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Handling multiple objectives in optimization of externalities as objectives for dynamic traffic management

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Dynamic traffic management (DTM) is acknowledged in various policy documents as an important instrument to improve network performance. This network performance is not only a matter of accessibility, since the externalities of traffic are becoming more and more important objectives as well. Optimization of network performance using DTM measures is a specific example of a network design problem (NDP) and incorporation of externality objectives results in a multi objective network design problem (MO NDP)). Solving this problem resorts in a Pareto optimal set of solutions. A framework is presented with the non-dominated sorting algorithm (NSGAII), the Streamline dynamic traffic assignment model and several externality models, that is used to solve this MO NDP. With a numerical experiment it is shown that the Pareto optimal set provides important information for the decision making process, which would not have been available if the optimization problem was simplified by incorporation of a compensation principle in advance. However, in the end a solution has to be chosen as the best compromise. Since the Pareto optimal set can be difficult to comprehend, ranking it may be necessary to assist the decision makers. Cost benefit analysis which uses the economic compensation principle is a method that is often used for ranking the alternatives. This research shows, that travel time costs are by far the most dominant objective. Therefore other ranking methods should be considered. Differences between these methods are explained and it is illustrated that the outcomes and therefore the eventual decisions taken can be different.

Keywords: *multi objective network design problem, transport externalities, dynamic traffic management, cost benefit analysis, multi criteria decision making.*

1. Introduction

Better utilization of our existing road network is an important part of mobility policies in many European and other countries in the world. In addition, many governments focus on facilitating

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mobility growth to allow for economic growth, but national and international policies postulate strict requirements on air quality, climate, noise and safety. Considering these externalities of traffic within the field of dynamic traffic management (DTM) is therefore an increasingly important trend, which is for example shown by extensions of the Dutch policy "Gebiedsgericht Benutten" (sustainable traffic management) and the European project eCoMove (Bresser et all., 2013). Besides economic objectives, the notion arises that DTM measures can also be used to improve livability objectives. Improvements are possible on a local level, where the level of service influences externalities, but also on a network level by influencing the amount of traffic using different road types. Minimizing externalities of traffic can therefore be objectives for the determination of settings of DTM measures.

Optimization of an objective using DTM measures is a specific example of a Network Design Problem (NDP). A significant portion of research on optimization in traffic and transport considers a single objective related to the economic objectives (Zhang and Lu, 2007; Gao et al., 2005). However as shown, it is of interest to incorporate externalities of traffic as objectives. The presence of multiple conflicting objectives makes the optimization problem interesting to solve. In general no single solution can be termed as the optimal solution, so the resulting multi-objective (MO) NDP resorts to a number of trade-off optimal solutions, known as Pareto optimal solutions. In our research a framework is developed for optimizing efficiency, climate, air quality, traffic safety and noise using DTM measures on a strategic level. The outcome of an optimization using this framework results in Pareto optimal traffic management strategies. These strategies concern the deployment of DTM measures in a network to optimize the externalities considering route choice effects. Using this framework provides knowledge for a decision support system which can help decision makers to choose the best traffic management strategy for a certain region. In this framework the objectives are intentionally considered separately and not weighted in advance. Mathematical modeling of such a highly complex socio-technical system provides insight into the extent to which objectives are conflicting or not and the consequences related to weights used concerning the trade-offs, which is very useful in the decision making process. However, in the end one solution has to be chosen for implementation, which represents the best compromise solution. The Pareto optimal set of solutions can become large, especially if the objectives are mainly opposed. As a consequence the Pareto optimal set may become difficult to analyze and to comprehend. In this case ranking the solutions part of this set is necessary to assist the decision maker.

Wismans et al. (2012) presented several pruning and ranking methods for the Pareto optimal set. In this paper we focus on the methods to rank the solutions, adding the results and consequences of the often used cost-benefit analysis. In addition, we further elaborate on the main ranking methods and their sensitivity for weighting factors. We use different ranking methods to show that the outcomes and decisions that are taken based on these can become quite different. In addition, we show that monetizing the effects is probably not the best way for weighting the objectives. Therefore, it is of importance to determine what method corresponds best with the underlying decision process and is in accordance with the data quality. These methods are applied using the outcome of solving the dynamic MO NDP in which minimizing externalities of traffic are the objectives and DTM measures are the decision variables. For this, we solved the dynamic MO NDP for a realistic network of the city Almelo in the Netherlands using the Streamline dynamic traffic assignment (DTA) model (Raadsen et al., 2010) and non-dominated sorting genetic algorithm II (NSGAII) developed by Deb et al. (2002).

2. Multi objective network design problem

The NDP is usually formulated as a bi-level problem in which the lower level describes the behavior of road users that optimize their own objectives (travel time and travel costs), modeled by solving the user equilibrium problem. Since DTM measures are the decision variables and traffic dynamics are important explanatory variables assessing the effects on externalities, a DTA model to solve the lower level is required. The upper level consists of the objectives that have to be optimized by solving the NDP. Because of the non convexity of the problem (Gao et al., 2005; Chiou, 2005), often heuristics are used to optimize the total system.

The NDPs are typically grouped into discrete problems (DNDP), in which the decision variable is a discrete variable (Gao et al., 2005; Poorzahedy and Turnquist, 1982), continuous problems (CNDP), in which is assumed that the decision variable is a continuous variable (Chiou, 2005; Dantzig et al., 1978; Friesz et al., 1993; Meng et al., 2001; Xu et al., 2009; Zhang and Lu, 2007), and mixed problems, which is a combination of both (Cantarella et al., 2006). Based on demand, NDPs can be grouped into fixed demand (Meng et al., 2001), stochastic demand (Waller and Ziliaskopoulos, 2001; Chen et al, 2010) and (stochastic) elastic demand (Ukkusuri and Patil, 2009). Based on the way time is considered, NDPs can be classified into static, in which stationary travel demand and infrastructure supply is assumed (used in all but one of the above mentioned studies), or dynamic, which is more realistic but rarely used (Waller and Ziliaskopoulos, 2001; Brands et al., 2009). Traditionally, the NDP is associated with the minimization of the total travel time using infrastructural investment decisions under a budget constraint. Most of the previous works consider fixed demand, and use a static user equilibrium to model the lower level. There are also other design variables of networks that can be considered as an NDP. Brands et al. (2009) studied for example optimal tolling and Cantarella et al. (2006) the optimal signal setting in combination with lane layout.

