2011 International Conference on Networking, Sensing and Control
Delft, the Netherlands, 11-13 April 2011

Comparison of Evolutionary Multi Objective Algorithms for the Dynamic Network Design Problem

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***Abstract*— In traffic and transport a significant portion of research and application is focused on single objective optimization, although there is rarely only one objective that is of interest. The externalities of traffic are of increasing importance for policy decisions related to the design of a road network. The optimization of externalities using dynamic traffic management measures is a multi objective network design problem. The presence of multiple conflicting objectives makes the optimization problem challenging to solve. Evolutionary multi objective algorithms has been proven successful in solving multi objective optimization problems. However, like all optimization methods, these are subject to the free lunch theorem. Therefore, we compare the NSGAII, SPEA2 and SPEA2+ algorithms in order to find a Pareto optimal solution set for this optimization problem. Because of CPU time limitation as a result of solving the lower level using a dynamic traffic assignment model, the performance by the algorithms is compared within a certain budget. The externalities optimized are noise, climate and accessibility. In a numerical experiment the SPEA2+ outperforms the SPEA2 on all used measures. Comparing NSGAII and SPEA2+, there is no clear evidence of one approach outperforming the other.**

I. Introduction

A significant portion of research and application of optimization in traffic and transportation considers a single objective (e.g. [*1,2*]), although most real-world problems involve more than one objective. Within the class of Network Design Problems (NDPs), which optimize by expanding or improving an existing network, this single objective is traditionally on improving accessibility. One specific example of an NDP is to optimize a network through the implementation of dynamic traffic management (DTM) measures that can influence the supply of infrastructure dynamically (e.g. traffic signals and rush hour lanes). However, due to the increasing attention for the externalities of traffic, it may no longer suffice to view a transport system as feasible or optimal when only accessibility is improved. Therefore, in this paper we focus not only on congestion, but also on climate and noise. The presence of multiple conflicting objectives makes the optimization problem interesting to solve. Since no single solution can be termed as an optimum solution, the resulting multi-objective (MO) optimization problem resorts to a number of trade-off optimal solutions, known as Pareto optimal solutions.

Mathematical modeling of such a highly complex socio-technical system provides insight in the extent to which objectives are conflicting or not, which is very useful in the decision making process. 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). The upper level consists of the objectives that have to be optimized for solving the NDP. Because of the non convexity of the problem [*2,3*]), often heuristics are used.

In the bi-level optimization studies, the solution approach using evolutionary algorithms has been proven successful. Classical optimization methods like the weighted sum approach can at best find one Pareto optimal solution in one simulation run, while evolutionary algorithms can find multiple optimal solutions in one single search due to their population-based approach. More recently algorithms such as the MO simulated annealing method DBMO-SA can find multiple solutions in one single search as well, but because of the local search used within this approach, it does not incorporate diversity in the search [*4,5*]. Many evolutionary MO algorithms (EMOAs) have been proposed, however, SPEA2 proposed by Zitzler et al., the NSGA-II proposed by Deb et al. and SPEA2+ proposed by Kim et al. provide excellent results compared to other proposed algorithms [*6,7,8*]. However, like all optimization methods, an EMOA is subject to the no free lunch theorem. This theorem states that all optimization methods perform on average equally well across all classes of optimization problems. So if an algorithm A outperforms an algorithm B in one class of problems, B outperforms A in another [*9,10*]. Therefore, we are interested in the performance of these three algorithms in solving the MO NDP optimizing externalities of traffic using strategic DTM measures influencing the supply of infrastructure. In addition, solving the NDP using DTM measures and modeling the objectives in a realistic manner incorporating traffic dynamics [*11*] results in solving the lower level using a dynamic traffic assignment (DTA) model, which increases the needed CPU time. Although we are mainly interested in finding improvements and not

Manuscript received September, 2010. This work was supported by Goudappel Coffeng and Transumo.

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necessarily the exact Pareto optimal set, it does limit the budget of solutions that can be considered. Therefore, we are especially interested in the performance by the algorithms within a certain budget.

II. Network Design Problem

The NDPs are typically grouped into discrete problems (DNDP), in which the decision variable is a discrete variable [*2,11,12*], continuous problems (CNDP), in which is assumed that the decision variable is a continuous variable [*3,13,14,15,16*], and mixed problems, which is a combination of both [*17*]. Based on demand, NDPs can be grouped into fixed demand [*15*], stochastic demand [*18,19*] and (stochastic) elastic demand [*20*]. 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 above mentioned studies), or dynamic, which is rarely used [*18,21*]. 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. [*21*] studied for example optimal tolling and Cantarella et al. [*17*] the optimal signal setting in combination with lane layout.

