Transportation
DOI 10.1007/s11116-016-9738-y

The multi-objective network design problem using minimizing externalities as objectives: comparison of a genetic algorithm and simulated annealing framework

Bastiaan Possel[1] · **Luc J. J. Wismans**[1,2] · **Eric C. Van Berkum**[2] · **Michiel C. J. Bliemer**[3]

Abstract Incorporation of externalities in the Multi-Objective Network Design Problem (MO NDP) as objectives is an important step in designing sustainable networks. In this research the problem is defined as a bi-level optimization problem in which minimizing externalities are the objectives and link types which are associated with certain link characteristics are the discrete decision variables. Two distinct solution approaches for this multi-objective optimization problem are compared. The first heuristic is the non-dominated sorting genetic algorithm II (NSGA-II) and the second heuristic is the dominance based multi objective simulated annealing (DBMO-SA). Both heuristics have been applied on a small hypothetical test network as well as a realistic case of the city of Almelo in the Netherlands. The results show that both heuristics are capable of solving the MO NDP. However, the NSGA-II outperforms DBMO-SA, because it is more efficient in finding more non-dominated optimal solutions within the same computation time and maximum number of assessed solutions.

Keywords Multi-objective network design problem · Externalities · Genetic algorithm · Simulated annealing · Accessibility · Traffic safety · Emission

✉ Bastiaan Possel
bpossel@goudappel.nl

[1] Goudappel Coffeng, P.O. Box 161, 7400 AD Deventer, The Netherlands

[2] Centre for Transport Studies, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands

[3] Institute of Transport and Logistics Studies, The University of Sydney Business School, Sydney, Australia

Published online: 18 October 2016

Introduction

Optimization of a transport system is often viewed as a problem to find the best way to expand or improve an existing network. This type of problem is generally referred to as the network design problem (NDP). Traditionally, this type of optimization is focused on improving accessibility, minimizing the total cost (e.g. travel time or travel expenses) possibly subject to a budget constraint or some boundary conditions regarding externalities like pollution and traffic safety. However, due to the increasing attention for these types of externalities, it may no longer suffice to view a transport system as feasible when it meets these conditions. Therefore we will view the NDP as an optimization problem with multiple objectives, where externalities are incorporated in the objective functions, which we will refer to as the multi-objective network design problem (MO NDP). In most cases the NDP is formulated as a bi-level optimization problem, which has an upper level representing a system optimal design and a lower level representing road users optimizing their own objectives. Usually this lower level is operationalized as solving a stochastic or deterministic user equilibrium problem (Chiou 2005; Gao et al. 2005; Mathew and Sharma 2006; Zhang and Lu 2007; Xu et al. 2009). This interaction results in a difficult optimization problem, identified as one of the most complex optimization problems in traffic and transport to solve (Yang and Bell 1998). To be more specific, NDPs are a NP-hard problem (non-deterministic polynomial time hard problem). This generally means that heuristics are needed to solve them (Johnson et al. 1978). There can be an enormous number of possible solutions, especially for large road networks where many possible traffic infrastructure measures can be taken, and every function evaluation requires solving a user equilibrium problem, which means that a fast and accurate heuristic is needed. The main objective of this paper is to formulate the introduced MO NDP and compare two heuristics optimization techniques for this problem. Solving this MO NDP for a realistic case provides insights in which infrastructure measures should be implemented in a road network in order to optimize the combined objectives environment, traffic safety and accessibility for a road network.

The NDP can be classified into two categories: discrete network design problems (DNDP) and continuous network design problems (CNDP). The main difference between these categories is the decision variable. In the DNDP the decision variable is an integer and usually either 1 (‘yes’) or 0 (‘no’). This decision variable can be used for new roads (Leblanc 1975; Poorzahedy and Turnquist 1982; Gao et al. 2005). With the CNDP, the decision variable can be any continuous variable and this is usually the size of the implemented traffic infrastructure measure. This decision variable can be used for the road capacity in which the variable is the size of the extra capacity (Dantzig et al. 1978; Friesz et al. 1993; Meng et al. 2001; Chiou 2005; Xu et al. 2009).

A different classification is the distinction of NDP considering a single objective versus multiple objectives. Mostly single objective network design problems are studied in which the total travel time in the traffic network (as a measure for accessibility) is used as the objective function (LeBlanc and Abdulaal 1978; Gao et al. 2005; Zhang and Lu 2007). Different studies incorporated the investment costs within the single objective function. Meng et al. (2001), Chiou (2005) and Xu et al. (2009) optimized total travel time in which the investment was translated in time using a conversion factor. Boyce and Janson (1980) and Cantarella et al. (2006) optimized total travel cost in which the travel time was translated into cost. The investment costs can also be added to these total travel costs (Poorzahedy and Turnquist 1982; Drezner and Wesolowsky 2003, 2009). Occasionally externality costs, like environmental costs (expressed in money), are added to the travel cost (Mathew and Sharma 2006). In these NDPs still a single objective is considered in which the objectives are weighted in advance. In most cases the objectives are weighted by transferring the objectives into costs. However, the size of the weights is a public policy decision and introduces uncertainty even if costs are used and therefore less desirable in an unbiased modeling framework. In MO NDPs the objectives are not weighted in advance, but the separate objectives are considered during the optimization process. As a result the outcome of the optimization process is not a single optimal solution, but several trade-off solutions. Most existing MO NDP consider the minimization of investment cost as second objective (Sharma et al. 2009). Friesz et al. (1993) for example, studied a MO NDP with user costs (money), construction costs (money) and total amount of traveled kilometers as objective functions. Relative little research is available in which all main elements of the externalities of traffic are incorporated as objective functions. However, there are examples in which aspects are considered. Sharma and Mathew (2011) for example used emission and system travel time as objective functions in a MO NDP.

The outcome of a MO NDP can provide valuable information about the trade-offs between the objectives and sensitivity for weighting the various objectives regarding the optimal design. However this also illustrates the additional complexity performing multi-objective optimization versus a single-objective optimization.

Figure 1 illustrates the objective space with several solutions (each mark represents a solution with a certain value for the objectives) for an optimization problem with two objectives. There is not one optimal solution but several optimal solutions called Pareto optimal solutions, indicated by the hollow marks. For these solutions the corresponding objectives cannot be improved for any objective without degradation of another. The collection of Pareto optimal solutions is called the Pareto optimal set or Pareto optimal front (because it forms the outer set of solutions in the objective space). The goal of multi-

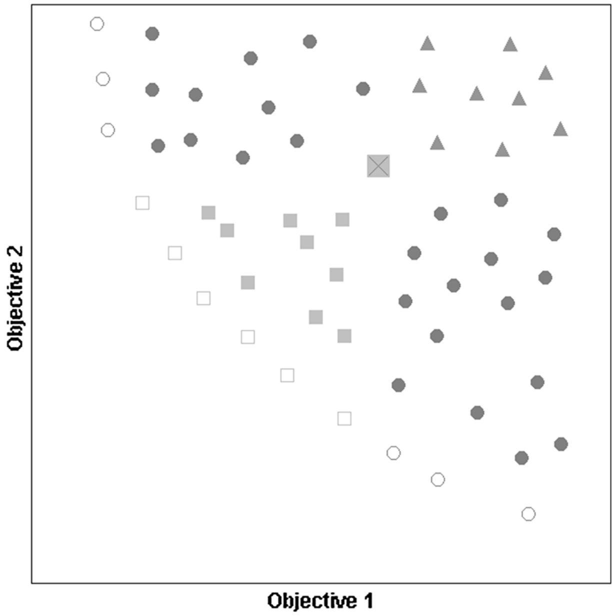


Fig. 1 An illustration of dominance (Smith 2006, p. 17)

objective optimization is to find this Pareto optimal set. Another difficulty is to determine whether a solution is better or worse than another solution. For this purpose, Pareto dominance can be used to rank the solutions as illustrated in Fig. 1. In this figure the relative dominance to the point marked with an 'X' is shown. The points marked with a square dominate point X. While the points marked with a triangle are dominated by the point X. The points marked with a circle neither dominate, nor are dominated by, the point X. The better a solution, it is less dominated. The best solutions are not dominated, i.e. the Pareto optimal set, which is indicated by the point with a hollow mark.

To solve the MO NDP heuristic methods are used. These methods use smart search techniques to try and find the Pareto optimal set within a bounded computation time. However, a heuristic method can not guarantee that it finds the Pareto optimal set. Yet, based on experiences in the literature there are several heuristics which are able to gives a (near) Pareto optimal set or a part of it within reasonable time. The most promising methods described in literature for the single and multi objective NDP are genetic algorithms (GA) and simulated annealing (SA). However there is no consensus on which one is best. Several studies claim that the GA performs best (Memon and Bullen 1997; Karoonsoontawong and Waller 2006; Zhang and Lu 2007; Sharma et al. 2009; Sharma et al. 2009), while other studies claim that the SA is best (Friesz et al. 1992, 1993; Chiou 2005; Xu et al. 2009). Furthermore, some studies state that there is little difference between the performance of GA and SA (Cantarella et al. 2006, 2009; Zhao and Zeng 2006). An overview of these studies is given in Table 1. In this paper two heuristics will be compared. The first heuristic is the non-dominated sorting genetic algorithm II (NSGA-II) from Deb et al. (2000). The second heuristic is the dominance based multi objective simulated annealing (DBMO-SA) method from Smith (2006). The NSGA-II is used, because it is a widely used heuristic and considered to be the leading multi-objective GA (Smith 2006). Moreover, it is well tested and proven to be effective for multi-objective optimization (Konak et al. 2006) and earlier successfully applied by Sharma and Mathew (2011) in a similar study with externalities emission and system travel time in a MO NDP. The DBMO-SA is used because it exhibits rapid convergence to the desired set for the current popular test problems DTLZ1-DTLZ7 (Deb et al. 2001, 2002) and according to Smith (2006) outperforms the NSGA-II and other multi-objective simulated annealing methods. Both heuristics are used in a framework for solving the MO NDP with the externalities of traffic as the objectives and infrastructural measures as decision variables and compared in a hypothetical test network as well as a real network of the city of Almelo.

