

MULTI-OBJECTIVE OPTIMIZATION OF MULTIMODAL PASSENGER TRANSPORTATION NETWORKS: COPING WITH DEMAND UNCERTAINTY

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Abstract. *Robustness of optimal solutions when solving network design problems is of great importance because of uncertainty in future demand. In this research the optimization of infrastructure planning in a multimodal passenger transportation network is defined as a multi-objective network design problem, with accessibility, use of urban space by parking, operating deficit and climate impact as objectives. In a case study in the city region of Amsterdam in The Netherlands, the location of park and ride facilities, train stations and the frequency of public transport lines are decision variables. The Pareto set is approximated by the Epsilon Non-dominated Sorting Genetic Algorithm (ϵ -NSGAI). In this case study, a demand forecast for 2030 is used, but the underlying demand model always contains uncertainty to a certain extent. Therefore, the differences are analyzed between Pareto sets resulting from solving the network design problem using two other demand scenarios as well: a 2020 demand prediction and a Transit-Oriented Development scenario. The Pareto solutions resulting from one demand scenario are assessed based on a different demand scenario to test whether they are still Pareto optimal under this different demand scenario. Furthermore, the values of the decision variables of the solutions in the sets are compared. Results indicate that a different transportation demand has a strong influence on the Pareto optimal performance of solutions in the set: 70% of the solutions do not perform Pareto optimal any more if assessed using a different transportation demand. However, the loss in objective function values is small (a 2% decrease in hypervolume value), so although performance is not optimal any more in most cases, loss in performance is limited. In addition, the resulting decision variables are relatively insensitive for transportation demand.*

1 INTRODUCTION

Highly urbanized regions in the world nowadays face well known problems in the traffic system, like congestion, use of scarce space in cities by vehicles and the emission of greenhouse gases. Improving the integration of transportation networks of cars, public transport (PT, which includes bus, tram, metro and train) and bicycles can be a cost effective solution to alleviate these sustainability problems. Transfers can be made easier, resulting in more multimodal trips, increasing the use of PT and bicycle and reducing the use of the car.

When infrastructure is planned by decision makers, the current practice is to design a few alternatives based on expert judgment, have these alternatives assessed by a transport model and choose the best performing alternative based on performance indicators related to the sustainability objectives. However, the alternative is still likely to have room for improvement. This is the reason for applying multi-objective optimization techniques in this context, to find the best possible transportation network, taking multiple objectives and certain constraints into account. The multiple objectives related to sustainability comprise various aspects, like accessibility, livability, environmental impact and costs. Earlier research showed that these objectives are opposed when optimizing the multimodal network, which means that a solution which performs well for livability performs non optimal for accessibility. A multi-objective optimization delivers the set of possibly optimal solutions, denoted as the Pareto optimal set, see [1]. The problem at hand (i.e. the multimodal multi-objective NDP) is formulated as a bi-level optimization problem, where the optimization of sustainability objectives forms the upper level, and the lower level is formed by individual travelers optimizing their own objectives. The lower level is operationalized by a multimodal transport model. The modelling framework was earlier described in [2].

The scores of the objectives of the transportation network designs in the Pareto set are influenced by a range of input data, like transportation demand, choice parameters, model structure and general parameters like oil prices. However, each of these input data is subject to a certain level of uncertainty. Effects of variation of these uncertain aspects on output of transportation models has received considerable attention in the literature, which is reviewed in [3]. However, in the same paper numerous undiscovered areas of research are identified. Since the objective values are assessed based on the outcomes of the transportation model, the effect of uncertainties on these outcomes is of interest.

Besides the effect on the objective values, these uncertainties also possibly affect the optimal physical transportation network designs: the question is whether the resulting Pareto set (i.e. decision support data) is sensitive to this uncertain input (taken from for example from assumptions or external developments). This paper provides a method to analyze these uncertainties in more detail as well as an application on a real large scale case. This will answer the question whether a Pareto set still performs well when different circumstances will occur in the future: if the Pareto set is robust with respect to an uncertain future or not. More specifically, the paper focusses on the robustness of the optimization result for a different transportation demand input.