In most cases, single objective network design problems are studied in which accessibility, expressed as the total travel time in the transportation network (Zhang and Lu, 2007; Gao et al., 2005), is optimized. Different studies incorporated the investment costs within the objective function. Chiou (2005), Meng et al. (2001) and Xu et al. (2009) optimized total travel time in which the investment was translated into time using a conversion factor. Or in which travel time is translated into cost (Poorzahedy and Turnquist, 1982; Drezner and Wesolowsky, 2003). Occasionally other costs, like environmental costs (expressed in money), are added to the travel cost (Cantarella et al., 2006; Matthew and Sharma, 2005). There are less studies that use multiple objective functions in the upper level. Chen et al. (2010) use travel time and construction costs as two separate objective functions and used an evolutionary algorithm. Friesz et al. (1993) focuses on minimizing the transport costs, construction costs, vehicle miles traveled and dwelling units taken for rights-of-way and used a weighted sum approach in combination with simulated annealing. Sharma et al. (2009) used an evolutionary algorithm to minimize total travel time and the higher moment for total travel time i.e. variance.

In general, solving the MO NDP results in a set of Pareto optimal solutions. The data characteristics of the outcome of most MO NDP are deterministic (i.e. point estimates) with a level of uncertainty. In the end, out of this Pareto optimal set one compromise solution for actual implementation has to be chosen. Surprisingly, this issue is rarely addressed in MO NDP literature. To support this decision often cost-benefit analysis (CBA) in which all effects are monetized, is used to select the best compromise solution. This kind of compensation principle is also often used to simplify the MO NDP into a single objective NDP as indicated earlier in this section. Next to CBA there are more multi-criteria decision making (MCDM) methods available and the literature on MCDM is extensive. However, Tzeng and Tsaur (1997) is one of the rare applications in which a ranking method was applied to select a compromise solution after solving a MO NDP: the ELimination Et Choix Traduisant la REalité III (ELECTRE III) method was used to select a compromise solution minimizing government budget and total travel time of road users by improving a metropolitan network. Because there are various MCDM methods available, it is of importance to determine what the consequences are of choosing a certain method related to the MO NDP.

3. Optimization problem and framework

3.1 Optimization problem

The MO optimization problem that we consider is formulated as the following MO MPEC (mathematical problem with equilibrium constraints):

$$\min_{S\in F}\begin{pmatrix} z_1(S) \\ z_2(S) \\ \vdots \\ z_I(S) \end{pmatrix}, \quad \text{subject to} \quad \big(q(S), v(S), k(S)\big) \in \Gamma^{DTA}\Big(G\big(N, A(C(S))\big), D\Big), \tag{1}$$

in which S is a set of applications (i.e., specific settings) of strategic DTM measures to be selected from a set of feasible applications F, and $z_i(S)$, $i=1,\dots,I$, the ith objective function, which is a function $f_i(\cdot)$ of link flows $q(S)$, link speeds $v(S)$, and link densities, $k(S)$, expressed as $z_i(S)=f_i\big(q(S),v(S),k(S)\big)$. These objectives in our case concern efficiency, climate, air quality, traffic safety and noise. Furthermore, the link flows, speeds, and densities are assumed to follow from solving a dynamic user equilibrium problem, indicated by Γ^{DTA}, for which the supply of infrastructure is given by network G with nodes N and links A (with corresponding characteristics C), and the (dynamic) travel demand by the set of time-varying origin-destination matrices D. The link characteristics without any DTM measures, which we denote by C_0, include the outflow capacity, the number of lanes, the free-flow speed, the speed at capacity, and the jam density, and are all captured in a fundamental diagram. Streamline (Raadsen et al., 2010), part of the OmniTRANS transport modelling software, is a state-of-the-art DTA model that we use to find a dynamic user equilibrium solution. It contains an advanced macroscopic network loading procedure, namely a multiclass second order cell transmission model with physical queuing and spillback, and a sophisticated route choice model that can handle route overlap, namely a paired combinatorial logit (PCL) model on a pre-generated route set. An iterative approach using the method of successive averages is used to converge to a dynamic user equilibrium.

The DTM measures considered and defined in S are the measures which influence the supply of infrastructure (e.g. traffic signals, ramp metering, rush hour lanes, dynamic speed limits). By determining the dynamic user equilibrium the route choice effects of changes in the supply of infrastructure are taken into account. However, this also means that DTM measures which influence route choice behavior directly (e.g. providing route information) are not considered. The DTM measures are modeled as measures that influence the characteristics C of the links where the measures are implemented. This means for example that if a Variable Message Sign (VMS) is used to change the speed limit, the free-flow speed and capacity of the links connected with this measure is changed. The characteristics C of links can therefore vary over time depending on the settings of the DTM measures, S. The impact of a measure depends on the actual settings, e.g. the green time for a certain direction on a signalized intersection. Activation times and settings of the DTM measures are discretized, so the upper level then becomes a discrete optimization problem where for each time period a certain DTM measure with a certain setting is implemented or not. The set of feasible solutions, F, is assumed to be a discrete set of possible applications of strategic DTM measures. If we assume that there are B different DTM measures available in the network, the application of the DTM measures in time step t is defined by $S(t)=\big(s_1(t),\dots,s_B(t)\big)$, where each $s_b(t)$, $b=1,\dots,B$, can have M_b different settings. We simply number these discrete settings from 1 to M_b. The set of feasible solutions can therefore be written as $F=\{S \mid s_b(t)\in\{1,\dots,M_b\}, \forall t=1,\dots,T\}$, such that there are $\big(\prod_b M_b\big)^T$ possible solutions. The set of applications of the DTM measures for all time periods is defined by $S=\big(S(1),\dots,S(T)\big)$ and forms a possible solution for the optimization problem.

3.2 Objective functions

Based on an extensive literature review (Wismans et al., 2011a), for each objective an objective function f_i is defined, where the input stems from the DTA user equilibrium solution. Efficiency is defined in terms of the total travel time in the network. Traffic safety is measured in terms of the total number of injury accidents and climate is represented by the total emission of CO_2. Air quality is defined as the weighted total amount of emissions of NO_x. The emission calculations are based on the ARTEMIS traffic situation based emission model (Infras, 2007), which means dependent on the level of service of the traffic flows. Traffic safety is defined as the number of accidents and determined based on an accident risk based model, derived from (Jansen, 2005). Finally, noise is calculated as the average weighted sound power level, in which the weights of noise emissions depend on the level of urbanization, and emissions are based on a load and speed dependent emission function of the Dutch RMV noise model (RMV, 2006). The weights of noise emissions and emissions related to air quality depend on the level of urbanization. The objective functions used, which all should be minimized, are listed in Table 1.