Problem formulations

Bi-level programming is an often used technique to represent the underlying processes of the CNDP and DNDP (Gao et al. 2005). This approach has been primarily used for NDP (Chiou 2005; Gao et al. 2005; Deb 2001, 2002, 2006, 2009; Zhang and Lu 2007; Xu et al. 2009; Yin 2002). Figure 2 shows the most basic form of bi-level programming. The upper level describes the transport planner task: determine traffic measures which minimize the objective functions given traffic flows that respond to these traffic measures. Next, the lower level described the travelers' behavior optimizing their individual objectives: find the user equilibrium traffic flows which minimize the travel costs for each traveler, with given traffic measures. This bi-level program will be used in the modeling framework.

Table 1 Overview of related studies

Study	Objective function(s)	Solution method(s)	Conclusion
Friesz et al. (1992)	Travel costs	SA, Hooke–Jeeves algorithm (HJ), Modular in-core nonlinear system (MINOS) Equilibrium decomposed optimization (EDO), Iterative optimization-assignment algorithm (IOA)	SA is superior in finding global optimal solution
Friesz et al. (1993)	User transport costs, construction costs and total traveled kilometers	SA	Only suitable for small, hypothetical networks
Mathew and Sharma (2009)	Travel time	SA and GA	GA outperforms SA
Mathew and Sharma (2011)	Emission and system travel time	Non-dominated sorting GA-II (NSGA II)	Use of NSGA-II for NDP recommended
Memon and Bullen (1997)	Optimizing traffic lights settings	GA and quasi-newton gradient search (QNEW)	GA is the most effective and efficient method
Chiou (2005)	Sum of total travel time and investment costs	SA, Gradient projection method (GP), conjugate gradient projection method (CG) and HJ, MINOS, EDO, IOA, QNEW	SA outperforms all other methods in all cases
Cantarella et al. (2006, 2009)	Optimizing traffic lane and traffic light settings for urban road networks	SA, GA, Tabu search (TB) and Hill Climbing method (HC)	SA, GA and TB perform very similar and outperform HC
Karoonsoontawong and Waller (2006)	Total travel time	SA, GA and random search (RS)	GA outperforms SA and RS
Zhao and Zeng (2006)	Minimize transfers and maximize service coverage for a transit network	SA and GA	SA and GA perform very similar
Zhang and Lu (2007)	Total travel time	GA	Use of GA for NDP recommended
Sharma et al. (2009)	Total travel time and expected value of the total travel time	Non-dominated sorting GA-II (NSGA II)	Use of NSGA-II for NDP recommended
Xu et al. (2009)	Total travel time	SA and GA	SA is more efficient than GA

Lower level

The lower level is operationalized by solving a deterministic static user equilibrium problem assuming fixed demand. Numerous earlier studies have also used this approach (LeBlanc 1975; Abdulaal and LeBlanc 1979; Boyce and Janson 1980; Poorzahedy and Turnquist 1982; Meng et al. 2001; Chiou 2005; Gao et al. 2005; Deb 2001, 2002, 2006, 2009; Poorzahedy and Rouhani 2007; Zhang and Lu 2007; Xu et al. 2009). A dynamic traffic assignment would provide more accurate results for the

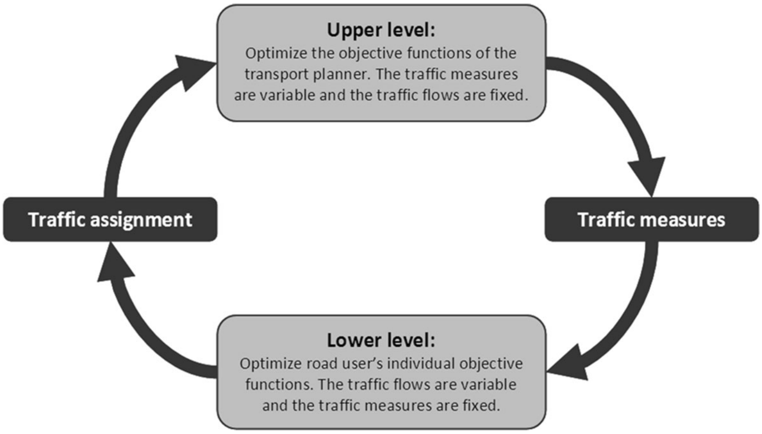


Fig. 2 Bi-level program

environmental objective functions. However, because the proposed infrastructure measures have a long term effect, a static traffic assignment is deemed sufficient for this research. Furthermore, a dynamic traffic assignment would increase the calculation time.

A traffic assignment is performed over a 24 h period, which is divided in three parts: morning rush hour (3 h), evening rush hour (3 h) and the remaining day (18 h). Also two vehicle classes are distinguished: light weight vehicles (LWV) and heavy weight vehicles (HWV). First the HWV are assigned according to an all-or-nothing (AON) principle. In an AON assignment the minimum (free flow) travel time path is determined between each origin–destination pair and all traffic between that pair is assigned to that path. The resulting HWV traffic flows are expressed in LWV equivalents (e.g. freight is translated in passenger car units). These traffic flows are the starting point for the Frank-Wolfe algorithm (Frank and Wolfe 1956), which is used to solve the deterministic static user equilibrium problem for the LWV.

Upper level

In the upper level a set of infrastructure measures is determined in order to minimize the given objective functions. The MO NDP is illustrated in Eq. (1) and the variables are shown in Table 2.

Table 2 Variables used in Eq. 1 for the MO NDP

Variable	Description
$E(x(s))$	Total emission with the traffic flows x with infrastructure measures s
$R(x(s))$	Total number of traffic accident fatalities with the traffic flows x with infrastructure measures s
$T(x(s))$	Total travel time with the traffic flows x with infrastructure measures s
s	Set of infrastructure measures
$s*$	Pareto optimal set of infrastructure measures
$x(s)$	Traffic flows with infrastructure measures s
$UE(s)$	User equilibrium problem with infrastructure measures s

$$\text{MO NDP}: s* = \min \begin{pmatrix} R(x(s)) \\ E(x(s)) \\ T(x(s)) \end{pmatrix} \\ \text{s.t. } x(s) \in UE(s) \tag{1}$$

The minimization problem is a multi-objective minimization problem, which excludes all solutions that are dominated.

Infrastructure measures

In the upper level traffic measures are implemented to optimize the objective functions. In almost all the literature reviewed either capacity expansion is used as traffic measure (Dantzig et al. 1978; Friesz et al. 1993; Meng et al. 2001; Chiou 2005; Xu et al. 2009) or the construction of new roads (Leblanc 1975; Poorzahedy and Turnquist 1982; Gao et al. 2005). The traffic infrastructure measures considered in this research are capacity expansion or reduction, adding new roads and changing the maximum speed. These measures are a combination of discrete and continuous decision variables. In order to use all three traffic measures, link type will be used as decision variable. This is a relative unknown decision variable which is not used often, but has been proposed earlier by Steenbrink (1974). Each link type represents typical road categories and has certain attributes like maximum speed, number of lanes and capacity. When changing the link type of a certain road these attributes are automatically changed, which is effectively the same as implementing traffic measures. For potential new roads a specific link type can be used. There is a "no road" linktype with no capacity and speed, when this linktype is changed in a linktype with a capacity and speed this simulates the construction of a new road. The resulting discrete NDP will be used in the proposed solution methods. Besides traffic related attributes like maximum speed, also objective function related attributes like risk factors can be assigned to link types. In this way changing a link type will also have a direct influence on the objective functions. The link types are based on the Dutch guidelines concerning road categories (CROW 2004). Every link in the road network will be assigned an initial link type which is the reference case. To reduce the solution space and the calculation time traffic related knowledge is incorporated by excluding unrealistic solutions. First of all, both directions of a link always have the same link type. Furthermore, all links will be divided over different link sets. Each link set contains links which have initially the same link type, the same function within the network and from a traffic engineering point of view are not allowed to change independently from each other (e.g. preventing changing successive links respectively into a freeway and an urban link). Finally, for each link set all possible link types will be defined and there will also be a link set of links for which the link type can not be changed. Now, the link type for each link set can be used as discrete decision variable reducing the number of feasible solutions considerably.

Objective functions

Three different objective functions are formulated. The PM_{10} emission, the total number of traffic accident fatalities (traffic safety) and the total travel (accessibility). The goal is to minimize these objective functions. The input to assess the objective functions is the output of the static traffic assignment (the number of vehicles and the travel time), link characteristics (length, capacity and maximum speed) and specific parameters assigned to each link type (risk factor). Table 3 shows the variables used in the objective functions.

It is also possible to incorporate objectives like CO_2 emission, NO_x emission and average sound power level. These objectives have not been used in order to keep the results more comprehensible and easier to analyze.

