Ph^{-1}\right)$	$x_a^{bike}\left(Ph^{-1}\right)$	$t_a^{car}(h)$	$t_a^{bus}(h)$	$t_a^{bike}(h)$
(1,2)	3824.864	2961.47	355.4657	0.145	0.232	0.317
(2,3)	2499.492	1948.719	204.038	0.157	0.238	0.322
(1,4)	4279.614	3146.423	431.4122	0.11	0.183	0.268
(2,5)	2863.554	2283.005	252.6912	0.149	0.242	0.33
(3,6)	3357.014	2451.044	327.242	0.157	0.275	0.371
(4,5)	3465.484	2537.735	327.2305	0.093	0.172	0.26
(5,6)	3117.016	2387.501	285.3323	0.106	0.182	0.267
(4,7)	2965.843	2110.591	262.0661	0.154	0.232	0.315
(5,8)	3061.923	2359.827	275.7005	0.169	0.272	0.359
(6,9)	3601.447	2887.229	343.5241	0.299	0.439	0.524
(7,8)	2965.843	2110.591	262.0661	0.109	0.187	0.271
(8,9)	4503.031	3220.665	443.3538	0.191	0.319	0.419

4. CONCLUSION AND FUTURE RESEARCH

The presented study tackles the problem of eco-efficient multi-modal routing in a complex transportation environment. For that reason, the corresponding network design model is formulated as a multi-objective optimization problem with the goal to minimize i. travel time for the end user and ii. emissions attributable to transport. In order to solve the problem, we investigate the application of evolutionary based algorithms, namely MOPSO and NSGA-II. The research directions that we will explore in depth in the coming time are related to i. exploring advanced emission estimation models within the multimodal routing problem, ii. including energy efficiency concepts in the optimization process, iii. investigating alternative optimization methods tailored to real time trip planning ensuring large scale application of the proposed module.

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