Table 1. Overview of measures and objective functions used

Objective	Measure	Remark
Efficiency	Total travel time (h)	Because fixed demand is assumed, minimizing total travel time is equal to minimizing vehicle lost hours.
	$z_1 = \sum_a \sum_t \sum_m \frac{q_{am}(t)\ell_a}{v_{am}(t)}$ (2)	
Traffic safety	Total number of injury accidents	Calculation based on using the relation between exposure and risk per road type.
	$z_2 = \sum_a \sum_t \sum_m \sum_d q_{am}(t)\delta_{ad} R_{md} \ell_a$ (3)	
Climate	Total amount of CO_2 emissions (grams)	Calculation based on traffic situation based emission model ARTEMIS.
	$z_3 = \sum_a \sum_t \sum_m \sum_d q_{am}(t)\delta_{ad} E_{md}^{\mathrm{CO2}}\left(v_{am}(t)\right)\ell_a$ (4)	
Air quality	Weighted total amount of NO_x emissions (grams)	Calculation based on a traffic situation based emission model ARTEMIS.
	$z_4 = \sum_a \sum_t \sum_m \sum_d w_a q_{am}(t)\delta_{ad} E_{md}^{NO_x}\left(v_{am}(t)\right)\ell_a$ (5)	
Noise	Weighted average Sound Power Level at the source (dB(A))	Calculation based on the standard calculation method (RMV) used in the Netherlands.
	$z_5 = 10\log\left(\frac{\sum_a \sum_w \delta_{aw}\ell_a 10^{\frac{\bar{L}_w - \eta_w}{10}}}{\sum_a \sum_w \delta_{aw}\ell_a}\right)$, with $\bar{L}_w = 10\log\left(\frac{\sum_a \sum_t \delta_{aw}\ell_a \Delta t \sum_m 10^{\frac{L_m(v_{am}(t))}{10}}}{T\sum_a \delta_{aw}\ell_a}\right)$, where $L_m\left(v_{am}(t)\right) = \alpha_m + \beta_m \log\left(\frac{v_{am}(t)}{v_m^{\mathrm{ref}}}\right) + 10\log\left(\frac{q_{am}(t)}{v_{am}(t)}\right)$ (6)	

with

z_1	: Objective function efficiency (= total travel time) *(h)*
z_2	: Objective function traffic safety (= number of injury accidents)
z_3	: Objective function climate (= total amount of CO_2 emissions) *(grams)*
z_4	: Objective function air quality (= weighted total amount of emissions of NO_x) *(grams)*
z_5	: Objective function noise (= weighted average sound power level at source) *(dB(A))*
$q_{am}(t)$	: Vehicle type m inflow to link a at time t *(veh)*
$v_{am}(t)$	: Average speed of vehicle type m on link a at time t *(km/h)*
R_{md}	: Injury accident risk of vehicle type m for road type d *(injury accidents/(veh*km))*
$E_{md}^{\mathrm{CO2}}(\cdot)$	: CO_2 emission factor of vehicle type m, depending on average speed *(grams/(veh*km))*
$E_{md}^{NO_x}(\cdot)$	:Emission factor of NO_x of vehicle type m on road type d, depending on average speed *(grams/(veh*km))*
$L_m(\cdot)$	: Average sound power level for vehicle type m, depending on the average speed *(dB(A))*
$\bar{L}_w$	: Weighted average sound power level on network part with urbanization level w *(dB(A))*
ℓ_a	: Length of link a (km)
δ_{ad}	: Road type indicator, equals 1 if link a is of road type d, and 0 otherwise
δ_{aw}	: Urbanization level indicator, equals 1 if link a has urbanization level w, and 0 otherwise
η_w	: Correction factor for urbanization level w *(dB(A)))*
w_a	: Level of urbanization around link a
α_m, β_m	: Parameters dependent of vehicle category for noise calculations
v_m^{ref}	: Reference speed dependent of vehicle category

3.3 Solution method

In bi-level optimization studies, solution approaches using evolutionary algorithms (EA) have been proven successful. A comparison of methods has shown that the NSGAII method performs well for the MO NDP (Wismans et al., 2011b). EA are inspired by the process of natural evolution, and are important tools for several real-world applications. They use a set of solutions (population) to converge to the optimal design. Within their search they use some fitness function to determine the performance of the different solutions, which is used within a selection process of parents (current solutions) which have a higher chance of survival and reproduction creating off-spring (i.e., new and hopefully better solutions). For reproduction, genetic operators like recombination and mutation are used. EA are robust optimization methods, which do not require gradients of the objective function, they can handle noisy objective functions, and they can avoid premature convergence to local optima. NSGAII, implemented in Matlab®, contains elitism, which means preservation of good solutions, and uses some kind of fitness sharing, which is a niching technique, to maintain population diversity. The preservation of good solutions is guaranteed by the environmental selection step, which is a deterministic step in which an archive is maintained containing the best solutions. The number of solutions contained in the archive is constant over time, which means that if the number of non-dominated solutions is smaller than the archive size, the archive is filled with all non-dominated and the best dominated solutions, while if the number of non-dominated solutions is larger than the archive size the archive only contains the best non-dominated solutions. In the latter case mainly the influence of fitness sharing is decisive for the solutions selected for the archive. This algorithm is highly efficient in obtaining good Pareto optimal fronts for any number of objectives, which makes it attractive for this research effort. Note that the algorithm itself, which depends on the archive size, already uses some kind of pruning in which diversity in the solution space is maintained.

NSGAII is developed by Deb et al. (2002). Within the algorithm the fitness assignment is carried out in two steps. In the first step called non-dominance sorting, the solutions are ranked based on Pareto dominance. This is determined by setting the rank of non-dominated solutions as rank 1, extract these solutions from the total set, and select from the remaining solutions again those non-dominated solutions and set those as rank 2, etc. The second step is sorting the solutions within a certain rank by using a crowded distance measure, which means sorting based on diversity in which solutions in a highly populated area will be assigned a lower fitness within its rank. The crowded distance is a measure that is determined by the distances between the neighbor solutions of the assessed solution in the objective space and the way fitness sharing is designed. The preservation of good solutions is done by the environmental selection step in which an archive is maintained containing the best solutions, based on their Pareto dominance, and if necessary their crowded distance sorting, considered so far. This archive contains the solutions used for the mating selection. This mating selection is done using binary tournament selection with replacement (i.e. parents selected for the current tournament are candidates for other tournaments).

NSGAII in steps, for more information we refer to Deb (2001) and Deb et al. (2002):

Step 1. *Initialization*: Set population size W_p, which is equal to the archive size W_u, the maximum number of generations *H*, and generate an initial population U_0. Set $h = 0$ and $Q_0 = \varnothing$.

Step 2. *Fitness assignment*: Combine archive U_h and children Q_h, forming $R_h = U_h \cup Q_h$ and calculate fitness values of solutions by dominance ranking and crowded distance sorting.

Step 3. *Environmental selection*: Determine new archive U_{h+1} by selecting the W_u best solutions out of R_h based on their fitness.

Step 4. *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of U_{h+1} with dominance rank 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.

Step 5. *Mating selection*: Perform binary tournament selection with replacement on U_{h+1} to determine mating pool of parents P_{h+1}.