Total PM_{10} emission For air pollution the total PM_{10} emission (μg) is used. To calculate the emission an approach using aggregated emission functions is applied. The functions used are formulated in the standard calculation method SRM. This is the prescribed method in the Netherlands to assess air quality and is provided by the Dutch ministry of Housing, Spatial Planning and the Environment (VROM 2006). It requires the total traffic flow per link per vehicle class and predefined parameters for each link type. Equation (2) shows this formula. The total 24 h period traffic flow from the static traffic assignment is determined for each link. This is multiplied with the predefined emission factors (which depends on link type) and summed over all modes. Finally, this is summed over all links (and multiplied with the link length).

Table 3 variables used in the objective functions

Variable	Description
A	Total number of links, with index a $(-)$
M	Total number of vehicle classes, with index m $(-)$
P	Total number of periods, with index p $(-)$
l_a	Length of link a (km)
L	Total length of all link in the network (km)
x_{amp}	Traffic flow on link a for vehicle class m and period p (vehicles)
t_{amp}	Travel time on link a for vehicle class m in period p (hours)
E	Total PM_{10} emission over all links, vehicle classes and periods (μg)
E_a^{ff}	Total free flow PM_{10} emission on link a over all vehicle class and periods (μg/km)
E_a^{sf}	Total stagnating flow PM_{10} emission on link a over all vehicle classes and periods (μg/km)
e_{am}^{ff}	Free flow traffic PM_{10} emission factor for the link type of link a and vehicle class m (μg/km)
e_{am}^{sf}	Stagnating traffic PM_{10} emission factor for the link type of link a and vehicle class m (μg/km)
φ_a	Fraction of stagnating traffic on link a $(-)$
R	Total number of traffic accident fatalities for the entire network $(-)$
r_a	Risk factor for the link type of link a $(-)$
T	Total travel time over the entire network (hours)
t_{am}^{ff}	Tree flow travel time on link a for vehicle class m (hours)
c_a	Capacity on link a $\left(\text{vehicles}^{\text{LWV}-\text{equivalents}}/\text{hour}\right)$
α_a	BPR parameter on link a $(-)$
β_a	BPR parameter on link a $(-)$
ρ_m	LWV equivalent factor for vehicle class m $(-)$

$$\begin{aligned}
&E=\sum_a l_a\cdot\left(\varphi_a\cdot E_a^{sf}+(1-\varphi_a)\cdot E_a^{ff}\right)\\
&\text{with } E_a^{ff}=\sum_m\left(e_{am}^{ff}\cdot\sum_p x_{amp}\right)\\
&\text{and } E_a^{sf}=\sum_m\left(e_{am}^{sf}\cdot\sum_p x_{amp}\right)\\
&\varphi_a=0\quad\text{if}\quad\frac{\sum_m\rho_m\cdot x_{amp}}{c_a}\le 0.6\\
&\text{where } \varphi_a=0.5*\frac{\sum_m\rho_m\cdot x_{amp}}{c_a}-0.3\quad\text{if}\quad 0.6\le\frac{\sum_m\rho_m\cdot x_{amp}}{c_a}\le 1.0\\
&\phi_a=0.2\quad\text{if}\quad\frac{\sum_m\rho_m\cdot x_{amp}}{c_a}\ge 1.0
\end{aligned}\quad. \tag{2}$$

Total number of traffic accident fatalities For traffic safety the total number of traffic accident fatalities is used as indicator. The method used is an accident risk based model in which accident risk figures per link type are used. The risk figures are provided by the Dutch Institute for Road Safety Research (Loon Van 2007). Each link type has a certain risk factor which is multiplied by the total number of traveled kilometers on a link over a 24 h period. This number is summed over all links to determine the total number of fatal casualties. Equation 3 shows the used formula.

$$R=\sum_a\left(r_a\cdot l_a\cdot\sum_p\sum_m x_{amp}\right). \tag{3}$$

Total travel time For accessibility the most commonly used indicator within NDP is the total travel. The BPR travel time function (Bureau of Public Roads 1964) is used within the traffic assignment to determine the travel time on a link. In the objective function shown in Eq. (4) the total travel time per link is calculated and multiplied by the total flow on that link for each vehicle class and period. This is summed over all links, periods and vehicle classes.

$$\begin{aligned}
&T=\sum_p\sum_m\sum_a t_{amp}\cdot x_{amp}\\
&\text{with } t_{amp}=t_{am}^{ff}\cdot\left(1+\alpha_a\cdot\frac{\sum_m\rho_m\cdot x_{amp}}{c_a}\right)^{\beta_a}.
\end{aligned} \tag{4}$$

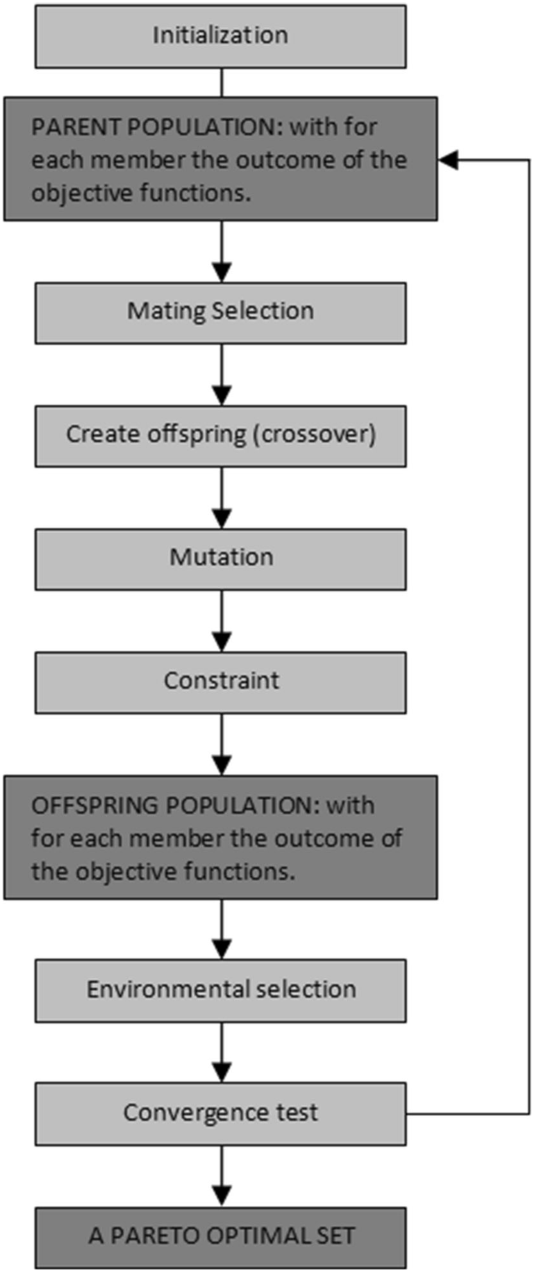
Solution methods

In this section two different heuristics for solving the MO NDP will be presented. First, the NSGA-II approach and second the DBMO-SA approach. Also, three performance measures for these methods are discussed.

NSGA-II framework

Figure 3 shows the NSGA-II framework. The NSGA-II algorithm from Deb et al. (2000) is designed to solve a multi-objective optimization problem. In this paper the NSGA-II has been modified in order to be used in a MO NDP. First of all, the use of link types has been

Fig. 3 The NSGA-II framework



implemented in order to make it a discrete NDP. Secondly a constraint is added to prevent that rejected solutions are assessed again.

In this GA a population of feasible solutions is evolved into a population of Pareto optimal solutions. The population is changed over several generations. In each generation, solutions are replaced by better solutions. These solutions (population members) are feasible solutions of the given multi-objective discrete network design problem. The size of the population remains the same throughout the different generations, only the members of the population are altered. Each member is a set of feasible link types for the distinguished link sets. This set is called a chromosome and each element (link type) of this chromosome is called a gene.

Initialization

In the first stage of the framework an initial population is chosen. The proposed framework is a network improvement algorithm, which requires a starting traffic network, which is the reference situation. Therefore the first member of the population is the reference situation and consists of the starting link types of each of the link sets in the road network. For the other members of the population a random feasible set of link types is chosen. A static traffic assignment is performed for each member (User Equilibrium problem in the lower level) and subsequently the values for the objective functions are determined (upper level). This is the first parent population.

Mating selection

Offspring is created in the mating selection. In this stage, parent pairs are selected from the parent population using the binary tournament selection method with replacement. The parents are ranked based on Pareto dominance (non-dominance sorting). All non-dominated solution get rank 1, all solutions only dominated by rank 1 solution get rank 2, etc. Within each rank the solutions are further ranked using a crowding distance measure (Deb et al. 2002). In the crowding distance algorithm all solutions are ranked based on the proximity of surrounding solutions within the objective space. Solutions with a lot of other solutions nearby will get al lower rank than solutions which stand further apart form other solutions in order to improve the diversity of the population. Next, two population members are randomly selected. The member with the highest rank is selected as the first parent. The other member is returned to the population. For the second parent (and all subsequent parent pairs) this process is repeated.

Create offspring (crossover)

Each parent pair will produce two offspring members through crossover using the uniform crossover method (Burke and Kendall 2005). Because only link types (genes) of the same link set (location in the chromosomes) are swapped the new offspring chromosomes remain feasible sets of link types. They are swapped with a certain swapping probability (ρ_s). Figure 4 gives an example of this method. The numbers are the genes of the chromosomes and represent the link types. The first set of numbers (837547) is parent 1 which mates with parent 2, the second set of numbers (648356). They produce two offspring through uniform crossover, child 1 (848557) and child 2 (637346).