Robustness is defined in various ways: robustness can be included as one of the objective functions during optimization, it can be included by creating a design that is flexible for future circumstances or it can be assessed after optimization. There are a few examples of multi-objective network design studies that include robustness in one of those three ways.

Examples of the first way are Santos [4] and Sharma [5]. Santos [4] defines robustness as one of the objective values in terms of reserve capacity in the network. In that case, the interpretation is the robustness of transportation networks themselves: the extent to which these networks perform well under disruptive circumstances, like a blocked link due to an accident

or extreme flows due to an event with a lot of visitors, like a concert. Although such a definition would make sense in the multimodal context of the problem considered in this paper, methods to cope with this interpretation of robustness of transportation networks in a multimodal context do not exist yet, according to Van Nes et al. [6]. Sharma [5] uses an additional objective, namely variance of the total travel time next to travel time itself, to integrate robustness for demand uncertainty into the network design problem.

The second possibility is described in [7], where a flexible investment scheme is introduced as a decision variable as an answer to demand uncertainty. The concept of designing strategies instead of single solutions is also called Dynamic Adaptive Policy Pathway [8], which, when combined with a multi-objective optimization algorithm, can lead to a Pareto optimal set of pathways, that is flexible with respect to future developments.

The third option is demonstrated by Kasprzyk [9], who integrates uncertainty in an iterative decision making process: first, by multi-objective optimization the Pareto set is determined. After that, for every Pareto solution the ranges that objectives may cover under different (uncertain) circumstances are calculated by evaluating the objective value for a range of so called 'states of the world', generated by Monte Carlo simulation.

Following the latter line of thought, in this paper robustness of optimal solutions is tested after optimization, due to the long computation times involved with the optimization problem at hand. This research is a first step to incorporate robustness into the design of transportation networks in a multimodal and multi-objective context. In addition, this research also tests the sensitivity of the Pareto set for model input: testing whether Pareto optimal solutions still perform well under different circumstances and by analyzing differences between Pareto sets resulting from optimization processes with different transportation demand assumptions. To the best of our knowledge, this approach has not been applied earlier.

The remainder of this paper is structured as follows. Section 2 defines the optimization problem, where first attention is given to its mathematical properties, formulation in this multi-objective context and definition. Then, objective functions, study area and decision variables in the case study are specified. To conclude the problem formulation, the demand forecasts, the lower level model and the solution method are described. Section 3 defines the methods and indicators that are used to in the robustness analysis. Section 4 presents the results of the comparison between optimization results using different demand input. Finally, section 5 contains the conclusions of the paper.

2 OPTIMIZATION PROBLEM

2.1 Bi-level problem

The transportation network design problem is often solved as a bi-level optimization problem, to correctly incorporate the reaction of the transportation system users to network changes, as is for example argued by [10]. In our research, the network design problem is regarded as a bi-level system as well (see figure 1). The upper level represents the behavior of the network authority, optimizing system objectives. In the lower level the travelers minimize their own generalized costs (e.g. travel time, cost), by making individually optimal choices in the multimodal network, considering variety in travel preferences among travelers. The network design in the upper level interacts with the behavior of the travelers in the network: the lower level. This is put into operation by a transport model, which assumes a stochastic user equilibrium (no driver can unilaterally change routes to improve his/her perceived generalized travel costs). For any network design the planner chooses, the transport model yields a network state (e.g. travel times and loads), from which the values of all objective functions can be derived. The equilibrium in the lower level is a constraint for the upper level problem.