Step 6. *Variation*: Apply recombination and mutation operators to the mating pool P_{h+1} to create offspring Q_{h+1}. Set $h = h+1$ and go to step 2.

3.4 Ranking methods

After obtaining the Pareto optimal set, ranking methods can be used to assist the decision maker to comparatively analyze a set of promising solutions. The ranking methods are basically methods used for MCDM. There are numerous ranking methods described in the literature that can be classified according to the type of data they use (deterministic, stochastic or fuzzy). However, there may be situations which involve combinations of data types. All methods basically try to rank the solutions by comparing the performance of these solutions on the individual objectives. In this paper these methods are used to rank the solutions within the Pareto optimal set $X^* = \{S_1^*, .., S_n^*\}$ obtained using NSGAII. Note that the solution method used determines a subset of an approximation (since it is a heuristic) of the Pareto optimal set of solutions. As a result the ranking methods are possibly subject to rank reversals (Triantaphyllou and Mann, 1989).

The CBA method is an often used ranking method to select the best compromise solution. However, there are more interesting methods available and also used within the field of transportation. In this research the CBA method and elementary Weighted Sum Method (WSM) are applied as well as the Analytical Hierarchy Process (AHP) and the ELECTRE III method which is an outranking method. These methods are chosen because these are widely used (Macharis and Ampe, 2007). In all ranking methods, weights can be used to consider the trade-offs between objectives and none of these ranking methods guarantees that there is only one solution with the best rank. Table 2 provides the methods which we all implemented in Matlab® (Triantaphyllou and Mann, 1989; Triantaphyllou et al., 1989; Saaty, 2008; Buchanan et al., 1999; Roy et al., 1986; Roy, 1991).

Table 2. Overview ranking methods

Method	Explanation
WSM	The weighted sum method calculates the score WSM of each solution S_p by summing the (normalized[4]) objective values $z_i^N(S_p)$ for each objective. Normalization in this case is done by scoring each solution on each objective between the maximum and minimum value within the Pareto optimal set. These normalized values can be weighted using relative weighting factors θ_i dependent on objective z_i. $WSM(S_p) = \sum_i \theta_i z_i^N(S_p)$ This is the traditional often used ranking method within the multi-criteria decision analysis in which all objectives are linearly weighted. Normalization or same units of measurement for all objectives is needed for this technique to assure each objective has more or less the same magnitude when all objectives are equally weighted. However, the

[4] Normalization of objective values itself can introduce rank reversal, dependent of the normalization procedure chosen. However, normalization is necessary while different units violates the additive utility assumption of WSM.

	normalization procedure can introduce rank reversal. The lower the value of WSM, assuming all objectives should be minimized, the higher this solution is ranked.
CBA	A variant of the WSM method is the also often used cost-benefit analysis in which the weights θ_i represent the economic trade-off between the objectives and therefore all effects are translated into costs. Within this research the monetary values are derived from the Handbook on estimation of external costs in the transport sector which is a product of the European project 'IMPACT' (Maibach et al., 2008). Point of attention is that all external costs use linear weighting except for noise.
AHP	Without decomposition of the MCDM problem into a system of hierarchies or using Saaty's scale of relative importance's, this method can be used to rank solutions based on their AHP score. This score is calculated by $$AHP(S_p)=\sum_i \theta_i \frac{z_i(S_p)}{\sum_n z_i(S_n)}$$ This method is also dimensionless, however is sensitive for rank reversal. The lower the value of AHP the higher this solution is ranked. Alternatively the revised AHP is proposed to reduce the influence of rank reversal, although it is not eliminated. This score is calculated by $$AHP_{rev}(S_p)=\sum_i \theta_i \frac{z_i(S_p)}{\max_n z_i(S_n)}$$ The similarity between the AHP and WSM is evident. The main difference is related to the normalization which is needed in WSM and incorporated in AHP.
ELECTRE III	The ELECTRE III method is specifically designed to deal with inaccurate or uncertain data for ranking problems, by using thresholds of indifference and preference. This method tests the assertion if $S_{p1}\mathbf{S}S_{p2}$, meaning solution S_{p1} is at least as good as OR is not worse than solution S_{p2} using a concordance and discordance principle. The concordance principle requires that a majority of criteria, considering their relative importance is in favor of the assertion. The discordance principle requires that the minority of criteria which do no support this assertion are not strongly against this assertion in terms of outcome in objective value and is taken into account by using a veto threshold. Within this approach a credibility matrix is produced, which assesses the strength of the assertion $S_{p1}\mathbf{S}S_{p2}$, by $$CI(S_{p1},S_{p2})=\begin{cases} C(S_{p1},S_{p2}), \text{ if } d_i(S_{p1},S_{p2})\le C(S_{p1},S_{p2}),\forall i \\ C(S_{p1},S_{p2}) \prod_{i\in I, I=\{i\mid d_i(S_{p1},S_{p2})>C(S_{p1},S_{p2})\}} \frac{1-d_i(S_{p1},S_{p2})}{1-C(S_{p1},S_{p2})} \end{cases}, \text{ otherwise, in which}$$ $$C(S_{p1},S_{p2})=\sum_i \theta_i c_i(S_{p1},S_{p2}) \text{ and}$$ $$c_i(S_{p1},S_{p2})=\begin{cases} 1, & \text{if } z_i(S_{p1})-\omega_i \le z_i(S_{p2}) \\ 0, & \text{if } z_i(S_{p1})-\rho_i \ge z_i(S_{p2}) \\ \frac{\rho_i+z_i(S_{p2})-z_i(S_{p1})}{\rho_i-\omega_i}, & \text{otherwise} \end{cases}$$ $$d_i(S_{p1},S_{p2})=\begin{cases} 0, & \text{if } z_i(S_{p1})-\rho_i \le z_i(S_{p2}) \\ 1, & \text{if } z_i(S_{p1})-\upsilon_i \ge z_i(S_{p2}) \\ \frac{z_i(S_{p1})-z_i(S_{p2})-\rho_i}{\upsilon_i-\rho_i} & \text{otherwise} \end{cases}$$

Within this approach three thresholds are used, the indifference threshold ω_i, the preference threshold ρ_i and the veto threshold υ_i, and relative weighting factors θ_i. Based on this credibility matrix using downward and upward distillation the final ranking is determined.

CBA is used to show the consequences of this often used compensation principle for the presented multi-objective optimization problem. Because there are various other approaches, which possibly correspond better with the underlying decision process and data quality, the other presented methods are also applied to illustrate the advantages and disadvantages of these methods.