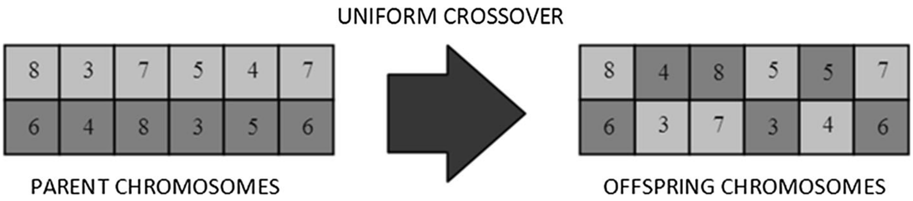


Fig. 4 Uniform crossover (Burke and Kendall 2005)

Mutation

After the offspring is created it can be randomly mutated in order to encourage diversity and ensures that it is possible to explore the entire solution space. In this stage genes of the offspring can be mutated (changed) randomly in another feasible value with a certain mutation probability (ρ_m).

Constraint

A checklist is used to check whether the chromosome of an offspring member has already been assessed. If this is the case this chromosome is randomly changed in a new unique chromosome using the repair constraint in order to improve the chance of finding the Pareto optimal set.

This results into an offspring population. A static traffic assignment is performed for each offspring member (User Equilibrium problem in the lower level) and subsequently the values for the objective functions are determined (upper level).

Environmental selection

Next the parent population and the offspring population are combined in one large population, from which a new parent population is created. This process is called the environmental selection which is a deterministic step preserving the good solutions (illustrated in Fig. 5). The combined population is sorted in Pareto fronts (solutions with the same rank) based on Pareto dominance (like in the mating selection stage). The next generation population will be filled with the highest ranked Pareto fronts until it has the same size as

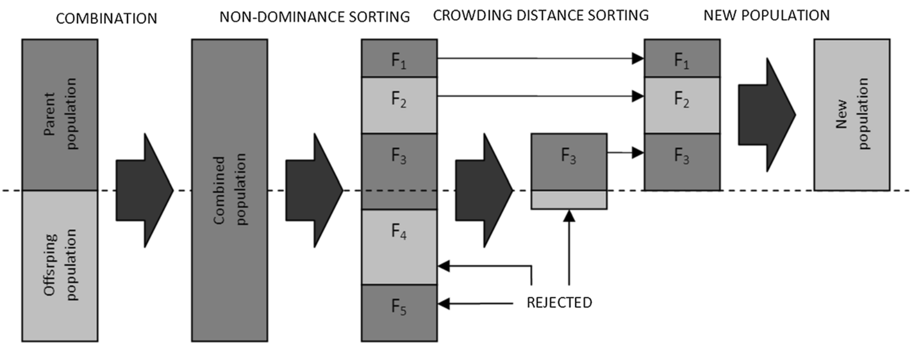


Fig. 5 Illustration of new population selection (Burke and Kendall 2005)

the initial population. The Pareto front that doesn't fit entirely will be ranked based on diversity (like in the mating selection stage) in order to determine which members are added to the next generation population.

Convergence test

The new population can either be the next generation parent population or the final population. The algorithm stops if the maximum number of generations has been reached or if the new population at the end of each generation has not changed over the last $\boldsymbol{n}$ generations (convergence test). When the framework is terminated the new population contains the (best-known) Pareto optimal set, because in the environmental selection only the best solutions in terms of Pareto optimality are selected out of the combined population of parents and offspring (also called elitism).

DBMO-SA framework

Figure 6 shows the second solution approach of this research. This framework uses the dominance based DBMO-SA method presented by Smith (2006). Smith has designed the DBMO-SA for a multi-objective optimization problem. In paper it has been modified in order to be used in a MO NDP. First of all, the use of link types has been implemented in order to make it a discrete NDP. Secondly a checklist is used to track all solutions that are determined in the framework. Finally, a new technique is introduced to create a new solution with a feasible set of link types that has not been determined earlier in the framework.

A SA method is performed according to an annealing schedule in a fixed number of steps, called temperature stages, and a fixed number of iterations per temperature stage. Each iteration starts with a single feasible solution for the multi-objective network design problem, called the starting state. A state is a set of feasible link types for the distinguished link sets. In each iteration a new state is created based on the starting state. This new state is also a set of feasible link types for the distinguished link sets. The goal is to find a new state using local search which is better than the starting state of that iteration. During the search an archive is built to store all states found thus far that are not dominated by any other state. Each time a new state is found, it is checked whether or not it dominates any state in the archive. If it does, these states are replaced with the new state. Therefore the archive has a variable size unlike the size of the population in the GA.

Initialization

The first state of the SA framework is the reference situation and consists of the starting link types of each of the link sets in the road network. The lower level is optimized by solving the User Equilibrium problem using a traffic assignment based on this road network with these starting link types. The outcome of this assignment is used to determine the values of the objective functions. The initial state is stored in an archive, because it is the only and therefore best state found so far.

Annealing schedule

The annealing schedule determines how many temperature stages are preformed and the amount of iterations per temperature stage. In each iteration a new state is created and

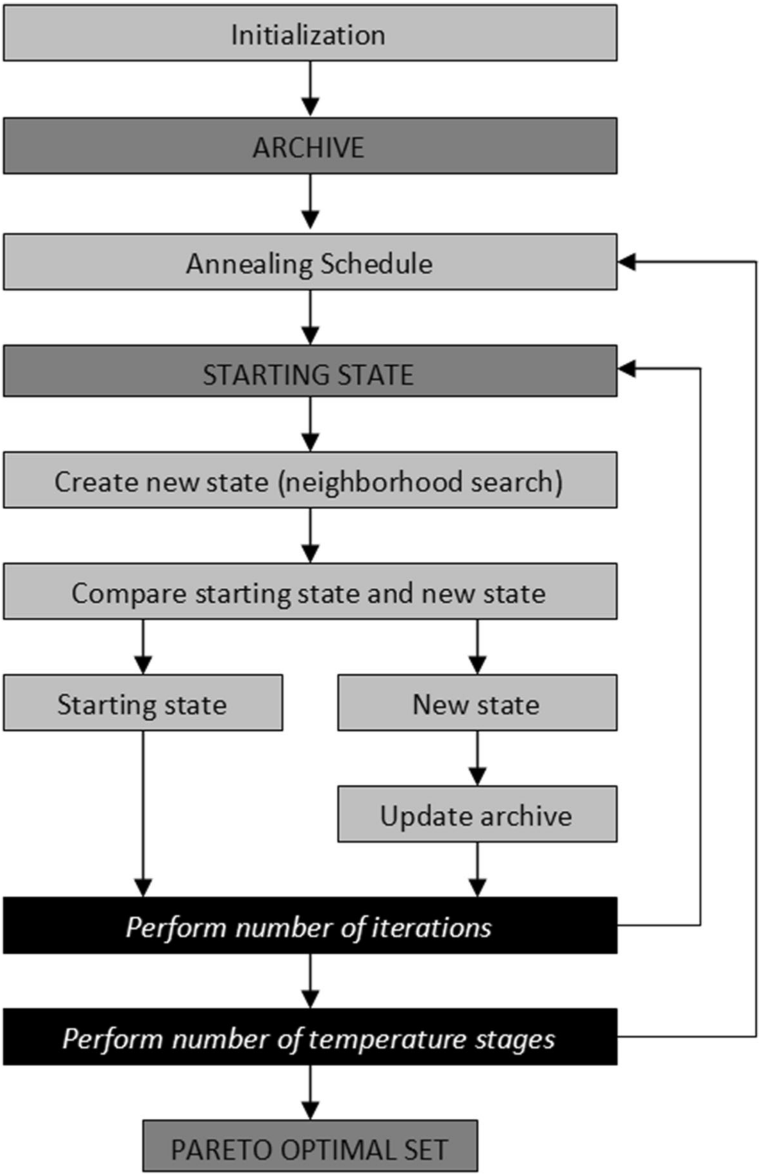


Fig. 6 The DBMO-SA framework

compared with the starting state. The framework is terminated when all iterations in all temperature stages have been preformed. No convergence test has been created because a SA method is expected to need the entire annealing schedule to find a Pareto optimal set. When the framework is terminated, the archive is the (best-known) Pareto optimal set.

Every iteration the starting state and new state are compared in order to determine with which one to continue. This is done with Eq. (5) (the variables are explained in Table 4).

Table 4 variables used in the DBMO-SA

Variable	Description
K	Number of temperature stage with index k $(-)$
U_k	Iterations at temperature stage k $(-)$
τ_k	Temperature at stage k $(-)$
τ_{start}	Starting temperature of the annealing schedule $(-)$
τ_{goal}	Near zero temperature of the annealing schedule $(-)$
k_{goal}	Temperature stage in which τ_{goal} is reached $(-)$
θ	Fraction with which τ_k is lowered per temperature stage k $(-)$
υ	Number of states in the archive
ω_{start}	Number of states in the archive dominated by the starting state
ω_{new}	Number of states in the archive dominated by the new state
ε	Value to determine whether to continue with the starting or the new state
Δ	Value to determine whether to continue with the new state if the starting state is better
$rand(0,1)$	Random number between 0 and 1

$$\begin{aligned} &\varepsilon = \frac{\omega_{start} - \omega_{new}}{\upsilon} \\ &\text{where} \quad \text{continue with new state} \quad \text{if} \quad \varepsilon < 0 \\ &\qquad\quad \text{continue with starting state} \quad \text{if} \quad \varepsilon \geq 0 \end{aligned} \tag{5}$$

However in order to encourage the search in the entire solution space and prevent a local convergence it is also possible that the framework continues with the new state, although the starting state is better. If the outcome of Eq. (5) dictates that the framework should continue with the starting state, then Eq. (6) has to be implemented (the variables are explained in Table 4).

$$\begin{aligned} &\Delta = \min\left(1, \exp\left(\frac{-\varepsilon}{\tau_k}\right)\right) \\ &\text{with } \tau_k = \theta^{k-1} \cdot \tau_{start} \text{ and } \theta = \left(\frac{\tau_{goal}}{\tau_{start}}\right)^{\frac{1}{k_{goal}-1}} \forall k \in K \quad . \\ &\text{where continue with new state} \quad \text{if} \quad \Delta \leq rand(0,1) \\ &\qquad \text{continue with starting state} \quad \text{if} \quad \Delta > rand(0,1) \end{aligned} \tag{6}$$

An important variable in this formula is the stage temperature. The SA framework has a starting temperature in the first starting stage. Each temperature stage the temperature is decreased. This temperature is used in all iterations within that temperature stage. The temperature is decreased according to the annealing scheme in Eq. (6). When the temperature is decreased this also decreases the probability of accepting the new state (which is not better than the starting state). The temperature is decreased every temperature stage until it reaches a near zero point. From this near zero point the framework effectively becomes a greedy search algorithm in which the starting state (which is better than the new state) is always chosen to continue the framework with.