In most cases, single objective network design problems are studied in which accessibility is optimized, where accessibility is expressed as the total travel time in the traffic network [*1,2*]. Different studies incorporated the investment costs within the objective function. Chiou, Meng et al. and Xu et al. [*3,15,16*] optimized total travel time in which the investment was translated in time using a conversion factor. Or in which travel time is translated into cost [*12,22*]. Occasionally other costs, like environmental costs (expressed in money), are added to the travel cost [*17,23*].

There are only few papers that use multiple objective functions in the upper level. Chen et al. [*19*] use travel time and construction costs as two separate objective functions and used an evolutionary algorithm. Friesz et al. [*14*] 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. [*24*] used an evolutionary algorithm to minimize total travel time and the higher moment for total travel time i.e. variance. Most MO NDP studies consider the minimization of investment cost as second objective as reported in [*24*].

In this research, instead of using static traffic models, focusing on a single objective, we propose an MO NDP in which the externalities of traffic are minimized using DTM measures and in which a DTA model is used to operationalize the lower level. This MO NDP is used to compare three EMOAs.

III. Optimization Problem and Framework

A. Optimization Problem

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

$$\min_{S\in F}\begin{pmatrix} z_1(S) \\ z_2(S) \\ \vdots \\ z_I(S)\end{pmatrix}, \text{s.t. } \left(q(S), v(S), k(S)\right)\in \Gamma^{DTA}\left(G\left(N, A\left(C(S)\right)\right), D\right)$$

in which S is a set of applications of strategic DTM measures to be selected from a set of feasible applications F, and $z_i(S)$, $i=1,\dots,I$, is a different objective function of the link flows $q(S)$, the link speeds $v(S)$, and the link densities, $k(S)$, expressed as $z_i(S)=f_i\left(q(S),v(S),k(S)\right)$. These objectives in our case concern accessibility, climate, and noise, but could be extended with air quality and safety. 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 G with nodes N and links A (with corresponding characteristics C), and the travel demand 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 captured in a fundamental diagram. The DTA model Streamline [*25*], which is a multiclass model with physical queuing and spillback, is used to solve for this dynamic user equilibrium.

The DTM measures defined in S are modeled as measures that influence the characteristics C of the links where the measures are implemented. This means for example that when a Variable Message Sign (VMS) is used to change the speed limit, the free speed and capacity of the links connected with this measure is changed. The characteristics C of links can therefore vary over time dependent of 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. Time 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 $S(t)=\left(s_1(t),...,s_B(t)\right)$, where each $s_b(t)$, $b=1,\dots,B$, can have M_b different settings, which we simply number from 1 to M_b. The set of feasible solutions can therefore be written as $F=\left\{S \mid s_b(t)\in\{1,\dots,M_b\}, \forall t=1,\dots,T\right\}$, such that there are $\left(\prod_b M_b\right)^T$ possible solutions. The set of applications of the DTM measures for all time periods is defined by $S=\left(S(1),...,S(T)\right)$ and forms a possible solution for the optimization problem.

B. Objective functions

Based on an extensive literature review [*11*], for each objective an objective function is defined, where the input stems from the DTA model. Accessibility is defined in terms of the total travel time in the network. Climate is defined as the total emission of CO_2. The emissions are determined based on the ARTEMIS traffic situation based emission model [*26*], which means dependent on the level of service of the traffic flows. 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 [*27*].

IV. EVOLUTOINAIRY MULTI OBJECTIVE ALGORITHMS

Evolutionary algorithms (EA) are inspired on 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 which have a higher chance of survival and reproduction. 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 minima. All three assessed algorithms contain elitism, which means preservation of good solutions, and use some kind of fitness sharing, which is a niching technique, to maintain population diversity. The preservation of good solutions in all approaches 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 the best dominated solutions and 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.

A. NSGAII

Deb et al. [*6*] developed an approach called non dominated sorting genetic algorithm II (NSGAII). 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 which is done using binary tournament selection with replacement.