4. Case study: numerical experiment

4.1 Case

A case study is used to demonstrate the results and differences of applying the different ranking methods described in Table 2. We consider a realistic network of the city of Almelo in the eastern part of the Netherlands, consisting of 636 links, 257 nodes, and a total travel demand of 45,218 vehicles, differentiated between passenger cars and trucks. The model contains the major roads and there are nine DTM measures available as shown in Figure 1. Each of the seven traffic signals distinguished nine pre-defined settings and the two variable message signs used to change the speed limit has three different settings. In total six time intervals for the DTM measures are distinguished, equally divided into 30 minute slices. As a consequence the feasible set contains $\left(\prod_b M_b\right)^T = \left(9^7 \cdot 3^2\right)^6 = 6.36\times10^{45}$ possible solutions. A three-hour morning peak is simulated and the OD-matrix is manipulated to increase congestion problems. Assessing one solution using the Streamline DTA model takes approximately 15 minutes.

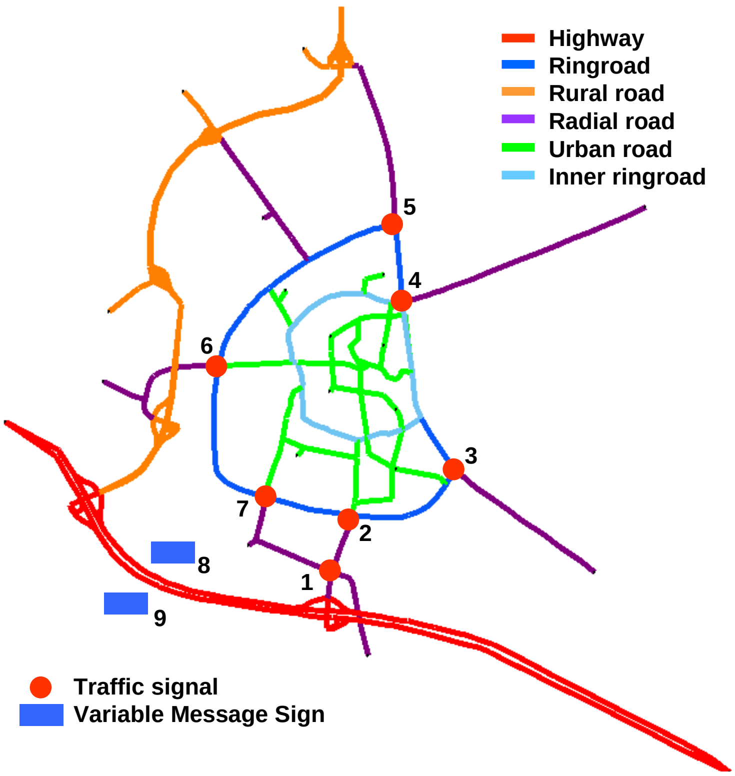

Figure 1. Network Almelo

4.2 Parameter settings

Within all ranking methods except for the CBA method relative weighting factors θ_i are used, which we varied to illustrate the differences between the methods. The monetary values used in the CBA method are based on the European IMPACT study (Maibach et al., 2008) and presented in Table 3. The ELECTRE III method also needs additional parameters related to the indifference ω_i, preference ρ_i and the veto υ_i thresholds. These thresholds depend of the uncertainties related to the used traffic models and externality models and depend, similar to the weighting factors, on the choices within the decision making process. In our numerical case we treated every objective the same (all weighting factors equal to 1) and defined the thresholds as percentages of the interval between the found maximum and minimum (the indifference threshold 1%, the preference threshold 50% and the veto threshold 99%). All used ranking methods are quick and can present their results within seconds for our numerical example.

Table 3. Overview monetary values (Maibach et al., 2008)

Objective	Monetary value	Explanation
Efficiency	11 €/hour	As an average of different purposes
Air quality	NO_x 6,600 €/ton	Because the emissions are already weighted within the objective function depended on level of urbanization, the monetary values are used for non-urban areas. Note that also other substances like PM_{10} are of importance when monetizing air quality effects, which are not taken into account here.
Climate	CO_2 25 €/ton	Central value for 2010
Traffic safety	19,000 €/slightly injured 236,600 €/severely injured 1,620,000 €/fatality 82,273 €/injury accident	Monetary value of severely injured (direct and indirect economic cost inclusive) in the Netherlands taken as an average. Because we calculate the number of injury accidents, we use average ratio's (Jansen, 2005) to determine slightly injured (1.23), severely injured (0.2341) and fatalities (0.00217).
Noise	$z_3^{mon} = 5.42 z_3^2 - 452.53 z_3 + 9444.7$	The monetary value within the handbook is expressed in per person exposed per year and depends on the Lden dB(A) level that is exceeded. Because the weighted average Sound Power Level is used as the objective in which the Sound Power Level at the source is lowered depending on average distance to the façade, the assumption is made that the total number of inhabitants of Almelo (72,500) is exposed to this weighted average Sound Power Level (i.e. exposure is implicitly taken into account in the objective function). The monetary value is multiplied by the ratio of simulation time period and hours in a year, because the optimization focuses on a rush hour. We fitted a quadratic polynomial which directly presents the monetized effects of the weighted average Sound Power Level

5. Case study: results

The case was used to illustrate the differences between the methods and to determine the feasibility of monetizing the effects to select the best solution, but first the outcome of the optimization process is presented.

5.1 Pareto optimal solutions

Figure 2 shows the found Pareto optimal solutions in two dimensions. Note that these are Pareto optimal solutions optimizing efficiency, air quality, climate, traffic safety and noise simultaneously. As depicted, the objectives efficiency, climate and air quality are aligned and opposed to traffic safety and noise. Optimizing efficiency aims at avoiding congestion using full capacity of the available routes, which is also good for minimizing CO_2 emissions. Optimizing NO_x emissions aim at avoiding congestion and high speeds and searches for the best trade-off between minimizing traffic using the urban roads and the level of congestion on the highway. Traffic safety aims at maximizing the use of the relatively safe highway route and avoiding use of the urban routes. Optimizing noise aims at lowering the driving speeds as much as possible and also aims to avoid traffic using the urban routes.