Create new state (neighborhood search)

Each iteration starts with finding a new state based on the starting state of that iteration. To prevent creating states that have already been explored or creating unfeasible states, a new method is uses in which one element (link type) of the state is randomly selected and all possible new states that can be created by changing this element into another feasible link type are determined. If this does not result in any new states, this step is repeated by randomly selecting a second element and creating all possible new states by changing these two elements. This is repeated until possible new states can be created. The new state is randomly chosen from these possible new states. For this new state the lower level is optimized by solving the User Equilibrium problem using a traffic assignment based on this road network with the link types of the new state. The outcome of this assignment is used to determine the values of the objective functions.

Compare starting state and new state

The next step is to decide whether to continue with the starting state or the new state. However, if there are a limited number of archive members a comparison with the archive is of little use. In this case several temporary states are added to the archive, called the attainment surface. An attainment surface consists of points in the objective space which do not nor are dominated by any of the archive members. The attainment surface members have therefore the same Pareto rank as the archive members. Now the number of attainment surface members that are dominated by the starting state is compared with the number of archive and attainment surface members that are dominated by the new state. In this case, the framework will continue with the state that dominates the most members. After which the temporary states from the attainment surface members are removed from the archive.

If the framework continues with the new state, the archive is updated with the new state and the archive members that are dominated by the new state are removed from the archive. This process is repeated over all temperature stages and iterations. When the framework is terminated, the archive is the (best-known) Pareto optimal set.

Performance GA and SA method

In the next chapter both frameworks will be applied. In general the strength of the GA is that it searches directly in the total solution area and will, by incorporating diversity in its search, give a fast insight in the Pareto optimal set. However, a GA has a fixed population size and setting the parameters can be a difficult task, because these are case dependent. Setting parameters for the SA method is also case dependent. An advantages is that the SA method has a variable solution size, but this is more computational expensive. Another strength of the SA algorithm is that it searches more thorough for optimal solutions locally and incorporates a mechanism to prevent ending up in local optima. However the SA method can't improve further over time because it gradually becomes a greedy search algorithm, while the GA can still improve the solution consistently when give sufficient time (Mathew and Sharma 2009). Three performance measures are used to compare the outcomes of the GA and the SA method: the spacing metric, the C-metric and the S-metric (Deb 2001; Tan et al. 2005; Wismans et al. 2011).

Spacing metric

The spacing metric examines if the set of solutions is evenly spread in the objective space. Equation 7 shows the function used for the spacing metric and the variables are explained in Table 5.

$$SM(S) = \frac{1}{\bar{d}} \sqrt{\frac{1}{N} \sum_{n=1}^{N} (d_n - \bar{d})^2} \text{ with } \bar{d} = \frac{1}{N} \sum_{n=1}^{N} d_n. \tag{7}$$

The solutions in the objective space have a value for the total PM_{10} emission, traffic accidents and travel time. These objectives have a different scale. In order to provide a comparable euclidean distance, the values for all solutions are indexed based on the values of the reference situation. If the spacing metric equals zero, the solutions are completely evenly spread in the objective space. While a higher value of the spacing metric indicates a less evenly spread. Therefore a small value of the spacing metric is desired. However, it is important to keep in mind that the spacing metric only focuses on the spread across the solutions part of the considered set, which means that a certain set which is not near the true Pareto optimal set or only contains a specific part of this set can still perform well on this metric.

C-metric

The C-metric measure is used to compare two sets based on the number of dominated solutions. Equation 8 shows the function used for the spacing metric and the variables are explained in Table 6. This equation determines the number of solutions from the second solution set ($s'' \in S''$), that are weakly dominated ($s' \succeq s''$, e.g. the objective functions values for solution s' are equal or better compared to the objective functions values for solution s'') by at least one solution from the first solution set ($\exists s' \in S'$) and divides it by

Table 5 Variables used in the function for the spacing metric

Variable	Description
$SM(S)$	Spacing metric for set S
S	$S = (s_1, s_2, \ldots, s_N)$ is a set of N solutions s_n, with index n
s_n	Solution in the objective space with values for the total PM_{10} emission, traffic accidents and travel time
d_n	Euclidean distance between solution n and its nearest solution

Table 6 Variables used in the function for the C-metric measure

Variable	Description
S'	$S' = (s'_1, s'_2, \ldots, s'_N)$ is the first set of N solutions s'_n, with index n
S''	$S'' = (s''_1, s''_2, \ldots, s''_N)$ is the second set of N solutions s''_n, with index n
s_n	Solution in the objective space with values for the total PM_{10} emission, traffic accidents and travel time
$CM(S', S'')$	C-metric indicating the coverage of set S' over set S''

the total number of solutions in the second solution set (S''). The resulting number is a degree of coverage of the first solution set (S') over the second solution set (S'').

$$CM(S', S'') = \frac{|\{s'' \in S'' \exists s' \in S', s' \succeq s''\}|}{|S''|} \tag{8}$$

If the C-metric value equals one, all solutions in the second set are covered by the solutions in the first set. In this case the first set is undisputable better than the second set. However, if the value equals zero, none of the solutions in the second set are covered by the solutions in the first set. Now, the first set is either equal or worse than the second set. In this way the two sets from both frameworks can be compared.

S-metric

The S-metric is used in this research to measure the convergence of the solutions in both frameworks. The S-metric equals the size of the objective space coverage by the solutions. Because this is a minimization problem, the objective space covered objective space is infinite. Therefore a maximum point in the objective space is chosen which is larger than any of the solutions. Now there is a confined objective space and the S-metric is the percentage of the confined objective space that is covered by the solutions.

The larger the value of the S-metric the better the space coverage. The S-metric also focuses on the ability to attain the global trade-offs, which means a set of solutions performs better if its space coverage is larger. This measure does not take into account the number of solutions which are dominated. In general a smaller subset of the Pareto optimal set results in a lower performance on the S-metric than a larger subset.

Application and results

Both solution approaches are applied in two case studies. The first case study is a small test case network for which it was possible to assess all possible solutions and therefore the actual set of Pareto optimal solutions. This case study will be used to validate both frameworks. The second case study is a more practical scenario for the Almelo road network. This case study is used to test the behavior of both frameworks on networks for which it is not realistic to asses all possible solutions. In this test case the performance measures will be used.

Case study I: small test case network

The network for the first case study is shown in Fig. 7 with the different link types. It contains 19 links and 4 centroids. In the network a fixed traffic demand is used. Four link sets are used, indicated by I through IV. Not all links are part of a link set. The link types for these links remain the same. All link sets are described in Table 7. There are 360 possible combinations of link types. Because of the relative small size of this test case it was possible to determine that there are 12 Pareto optimal solutions out of the 360 possible solutions.

This case study is used to check whether the frameworks can find the Pareto optimal solutions and determine which values should be used for the parameters in both frameworks to find the most of the Pareto optimal solutions. Based on the suggested parameters

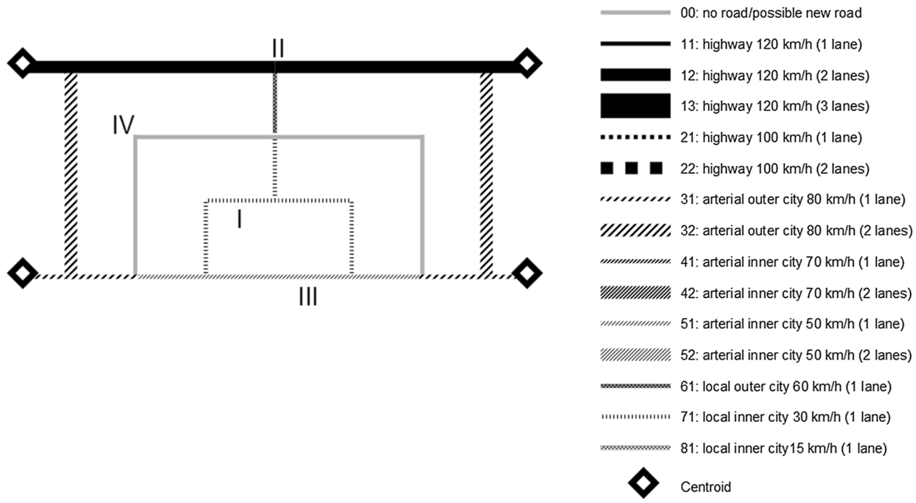


Fig. 7 Test case network for the framework validation

Table 7 Link sets with the number of possible link types

Link set	Description	Current link types	Alternative link types	Possibilities
I	Inner city local roads	61	51, 71	(3×)
II	Highway	12	13, 22, 21	(4×)
III	Inner city arterial road	51	42, 41, 61, 71	(5×)
IV	Possible new road	00	32, 31, 42, 41, 51	(6×)

from Deb et al. (2000) and Smith (2006) several possible values for each parameter are determined. For each combination of these possible values the framework is preformed 10 times. The combination that finds on average the most of the Pareto optimal solutions is considered the most promising set of parameters. Table 8 shows the sets of parameters for both frameworks for which this is the case.