B. SPEA2

Zitzler et al. [*8*] developed the approach called strength Pareto evolutionary algorithm 2 (SPEA2). Within the algorithm, the fitness assignment is carried out in three steps. First, the strength of each solution is determined, representing the number of solutions it dominates. Secondly, the raw fitness of each solution is determined by summation of the strengths of its dominators. Thirdly, determination of the fitness by incorporation of density information in the raw fitness value, which assigns a lower fitness to solutions in a highly populated area. The density of a solution is measured in the objective space as a decreasing function of the distance to the k-th nearest neighbor. This density information forms 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 fitness, considered so far. Within the SPEA2 approach, an archive truncation procedure is used if the size of the non dominated solutions exceeds the archive size. This procedure iteratively removes individuals from the non dominated solutions based on the distances between the solutions in the objective space, until the size of the non dominated solutions equals the archive size. The method used is different from the niching method used to determine the fitness value. In the truncation procedure, the solution that has the minimum distance to another solution is chosen for removal and if there are several solutions with minimum distance the tie is broken by considering the second smallest distances and so on. This archive contains solutions used for the mating selection which is done using binary tournament selection with replacement.

C. SPEA2+

Kim et al. [*7*] adapted the SPEA2 approach, as they argued that the crossover mechanism within NSGAII and SPEAII had not yet explored and both lack maintaining diversity in the solution space, while fitness sharing is performed using information on the objective space. The SPEA2+ approach differs in three ways of the SPEA2 approach. First, it uses neighborhood crossover, which crosses over solutions close to each other in the objective space. Secondly, within the mating selection, all solutions within the archive are selected as parents. Thirdly, maintaining two archives in which in case of the truncation procedure in one archive truncation is done by using the distances within the objective space and in the other archive in the solution space..

D. Performance measures

We first introduce some definitions. The set of solutions $X^* = \{S_1^*,...,S_n^*\}$, which is the outcome of our MO MPEC problem, consists of all solutions for which the corresponding objectives cannot be improved for any objective without degradation of another and is known as the Pareto optimal set. However, if the size of this solution set is greater than the archive, i.e. if $n > N$, then we only find a subset of solutions that are non dominated within the assessed solutions. In this research, the exact Pareto optimal set is not known, hence we aim at finding such a subset. Mathematically, the concept of Pareto optimality is as follows. If we assume two solutions $S_1, S_2 \in F$, then S_1 is said to weakly dominate S_2 (also written as $S_1 \succeq S_2$) if $z_i(S_1) \le z_i(S_2)$ for all *i*.

In order to compare the three algorithms, we used different complementary measures to evaluate the trade-off fronts, namely, the spacing metric, the coverage of two sets (C-metric) and the size of the space coverage (S-metric) [*5,8,28,29*]. Let us introduce $X' = (S_1', S_2',..., S_N') \subset X$ be a set of solutions to explain these measures. The spacing metric determines how well the solutions are distributed in the objective space, function $SMO(X')$, and solution space, function $SMS(X')$.

$$SMO(X') = \frac{1}{\bar{d}}\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(d_n - \bar{d}\right)^2}, \text{ with } \bar{d} = \frac{1}{N}\sum_{n=1}^{N} d_n.$$

d_n is the Euclidean distance between each solution and its nearest solution. In function $SMO(X')$ this distance is measured in the objective space, while in function $SMS(X')$ in the solution space. The smaller the value of $SMO(X')$, the better the distribution of the solutions in X'. The C-metric, function $CTS(X', X'')$, is used to determine whether the Pareto optimal set found by a certain approach is dominated by a Pareto optimal set found by another approach. The function determines the coverage of two sets of the ordered pair (X', X''), which means the level in which the solutions X' weakly dominates X''.

$$CTS(X', X'') = \frac{\left|\{S'' \in X''; \exists S' \in X' : S' \succeq S''\}\right|}{|X''|}$$

The value $CTS(X', X'') = 1$ means that all solutions in X'' are covered by the solutions in X'. The opposite, $CTS(X', X'') = 0$ represents the situation where none of the solutions in X'' are covered. The S-metric, function $SSC(X')$ determines if the solutions of one approach covers a larger space in the objective space. It calculates the (hyper)volume enclosed by the union of the polytopes formed by the intersection of the following hyperplanes arising out of every single solution along with the axis in the objective space. For the minimization problem, the origin and therefore the axis are moved to a point representing the upper bound of each objective, defined by $w\left(z_1^{\max}(S_i), z_2^{\max}(S_j)\right)$. Because the true maximum values of the objective functions are not known, we choose a conservative point, based on the evaluated solutions. In the two-dimensional case, each polytope represents a rectangle defined by this point $w\left(z_1^{\max}(S_i), z_2^{\max}(S_j)\right)$ and $\left(z_1(S_i), z_2(S_i)\right)$. The hypervolumes are calculated based on the Hypervolume by slicing objectives (HSO) algorithm introduced by While [*30*]. The larger the value of $SSC(X')$, the better the space coverage. All these metrics mainly examine the performance in two aspects, i.e. the spread across the Pareto optimal front and the ability to attain the global tradeoffs.