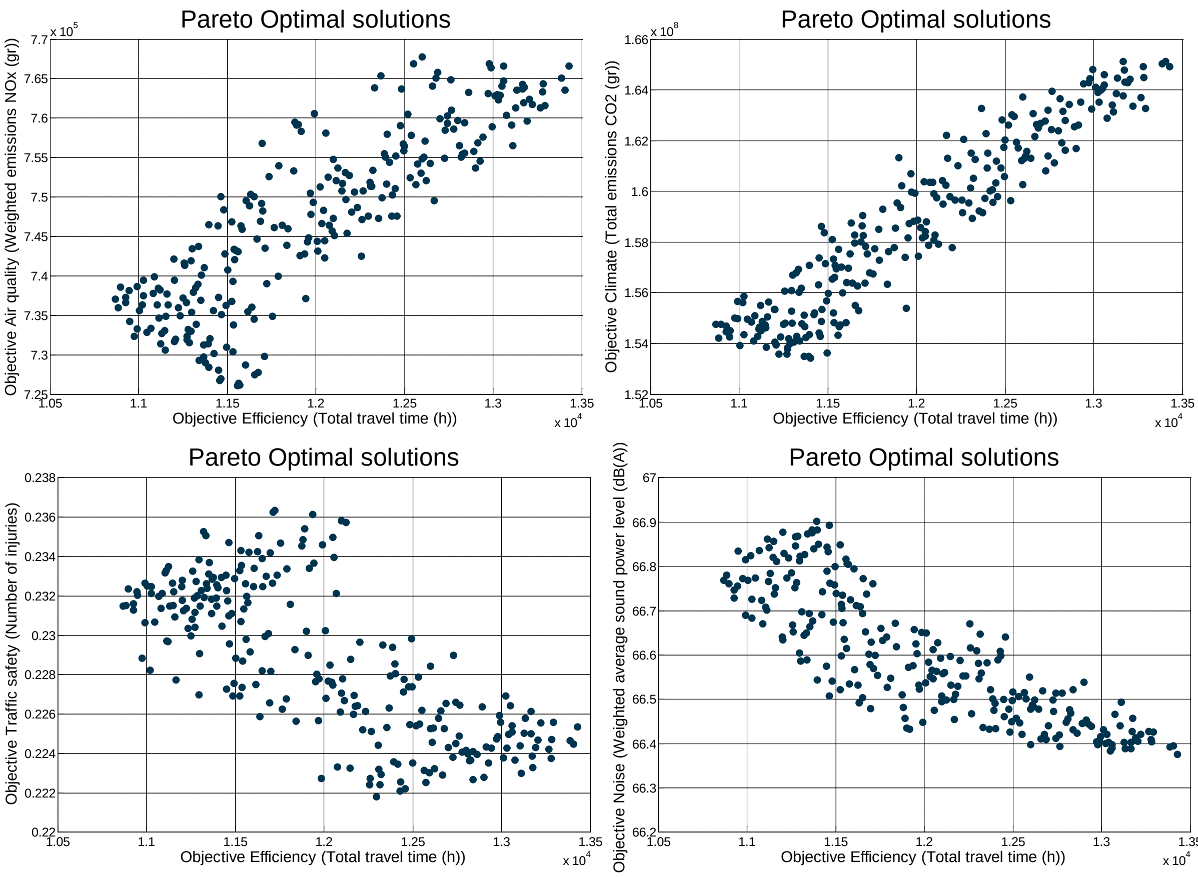

Figure 2. Pareto optimal solutions

However, this does not mean that there is a single solution which optimizes the three aligned objectives. The solution which minimizes NO_x emissions for example results in approximately 6% higher total travel time and the solution which minimizes CO_2-emissions in 5% higher total travel times, in vehicle lost hours this is respectively 29% and 22%. Based on the Pareto optimal set the average trade-offs are determined and presented in Table 4. This means for example that in this numerical case we could reduce 2.5 kg CO_2 emissions, accepting an increase of 1 hour of vehicle lost hours (or 4.0×10^{-4} hour, accepting an increase of 1 gram CO_2 emissions), or 150 gram CO_2 emissions, accepting 1 gram more weighted NO_x emissions. Note that these average trade-offs are determined by comparison of two objectives, which means that the trade-offs between these two also will result in effects on other objectives (positively or negatively). These effects on other objectives are related to the level in which the different objectives are aligned or opposed as presented in Figure 2.

Table 4. Average trade-offs between objectives

	Efficiency	Air quality	Climate	Traffic safety	Noise
Efficiency (h)		6.3×10^{-2}	4.0×10^{-4}	$1.5 \times 10^{+5}$	$6.5 \times 10^{+3}$
Air quality (weighted gr NO_x)	$1.6 \times 10^{+1}$		6.6×10^{-3}	$2.0 \times 10^{+6}$	$9.2 \times 10^{+4}$
Climate (gr CO_2)	$2.5 \times 10^{+3}$	$1.5 \times 10^{+2}$		$5.8 \times 10^{+8}$	$2.4 \times 10^{+7}$
Traffic safety (injury accidents)	6.8×10^{-6}	5.0×10^{-7}	1.7×10^{-9}		1.5×10^{-2}
Noise (weighted dB(A))	1.5×10^{-4}	1.1×10^{-5}	4.1×10^{-8}	$6.6 \times 10^{+1}$	

5.2 Single objective by monetizing versus Multi objective

Multi objective optimization problems in traffic and transport are often reformulated as a single objective optimization problem by monetizing the effects to reduce complexity. However, every used compensation principle which is input for ranking methods is a public policy decision and by this reformulation, information that can help decision makers concerning for example trade-offs as presented in Table 4, cannot be determined. To illustrate the consequence of monetizing the effects we used the numerical experiment.

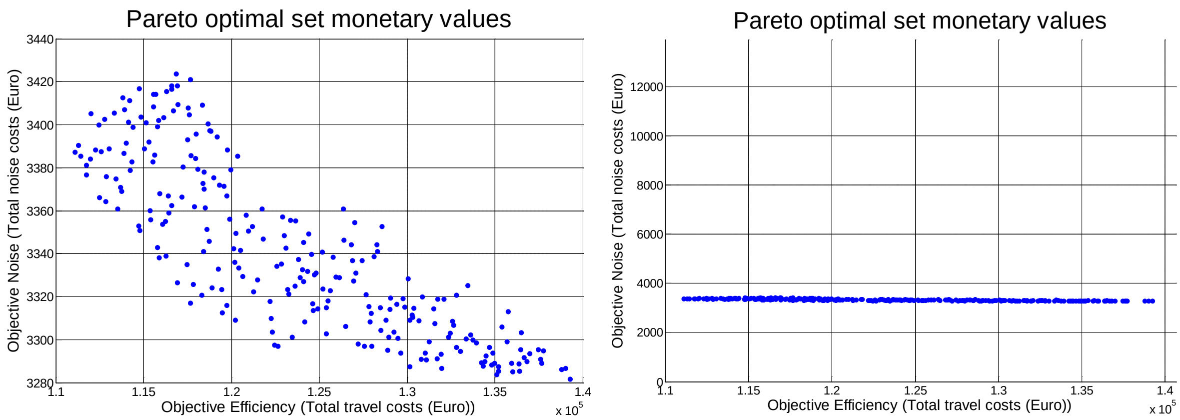

Figure 3. Pareto optimal sets in which externalities are monetized

When the different externalities are monetized the Pareto optimal solution which minimizes total travel time prevails. Even if we introduce a possible error of 50% in the monetary values the same solution turns out to be the best in all cases. This is illustrated in Figure 3, in which the Pareto optimal set is shown after monetizing the different objectives. A slight decrease of noise costs, which you even cannot see in the second figure when the axes are scaled on a more equal level, results in a major increase in travel time costs and are therefore by far the most dominant. Although the monetary values used in this study are often used within cost-benefit analysis, incorporating externalities as objectives for optimization of DTM-measures in this way, will not result in choosing solutions in which an increase in travel times is accepted, while reducing other externalities. Only the externalities that are aligned with efficiency (see Figure 2) will profit to some extent of minimizing the monetized costs. Formulating the MO NDP as a single objective optimization problem from the start would not have resulted in the ability to provide this information to the decision maker.