Both frameworks were applied 100 times with the best parameter sets for further analysis. Both the GA and SA framework had a similar performance concerning the outcome of the search, and always found more than 95 % of this Pareto optimal set (on average respectively 96.4 and 96.8 %). In summary, both frameworks are capable of finding the majority of the Pareto optimal solutions for this case study.

Table 8 Parameters for the GA and SA framework

GA framework	SA framework
Population size $I = 20$	Temperature stage $K = 20$
Maximum generation $G = 10$	Iteration per stage $U_k = 10$
Uniform crossover $\rho_s = 0.6$	Starting temperature $\tau_{start} = 0.2$
One-gen mutation $\rho_m = 0.05$	Near zero value $\tau_{goal} = 10^{-3}$
	Near zero location $k_{goal} = 2/3$
	Minimum archive size $Z = 5$

Case study II: Almelo road network

In the second case study the main road network of Almelo is used. This is a medium size city in the eastern part of the Netherlands. In the inner city of Almelo traffic causes problems concerning traffic safety and environment. For these problems alternative link types are used which either provides more capacity to better facilitate the traffic demand or link types with less capacity that discourages traffic to use those roads. There are also several congestion problems on the highway, for which several link types with more capacity can be used. Furthermore a wide variety of possible traffic measures and many different link types are available in Almelo. For this case study we enlarged the existing traffic problems to increase possible conflicting objectives and all possible traffic measures considered are fictional. The network contains 193 links, 18 centroids and 10 link sets. In the network a fixed traffic demand is used. The link sets that are distinguished in this case study are shown in Fig. 8 and described in Table 9.

The choice for these link sets and the subsequent available link types are based on the earlier mentioned criteria. This means that the link sets contain links which have initially the same link set, the same function within the network and from a traffic engineering point of view are not allowed to change independently from each other.

This formulation results in 729,000 possible combinations of feasible link types. Solving the lower level optimization problem performing a traffic assignment takes about 1 min, which means assessing all options would take almost 1.5 years (all calculation where done with MatLab on one Windows 7 computer with 8 Gb RAM). Within this case study three conflicting objectives are optimized: air quality by minimizing total PM_{10} emissions, traffic safety by minimizing total number of traffic accident fatalities and accessibility by minimizing total travel time.

In the first case study several combinations of parameters have been tested. For this case study the same parameters will be used except for the parameters concerning the maximum number of assessed solutions (population size and maximum generation for the GA

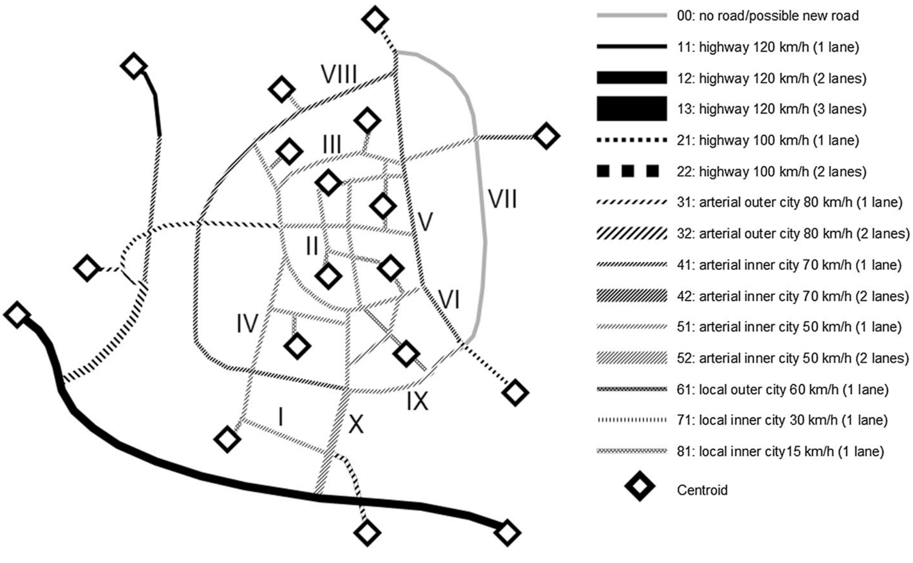


Fig. 8 Link types and link sets in the Almelo road network

Table 9 Link sets with the number of possible link types

Link set	Description	Current link types	Alternative link types	Possibilities
I	Inner city local roads	51	71, 81	(3×)
II	Inner city arterial roads	51	52, 41	(3×)
III	Inner city ring	51	52, 41	(3×)
IV	Roads between the rings	51	52, 41	(3×)
V	Overlapping part rings	41	71, 51, 52, 42	(5×)
VI	Eastern part outer ring	41	71, 51, 52, 42	(5×)
VII	New part of outer ring	00	52, 41, 42, 31, 32	(6×)
VIII	Outer ring 70 km/h	41	52, 42, 31, 32	(5×)
IX	Outer ring 50 km/h	51	52, 41, 42, 31, 32	(6×)
X	Road to outer ring	52	42	(2×)

framework and temperature stage and iterations per stage for the SA framework). In this case study a maximum of 2000 solutions can be assessed in both frameworks. Because solving the User Equilibrium problem in the lower level is by far the most time consuming task in both algorithms both algorithms were given the same number of total assessed solutions. This also ensures the comparability of both frameworks concerning the computation time and percentage of the solution space that can be explored. The used parameters are presented in Table 10.

Both frameworks are preformed 10 times with these parameters. The calculation time for each run is 32 h. If, in order to improve the performance, more solutions should be considered (e.g. a bigger population size or more stages) or a real-world network would be used the calculation time would increase significantly. In these cases more and/or powerful machines are necessary. It is also possible to improve the algorithm by programming it more efficiently. In the next section the results will be discussed concerning the Pareto optimal solutions. Next the chosen link types are investigated and finally the performance measures for both frameworks will be presented.

Pareto optimal solutions

It is not possible to determine whether the Pareto optimal solutions have been found. However, the solutions in the objective space present some interesting issues. Figure 9 shows the objective space for all three objectives. This is the objective space of the first time the frameworks are performed in case study II. The values of the objective functions

Table 10 Parameters for the GA and SA framework

GA framework	SA framework
Population size $I = 50$	Temperature stage $K = 50$
Maximum generation $G = 40$	Iteration per stage $U_k = 40$
Uniform crossover $\rho_s = 0.6$	Starting temperature $\tau_{start} = 0.2$
One-gen mutation $\rho_m = 0.05$	Near zero value $\tau_{goal} = 10^{-3}$
	Near zero location $k_{goal} = 2/3$
	Minimum archive size $Z = 5$

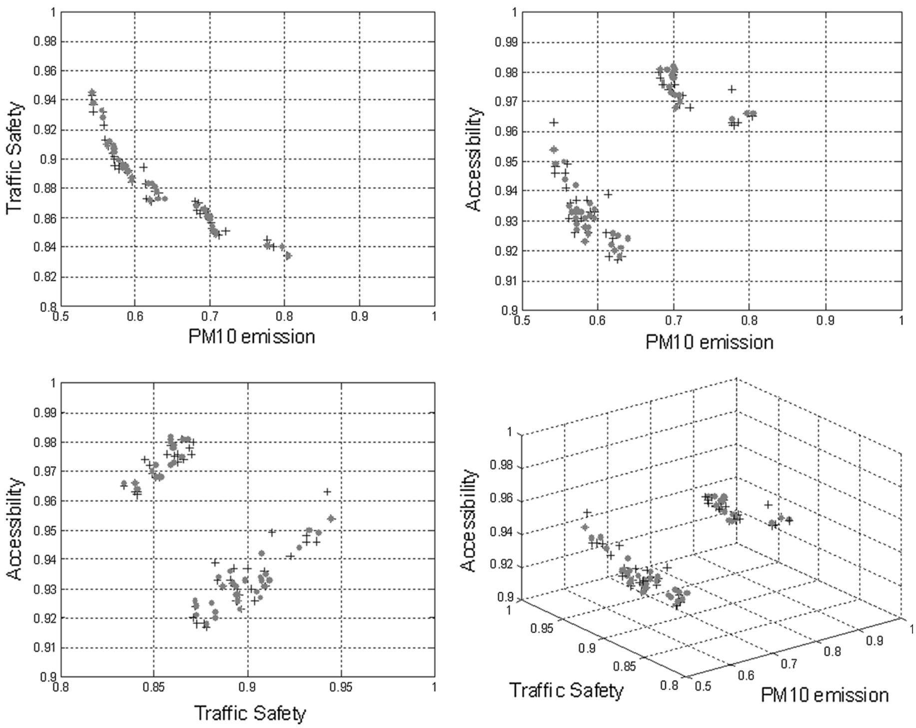


Fig. 9 GA (+) and SA (●) results in the objective space

of all non-dominated solutions found by both frameworks are expressed as relative values to the reference case.