V. Case Study: Numerical Experiment

A. Case

For providing a clear demonstration, a simple transport network is hypothesized, consisting of a single origin-destination relation with three alternative routes. One route runs straight through a city with urban roads (speed limit of 50 km/h); the second route is via a ring road using a rural road (speed limit of 80 km/h); the third route is an outer ring road via a highway (speed limit of 120 km/h). A three-hour morning peak was simulated between 6am and 9am. The travel demand varies with time over the simulation period (maximum of 6,300 pcu/h in the morning peak) consists of passenger cars and trucks (10% of total demand).

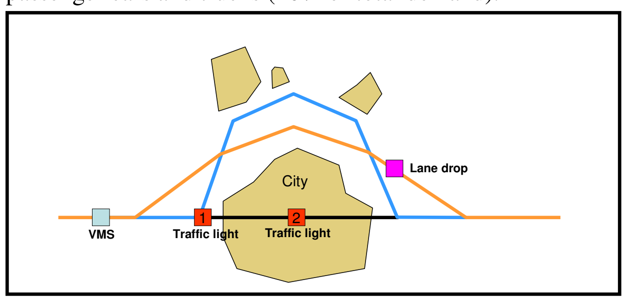


Fig. 1. Representation of network

Within the network, there are three measures available, namely two traffic lights and a VMS used to change speed limits. The first traffic light is split into two measures while the two signaled directions are independent. These measures can be used to optimize the different objectives (possible settings listed in Table 1). In total six time intervals for the DTM measures are distinguished, equally divided into 30 minute slices, which means $t \in \{1,...,6\}$.

Although the network is small, it incorporates important elements like urban and non-urban routes when using DTM measures to optimize the externalities. Moreover, these objectives were modeled in a realistic manner incorporating traffic dynamics. In addition, these possible settings in this case study already results in 4.05×10^{21} possible solutions. Because the evaluation of one solution means solving the lower level DTA problem, which requires approximately one minute of CPU time, it would take 7.7×10^{15} years in order to assess all possible solutions.

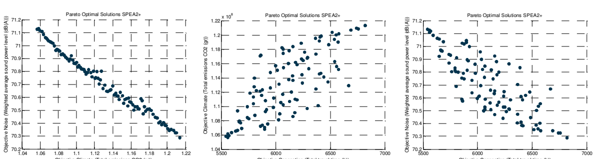
TABLE I
OVERVIEW MODELING DTM MEASURES

	$s_b(t)$	*Characteristic*	$C(s_b(t))$
Traffic light 1	$s_1(t)\in\{1,...,11\}$	Outflow capacity	$C(s_1(t))\in\{500,600,...,1400,1500\}$
	$s_2(t)\in\{1,...,11\}$	Outflow capacity	$C(s_2(t))\in\{500,600,...,1400,1500\}$
Traffic light 2	$s_3(t)\in\{1,...,11\}$	Outflow capacity	$C(s_3(t))\in\{500,600,...,1400,1500\}$
VMS	$s_4(t)\in\{1,...,3\}$	Free-flow speed, Capacity increase	$C(s_4(t))\in\{\begin{pmatrix}80\\0.05\end{pmatrix},\begin{pmatrix}100\\0.025\end{pmatrix},\begin{pmatrix}120\\0\end{pmatrix}\}$

B. Parameter settings

In order to restrict computation time, we limit the budget of solutions that can be considered. In the comparison of the approaches, the total number of solutions evaluated after the initialization is a fixed number of 5,000 solutions. The algorithms are not fully converged as they can improve the S-metric on average with 1%. For all three algorithms we used the same genetic operators, namely uniform crossover with a recombination rate ρ_{rec} of 1 for recombination and mutation in which the mutation rate ρ_{mut} decreases with 95% within the first 10 generations. Only small mutations occur, as we assume that mutation results in shifting the DTM application one up or down, i.e., if $s_b(t)$ is selected for mutation, its value after mutation becomes either $s_b(t)-1$ or $s_b(t)+1$. For all approaches we varied the population size N_p, 50 or 100 solutions, and the initial mutation probability ρ_{mut}^{init}., 0.2 or 0.05, which means in total 12 different approaches. Because genetic algorithms are stochastic in nature, all approaches were carried out 5 times. On a single fast computer, all these computations would take approximately 8 months, hence we distributed the computations over multiple computers.