Monetizing the effects will therefore not help in reducing externalities. In addition, the monetary values are debatable, because they are based on different assumptions and do not take into account the difficulty of reaching certain policy goals or the increasing marginal costs in reducing the externalities (Rothengatter, 2009; Mouter et al., 2011; MacKie, 2010). For our numerical experiment we determined monetary values presented in Table 5 for which the trade-offs between the objectives are equal on average with travel time costs. This results in monetary values for most externalities which should be much larger (more than 20 times larger) if we would like them to be equally weighted with travel time costs. Note, that these values are related to the average trade-offs presented in Table 4 and the relative differences between the factors would be similar if we would have used air quality, climate, traffic safety or noise as the reference case. In addition, these values will differ per case and the calculation of the external costs can be further refined (e.g. in accounting for urbanization, time of day and trip purpose). However, it does show, because of the large factors, that travel time costs are expected to be highly dominant in most cases when using monetized weights.

Table 5. Correction factor monetary values if equally weighted with travel time costs

	Air quality	Climate	Traffic safety	Noise[5]
Monetary values	6,600 €/ton	25 €/ton	82,273 €/accident	3,341 €
Values if equally weighted	694,796 €/ton	4,414 €/ton	1,625,341 €/accident	71,691 €
Factor	105	177	20	21

5.3 Ranking results

Since monetizing the effects will mainly result in reducing travel times when the monetary values are not reconsidered, other ranking methods should be applied to better incorporate policy objectives concerning externalities. All presented ranking methods need a compensation principle, which determines how the trade-offs are weighted. Setting the weighting factors should be an outcome of the decision making process. By determination of the Pareto optimal set in advance, information is available concerning the sensitivity for these weighting factors and therefore the consequences of setting these factors. The different ranking methods which are available can result in a different prevalent solution, even though the weighting factors are the same (see for example Figure 4a).

The main difference between WSM and AHP is the way the objectives are normalized, which naturally influences the outcome and level of sensitivity for weighting factors. When the weighting factors are equal and the shape of the Pareto optimal frontier is convex, the WSM method will highly rank solutions that score average on the individual objectives even though the relative differences between solutions for an objective are small. This is also the case for the ELECTRE III method in this bi-objective case because the thresholds are essentially the same for all objective functions (see Figure 4b). In the multi-objective case this is not true, because the other objectives and its fuzzy approach based on the thresholds influence the results (see Figure 4a). The AHP method is sensitive to relative differences between solutions, which means that objectives in which these differences are large will dominate the ranking procedure (see Figure 4b). This means for example that the ranking in these methods can be different if we use total travel time instead of total vehicle lost hours for efficiency.

[5] Based on average Sound Power Level

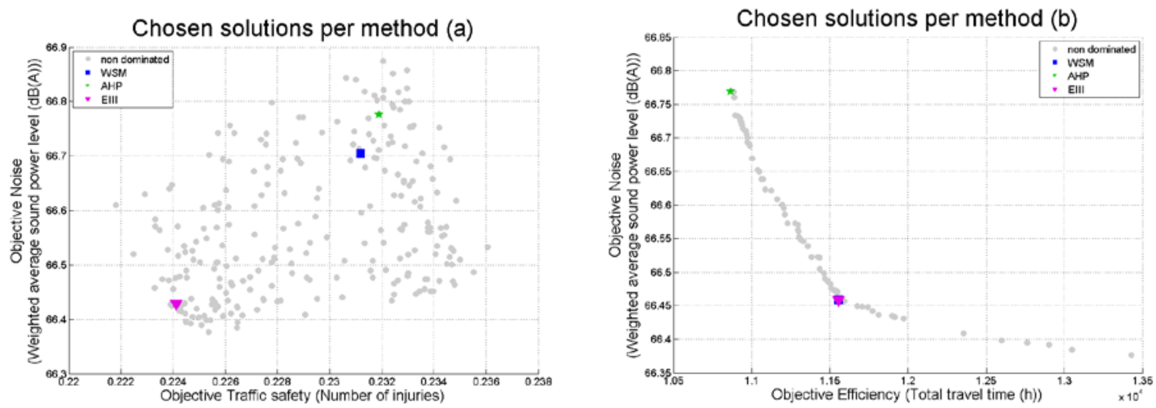

Figure 4. Differences in chosen solutions per method

Analysis of the sensitivity of the methods for the weighting factors shows that the ELECTRE III method is most sensitive to the weighting factors. One of the reasons is that WSM and AHP only will find best solutions that are part of the convex hull. WSM is slightly more sensitive than AHP, which is due to the difference in normalization used in these methods. Figure 5 shows the chosen solutions based on a sensitivity analysis in which the weighting factors for two objectives can range between 1 and 2 (i.e. the weight of one objective can be twice as high as the other).