Both frameworks found solutions in the same areas of the objective space. But GA and SA mostly found different solutions, a bigger population size (GA) or more stages (SA) could be considered to improve the results. However, the fact that the solutions are found in the same areas of the objective space makes it more plausible that they found the Pareto optimal front. In the next four sections the four different figures are examined more closely.

Traffic safety—PM$_{10}$ emission figure The first figure shows a classic curve for a Pareto optimal set in the objective space of the PM$_{10}$ emission and casualties. In this figure all solutions are clearly uniformly distributed along an optimal set.

Accessibility—PM$_{10}$ emission figure The second figure shows a classic curve divided over two clusters in the objective space of the PM$_{10}$ emission and total travel time. Link set 1 causes the two clusters. For link set 1 either 15 km/h or 30 km/h local roads are used for, which has no effect on the traffic safety, because the same risk factors are used, but which has a serious effect on accessibility and PM$_{10}$ emission. Furthermore, the links in link set 1 are mostly concentrated around the zones in the inner city of Almelo. So for the trips originating or heading to those zones there are hardly any route choice possibilities and thus most of those trips use these links regardless the use of either 15 km/h or 30 km/h local roads. With a lower speed, the total travel time increases due to a higher travel time and the PM_{10} emission increases due to a higher emission factor. If only accessibility and PM_{10} emission is used as objective function, the solutions with the 15 km/h local roads would have been dominated. But because traffic safety is also an objective function, these solutions are not dominated.

Accessibility—Traffic safety figure A cluster can also be recognized in the third figure, which shows the accessibility and traffic safety. However, instead of a classic curve, the two objectives seem to be aligned. This alignment can be explained by the fact that in most optimal solutions for accessibility all links of initial link type arterial 50 km/h have been replaced by 70 km/h arterial roads, which in our test case have a lower risk factor.

Accessibility—Traffic safety—PM_{10} emission figure Finally, the fourth figure shows the objective space for all three objective functions. In this figure both the classic curve and the two clusters can be recognized.

Chosen link types

When investigating the solution space (the first time the frameworks are preformed), both frameworks have explored a large variety of different solutions in the solution space, because on average 7 link sets of the 10 distinguished of the final solutions contain different link types than the reference case. In order to get to this outcome a lot of link types of the initial link types had to be altered. Subsequently, this means that both frameworks work correctly and are able to explore a large area in the solution space while the maximum number of solutions that can be considered is relatively low (0.25 % of the solution space). This means that a lot of different solutions have been considered widely spread over the solution space.

Table 11 shows the link types most often used for the link sets in the final solutions. Clearly from the available link types mostly the link types with the highest maximum speed and capacity where most often chosen. In most of the final solutions (in which case the link types shown in Table 10 are mostly used) the use of the inner city links is lowered because more traffic use the outer city links (compared to the reference case). This has mainly a positive effect on the accessibility and traffic safety. A positive effect on the accessibility is due to the fact that link types with a higher maximum speed and capacity (compared to the reference case) are used, resulting in lower free flow travel times. These

Table 11 Link types most often used for the link sets in the final solutions

Link set	GA framework (%)	SA framework (%)
I	Arterial (1 lane) 50 km/h (58)	Arterial (1 lane) 50 km/h (62)
II	Arterial (1 lane) 70 km/h (86)	Arterial (1 lane) 70 km/h (72)
III	Arterial (2 lanes) 50 km/h (46)	Arterial (2 lanes) 50 km/h (46)
IV	Arterial (1 lane) 70 km/h (70)	Arterial (1 lane) 70 km/h (84)
V	Arterial (2 lanes) 70 km/h (46)	Arterial (1 lane) 70 km/h (42)
VI	Arterial (2 lanes) 70 km/h (74)	Arterial (2 lanes) 70 km/h (40)
VII	Arterial (2 lanes) 80 km/h (82)	Arterial (2 lanes) 80 km/h (66)
VIII	Arterial (2 lanes) 80 km/h (50)	Arterial (2 lanes) 80 km/h (56)
IX	Arterial (2 lanes) 80 km/h (64)	Arterial (2 lanes) 80 km/h (56)
X	Arterial (2 lanes) 70 km/h (100)	Arterial (2 lanes) 70 km/h (100)

link types are mainly available on the outer city links, which is why more traffic use these links instead of the inner city links. This has also a positive effect on the traffic safety because less 50 km/h links are used (which has the highest risk factor) and more, safer, 70 km/h or 80 km/h roads are used (which have a lower risk factor). That is why both objective functions prefer link types with higher maximum speeds and capacity on the outer city links, which explains why the solutions are aligned instead of opposed in the objective space of the traffic safety and accessibility (Fig. 9). However, this is conflicting with the objective functions for the environment, because it requires less traveled kilometers and using the outer city links increases the total traveled kilometers. Environment is therefore conflicting with accessibility and traffic safety which is clearly shown in the objective space of traffic safety and environment as in the objective space of accessibility and environment (Fig. 9). Overall, all objectives are improved in the final solutions compared to the reference case. This can be explained because the reference case contained many 50 km/h links. Both frameworks show that changing part of the 50 km/h outer city links in 70 km/h or 80 km/h while keeping the maximum speed on other links the same (50 km/h) will result in an improvement of all objective functions. These findings can be used as policy recommendations for the city of Almelo.

Performance of both frameworks

Unfortunately, without determining all possible solutions, it is not possible to check whether the Pareto optimal have been found. But with the performance measures spacing metric, C-metric and S-metric it is possible to determine which of the frameworks performs the best.

Both frameworks have been preformed 10 times. For each time the spacing metric is determined. The average spacing metric is shown in Table 10. The average spacing metric for the GA is less than the one for the SA framework. It can therefore be concluded that the solutions of the GA are more evenly spread in the objective space than the solutions of the SA framework.

The average C-metric is also shown Table 12. This value is determined by calculating the C-metric for each comparison of the 10 GA framework results with all 10 results from the SA framework (and visa versa). The average C-metric value for GA of 0.68 means that the Pareto optimal sets of the GA framework are covered for 68 % by the SA framework on average, while vice versa this is 84 %. This indicates that the GA framework on average dominates more solutions of the SA framework. It can be concluded that the GA outperforms the SA framework. This is probably because the SA searches more locally than the GA.

Another indication that the GA outperforms the SA framework are the results for the S-metric. The S-metric requires a maximum point. Every Pareto optimal solution found dominates the reference situation. The reference situation is therefore chosen as the maximum point. The average S-metric for both frameworks is illustrated in Fig. 10. For each iteration the average percentage of the objective space that is covered by the solutions

Table 12 Average results spacing metric and C-metric

Framework	Spacing metric	C-metric
GA	0.26	0.68
SA	0.19	0.84

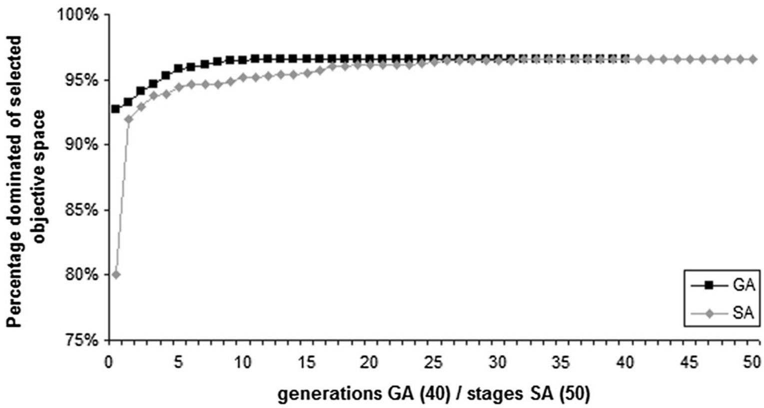


Fig. 10 Average convergence GA framework and SA framework (S-metric)

is determined over all 10 results of each framework. Figure 10 clearly shows that the GA framework convergences before the SA framework.

Whether or not the frameworks have produced the Pareto optimal set remains the question. This question can of course never be answered without determining the objective functions for all possible solutions. However, comparison the performance measures of both frameworks indicates that the GA framework performs better, because it is more efficient in finding more non-dominated optimal solutions within the same computation time and maximum number of assessed solutions.

Application

The next step is for policy makers to make a decision on which solution should be implemented. As there is no 'one best solution' and there are different political and legal demands concerning traffic problems it can be very useful that a choice can be made from different (optimal) solutions. However, 40 different solutions (like in the second test case) still leaves to many choices. It may therefore be useful to reduce this number by determining which solutions fit within the constraints like budget for infrastructure investments and environmental legislation or by using pruning methods. Pruning methods try to reduce the size of the Pareto optimal set while maintaining its main characteristics. It is also possible to incorporate constraint within the algorithms itself. Within the GA this can be incorporated when the fitness of the solutions is determined and within the SA method when a new state is created. To choose the final best compromise solution, multi criteria decision making methods (Tzeng and Tsaur 1997; Wismans et al. 2014) can play an important role. Choosing the best compromise solution is not within the scope of this paper, but can be applied in future studies on this subject.

Conclusions

In a small test case network both the GA and SA framework were validated and tested. The small test case network is a relative small road network for which the traffic assignment and subsequent objective functions for all possible combinations of feasible link types can be determined. In this way all optimal solutions can be determined in advance and can be used as frame of reference in the validation of both frameworks. After the validation both frameworks performed similar in the first test case and found more than 95 % of the Pareto optimal set.