C. Results



a) Noise vs Climate b) Climate vs congestion c) Noise vs Congestion
Fig. 2. Pareto optimal solutions

Figure 2 shows the solution set obtained by SPEA2+ for one single run, the other approaches show similar results.

The results show that the objectives congestion and climate in this case are strongly aligned, while there is one single optimal solution (in the different approaches not necessarily the same solution) which minimizes both objectives. However, both objectives are opposed to the objective noise. This can be explained as follows. Optimizing congestion aims at avoiding congestion using full capacity of the available routes, which is also good for minimizing CO_2 emissions. Optimizing noise aims at lowering the driving speeds as much as possible and also avoiding traffic using the urban routes.

TABLE 2
OVERVIEW RESULTS SPACING METRIC AND S-METRIC

	N_p	ρ_{mut}^{init}	$SMS(X')$	$SMO(X')$	$SSC(X')$
NSGAII	100	0.20	0.32	0.72	2.03E+11
	100	0.05	0.35	0.79	2.03E+11
	50	0.20	0.43	0.68	2.01E+11
	50	0.05	0.43	0.77	2.04E+11
	Average		**0.38**	**0.74**	**2.03E+11**
SPEA2	100	0.20	0.28	0.37	2.02E+11
	100	0.05	0.24	0.40	1.98E+11
	50	0.20	0.31	0.24	2.02E+11
	50	0.05	0.31	0.24	2.01E+11
	Average		**0.29**	**0.31**	**2.00E+11**
SPEA2+	100	0.20	0.21	0.39	2.06E+11
	100	0.05	0.20	0.27	2.03E+11
	50	0.20	0.26	0.20	2.01E+11
	50	0.05	0.24	0.23	2.01E+11
	Average		**0.22**	**0.27**	**2.02E+11**

Table 2 shows the average results of the spacing metric and S-metric. The SPEA2 and SPEA2+ approaches perform better than the NSGAII approaches concerning the spacing metric in the solution space as well as in the objective space. The S-metric shows that on average the NSGAII and SPEA2+ approach perform slightly better than the SPEA2 approach. Concerning the population size, the spacing in the objective space show better results when the population size is 50 compared to 100 solutions and slightly worse concerning the S-metric. This can be explained because the population size is smaller, the number of generations is higher and the impact of fitness sharing in the algorithms is larger. However, a smaller population size will automatically result in a smaller S-metric when the solutions of both approaches are part of the same efficient frontier. The results concerning the spacing metric are relatively insensitive to the mutation rate. The S-metric shows a slightly better result with a mutation rate of 0.2.

TABLE 3
OVERVIEW RESULTS C-METRIC

$CTS(X', X'')$

	NSGAII	SPEA2	SPEA2+
NSGAII		0.12	0.09
SPEA2	0.20		0.11
SPEA2+	0.23	0.18	

The average results of the C-metrics (shown in Table 3) indicates that there are no approaches which completely cover the results of another approach, hence we cannot indicate a single best approach. It also shows that the SPEA2+ approach shows on average a larger coverage of other approaches. The approaches with population size of 50 are in general more covered (on average 0.26 vs. 0.07) and the results concerning mutation rates are similar.

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VI. Discussion, Conclusion and Further Research

The results of the numerical experiment indicate that the SPEA2 and mainly the SPEA2+ approach is able to obtain a more diverse solution set in the objective space as well as in the solution space than the NSGAII approach. However, the NSGAII approach is able to obtain a slightly larger space coverage. The SPEA2+ approach is also able to cover more of the sets attained by the NSGAII and SPEA2 approach. On average, the SPEA2+ outperforms the SPEA2 in this optimization problem on all used measures. Comparing NSGAII and SPEA2+, there is no clear evidence of one approach outperforming the other. However, since the ability to attain the global tradeoffs by both approaches is similar and SPEA2+ does show more diverse solutions, the SPEA2+ approach is recommended. The size of the population influences the performance on the measures. A larger population results on average in a larger space coverage, while a smaller population size results in higher performance on spacing. Most performance measures are relatively insensitive for the mutation rate, only the space coverage show slightly better results for the mutation rate of 0.2 versus 0.05.

Since we compared the algorithms using only one single numerical experiment and since objective functions may behave differently in other cases, research should be done on other networks to be able to draw more general conclusions. While we used a DTA model to solve the lower level, the needed CPU time is large. Possible interesting directions lowering the needed CPU time are incorporation of local function approximation, utilizing parallel computing methods for which EMOAs are suitable and marginal computing.

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