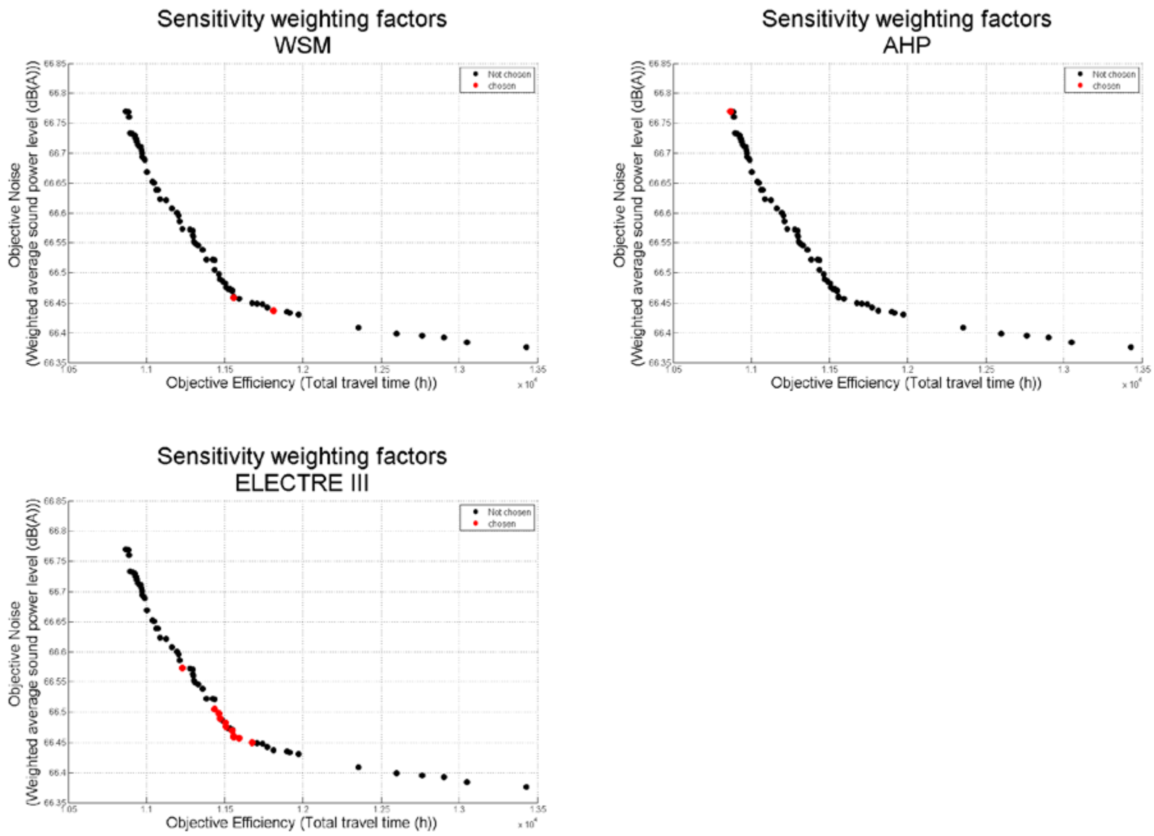

Figure 5. Sensitivity for weighting factors

The ELECTRE III method relies less on the exact outcome of the solutions on the different objectives. This method is a fuzzy approach using certain thresholds for indifference, preference and veto. Therefore the ELECTRE III method is the only method that can also rank solutions not part of the convex hull (illustrated in Figure 6) as the best compromise solution. This method also offers the possibility to take uncertainties concerning the exact outcome of the objective values into account (i.e. not necessarily interpret the outcome on a ratio scale) and using this method reduces the chance of neglecting interesting solutions which would not be considered using WSM or AHP in a strict way. The ELECTRE III method needs additional parameters to set, determined by the decision maker and quality of the data, which are more difficult to interpret in advance. The sensitivity for the threshold parameters will differ per case. In this numerical example the outcome is most sensitive for the preference threshold, which indicates when a certain solution outperforms another solution on a specific objective. Despite these additional needed parameters, the ELECTRE III method is possibly a more suitable method to rank solutions in this case, because it takes uncertainty into account.

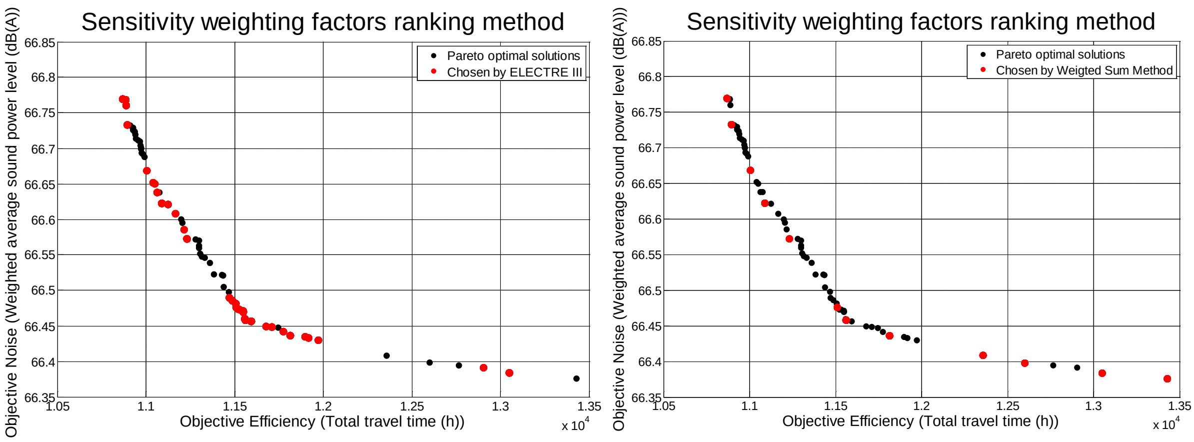

Figure 6. Sensitivity ranking method for weighting factor

6. Conclusions

Optimization of network performance using DTM measures is a specific example of an NDP in which these measures are optimized on a strategic level and provides DTM settings or scenarios which on the long term optimize the network performance. To incorporate externalities as objectives for optimization of network performance using DTM measures, a compensation principle is needed to eventually choose one compromise solution. This compensation principle can be part of the optimization problem, for instance by monetizing the effects, which is widely used. Solving this problem will typically result in a single optimal solution (although there may be multiple solutions that all have an equal monetary cost). However, this research showed in a numerical example that because travel time costs dominate these costs by far, using a CBA applying generally accepted monetary values derived from the European IMPACT study does not help in reducing externalities such as noise and NO_x and CO_2 emissions. Only if the monetary values of the externalities were multiplied by a factor of more than 20 the externalities are weighted evenly with travel time costs. In addition, monetary values are debatable and given these results should be reconsidered if used in this context. Although it is recommended to test this on a variety of other cases, and a further refinement of the calculation of the external cost, it is also possible not to incorporate the compensation principle in advance by solving a multi-objective NDP. Solving the MO NDP yields a Pareto optimal set, which can provide additional information like trade-offs between objectives for the decision making process. This research presented a framework for solving this MO NDP. However, a Pareto optimal set can be difficult to comprehend and therefore ranking is necessary to assist the decision makers. There are many ranking methods available and because of the results using CBA, we discussed different methods such as WSM, AHP and ELECTRE III. All these methods need information on the weighting factors and basically aim to rank the solutions by comparing the performance of these solutions on the individual objectives. The main difference between WSM and AHP is the way the objectives are normalized, which naturally influences the outcome and level of sensitivity to weighting factors. The ELECTRE III method relies less on the exact outcome of the solutions on the different objectives and therefore takes uncertainties concerning the exact outcome into account. This also means that unlike WSM and AHP this method can also rank solutions not part of the convex hull as the best compromise solution, but also increases the sensitivity of this method to the weighting factors. The ELECTRE III is possibly a more suitable method to support the decision making process in this context, because it is the only method discussed which can deal with the data characteristics of the MO NDP, i.e. deterministic with a level of uncertainty.

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