The application of both frameworks for the Almelo road network, which is a much larger optimization problem than the first test case network has also shown that both modeling frameworks are capable of dealing with solving the MO DNDP. Both frameworks explored a large variety of different solutions in the solution space, while the maximum number of solutions that is considered is relatively low (0.25 % of the solution space). In the Almelo test case the total travel time (accessibility) and traffic safety where minimized by the use of higher maximum speeds and capacity on the outer city links (which increased the total kilometers traveled), while environment was minimized by taking the shortest route using the inner city links (which decreased the total kilometers traveled). Due to this conflict there is not one optimal solution. However this research shows that both presented approaches are applicable to solve such a problem and present several solutions which where an improvement for all objective functions compared to the reference case. These findings can be used as policy recommendations for the city of Almelo.

In order to further compare the results of the GA and SA framework, the spacing metric, C-metric and S-metric measure are used. The GA had a better score for all measure than the SA framework. It can be concluded that the GA outperforms the SA framework. This is probably because the SA framework searches more locally than the GA.

The performance could be different for other test cases, and therefore more research is needed. Here new specifications can be taken into account such as the fact that emission in urban areas is much less desirable than in non urban areas and that the objective functions and used link types could be different for other specific test cases.

This research showed that both frameworks are capable of finding suitable solutions for a MO DNDP in which the objectives are maximizing accessibility and minimizing the externalities of traffic. These frameworks can therefore be used as a tool to design sustainable networks, with a slight preference for the GA framework.

Acknowledgments The authors are grateful for the financial contributions of Goudappel Coffeng and the ATMA (Advanced Traffic MAnagement) and Pay-as-you-drive projects of the TRANSUMO program. TRANSUMO (TRANsition SUstainable MObility) is a Dutch platform for companies, governments and knowledge institutes that cooperate in the development of knowledge with regard to sustainable mobility.

References

Abdulaal, M., LeBlanc, L.J.: Continuous equilibrium network design models. Transp. Res. B **13B**, 19–32 (1979)

Boyce, D.E., Janson, B.N.: A discrete transportation network design problem with combined trip distribution and assignment. Transp. Res. B **14B**, 147–154 (1980)

Bureau of Public Roads: Traffic assignment manual, Urban Planning Division. US Department of Commerce, Washington DC (1964)

Burke, E.K., Kendall, G.: Search methodologies: introductory tutorials in optimization and decision support techniques. In: Sastry, K., Goldberg, D., Kendall, G. (eds.) Chapter 4: genetic algorithms. Springer Science + Business Media, Inc, Berlin (2005)

Cantarella, G.E., Pavone, G., Vitetta, A.: Heuristics for urban road network design: lane layout and signal settings. Euro. J. Oper. Res. **175**, 1682–1695 (2006)

Chiou, S.: Bi-level programming for the continuous transport network design problem. Transp. Res. Part B **39**, 361–383 (2005)

CROW (2004). Richtlijn essentiële herkenbaarheidkenmerken van weginfrastructuur: wegwijzer voor implementatie. Publicatie 203. CROW kenniscentrum voor verkeer, vervoer en infrastructuur, Ede

Dantzig, G.B., Harvey, R.P., Lansdowne, Z.F., Robinson, D.W., Maier, S.F.: Formulating and solving the network design problem by decomposition. Transp. Res. B **13B**, 5–17 (1978)

Drezner, Z., Wesolowsky, G.O.: Network design: selection and design of links and facility location. Transp. Res. Part A **37**, 241–256 (2003)

Deb, K.: Multi-objective optimization using evolutionary algorithms. Wiley, New York (2001)

Deb K, Agrawal S, Pratap A and Meyarivan T.: A Fast elitist no dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: Proceedings of sixth international conference on parallel problem solving from nature (PPSN VI), Paris, France, September 2000, pp. 849–858. Springer, Berlin (2000)

Deb, K., Agrawal, S., Pratap, A., Meyarivan, T.A.: A fast elitist multi-objective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. **6**(2), 182–197 (2002)

Frank, M., Wolfe, P.: An algorithm for quadratic programming. Naval Res. Logist. Quart. **3**, 95–110 (1956)

Friesz, T.L., Cho, H.J., Mehta, N.J., Tobin, R.L., Anandalingham, G.: A simulated annealing approach to the network design problem with variational inequality constraints. Transp. Sci. **26**, 18–26 (1992)

Friesz, T.L., Anandalingam, G., Mehta, N.J., Nam, K., Shah, S.J., Tobin, R.L.: The multi-objective equilibrium network design problem revisited —A simulated annealing approach. Eur. J. Oper. Res. **65**, 44–57 (1993)

Gao, Z., Wu, J., Sun, H.: Solution algorithm for the bi-level discrete network design problem. Transp. Res. Part B **39**, 479–495 (2005)

Johnson, D.S., Lenstra, J.K., Rinooy Kan, A.H.G.: The complexity of the network design problem. Networks **8**, 279–285 (1978)

Karoonsoontawong, A. and Waller, S.T.: Dynamic continuous network design problem—Linear bi-level programming and meta-heuristic approaches. Network Modeling 2006, Transp. Res. Rec., 104–117 (2006)

Konak, A., Coit, D.W., Smith, A.E.: Multi-objective optimization using genetic algorithms: a tutorial. Reliab. Eng. Syst. Saf. **91**, 992–1007 (2006)

LeBlanc, L.J.: An algorithm for the discrete network design problem. Transp. Sci. **9**, 183–199 (1975)

LeBlanc, L.J., Abdulaal, M.: An efficient dual approach to the urban network design problem. Comput. & Math. Appl. **5**, 11–19 (1978)

Loon Van, A.A.P.M., Wismans, L.J.J.: Gebiedsgericht Benutten plus Duurzaam Veilig met RBV. Verkeerskunde DVM-congres 2007 (2007)

Mathew, T. V., S. Sharma.: Continuous network design with emission pricing as a bi-level optimization problem. Applications of advanced technology in transportation. In: Proceedings of the Ninth international conference on applications of advanced technology in transportation, Chicago, IL (2006)

Mathew, T.V., Sharma, S.: Capacity Expansion Problem for Large Urban Transportation Networks. J. Transp. Eng. ASCE **135**(7), 406–415 (2009)

Mathew, T.V., Sharma, S.: Multiobjective network design for emission and travel-time trade-off for a sustainable large urban transportation network. Environ. Plan. B Plan. Des. **38**, 520–538 (2011)

Memon, G.Q., Bullen, A.G.R.: Multivariant optimization strategies for real-time traffic control signals. Transp. Res. Rec. **1554**, 36–42 (1997)

Meng, Q., Yang, H., Bell, M.G.H.: An equivalent continuously differentiable model and a locally convergent algorithm for the continuous network design problem. Transp. Res. Part B **35**, 83–105 (2001)

Ministerie van Volkshuisvesting, Ruimtelijke Ordening en Milieubeheer (VROM): Meet- en rekenvoorschriften voor luchtkwaliteit, www.vrom.nl (2006) (last visit: 14-08-2009)

Poorzahedy, H., Turnquist, M.A.: Approximate algorithms for the discrete network design problem. Transp. Res. B **16B**, 45–55 (1982)

Poorzahedy, H., Rouhani, O.M.: Hybrid meta-heuristic algorithms for solving network design problem. Eur. J. Oper. Res. **182**, 578–596 (2007)

Sharma, S., Ukkusuri, S.V., Mathew, T.V.: Pareto optimal multi-objective optimization for robust transportation network design problem. Transp. Res. Rec. **2090**, 95–104 (2009)

Sharma, S., Mathew, T.V.: Multi-objective network design for emission and travel-time trade-off for a sustainable large urban transportation network. Environ. Plann. B **38**, 520–538 (2011)

Smith, K.I.: A study of simulated annealing techniques for multi-objective optimization. Thesis for the degree of Doctor of Philosophy in Computer Science at the University of Exeter, Exeter (2006)

Steenbrink, P.A.: Optimization of transport network. John Wiley, New York (1974)

Tan, K.C., Khor, E.F., Lee, T.H.: Multiobjective evolutionary algorithms and applications. Springer, London (2005)

Tzeng, G.H., Tsaur, S.H.: Application of multiple criteria decision making for network improvement. J. Adv. Transp. **31**(1), 49–74 (1997)

Wismans, L.J.J., van Berkum, E.C., Bliemer, M.C.J.: Comparison of multiobjective evolutionary algorithms for optimization of externalities using dynamic traffic management measures. Transp. Res. Rec. **2263**, 163–173 (2011)

Wismans, L.J.J., Brands, T., Van Berkum, E.C., Bliemer, M.C.J.: Pruning and ranking the Pareto optimal set, application for the dynamic multi-objective network design problem. J. Adv. Transp. **48**(6), 588–607 (2014)

Xu, T., Wei, H., Wang, Z.: Study on continuous network design problem using simulated annealing and genetic algorithm. Exp. Syst. Appl. **36**, 2735–2741 (2009)

Yang, H., Bell, M.G.H.: Models and algorithms for road network design: a review and some new developments. Transp. Rev. **18**(3), 257–278 (1998)

Yin, Y.: Multiobjective bilevel optimization for transport planning and management problems. J. Adv. Transp. **36**(1), 93–105 (2002)

Zhang, G., Lu, J.: Genetic algorithm for continuous network design problem. J. Transp. Syst. Eng. Inform. Technol. **7**, 101–105 (2007)

Zhao, F., Zeng, X.: Simulated annealing-genetic algorithm for transit network optimization. J. Comput. Civil Eng. **20**, 57–68 (2006)