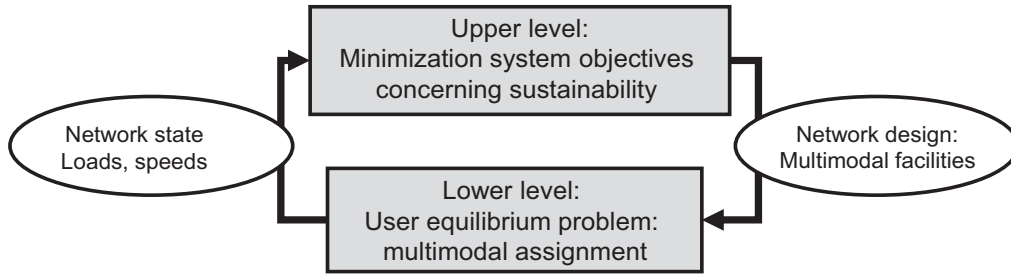


Figure 1: The bi-level optimization problem.

2.2 Mathematical formulation

We define a decision vector \underline{y} (or a solution), that consists of V decision variables: $\underline{y} = \{y_1, \dots, y_v, \dots, y_V\}$. Y is the set of feasible values for the decision vector \underline{y} (also called decision space). The objective vector \underline{Z} (consisting of W objective functions, $\underline{Z} = \{Z_1, \dots, Z_w, \dots, Z_W\}$) depends on the value of the decision vector \underline{y} . Every \underline{Z} is part of the so called objective space, and in principle \underline{Z} may be any value in \mathbb{R}^W , but depending on its meaning, an objective function may be subject to natural bounds. In this paper we will suffice with a formulation that states that the lower level should be in user equilibrium (see also section 2.7). For a more detailed formulation of the optimization problem we refer to [2].

$$\begin{aligned} \min \underline{Z}(\underline{y}), \quad & \text{subject to} \\ & \underline{y} \in Y \\ & G(N, A(C_a(\underline{y})), L(C_l(\underline{y})), S(C_s(\underline{y}))) \text{ satisfies SUE for } q \end{aligned} \quad (1)$$

2.3 Multi-objective optimization: Pareto optimality

Mathematically, the concept of Pareto optimality is as follows. If we assume two decision vectors $\underline{y}_i, \underline{y}_{i'} \in Y$, then \underline{y}_i is said to strongly dominate $\underline{y}_{i'}$, iff $Z_w(\underline{y}_i) < Z_w(\underline{y}_{i'}) \forall w$ (also written as $\underline{y}_i \prec \underline{y}_{i'}$). Additionally, \underline{y}_i is said to weakly dominate (or cover) $\underline{y}_{i'}$, iff $Z_w(\underline{y}_i) \leq Z_w(\underline{y}_{i'}) \forall w$ (also written as $\underline{y}_i \preceq \underline{y}_{i'}$). All solutions that are not weakly dominated by another known solution are possibly optimal for the decision maker: these solutions form the Pareto-optimal set P .

2.4 Network and demand definition

The multimodal transportation network is defined as a directed graph G , consisting of node set N , link set A , a line set L and a stop set U . For each link one or more modes are defined that can traverse that link with a certain speed and capacity: the link characteristics C_a . Transportation zones and act as origins R and destinations S and are subsets of N . Total fixed transportation demand q is stored in a matrix with size $|R| \times |S|$. Furthermore, transit service lines L are defined as ordered subsets A_l within A and can be stop services or express services. PT flows can only traverse transit service lines. Transit stations or stops U are defined as a subset within N . Consequently, a line l traverses several stops. The travel time between two stops and the frequency of a transit service line l are line characteristics C_l . Access / egress modes and PT are only connected through these stops. Whether a line calls at a stop u or not, is indi-

cated by stop characteristics C_u . All together, the transportation network is defined by $G(N, A, L, S)$, where A, L and S are further specified by C_a, C_l and C_u .

2.5 Objective functions

In this paper we consider 4 policy objectives related to sustainability, concerning accessibility, use of urban space by parking, climate impact and costs. These objectives are operationalized as follows (more details can be found in [2]). In our case of a fixed total demand, total travel time is used to represent accessibility in Z_1 . The urban space used by parking is represented by the number of car trips to or from zones that are classified as highly urban, because such a trip requires a parking space that cannot be used for other urban land uses (Z_2). These alternative land uses give additional value to property [11]. Operating deficit of the PT system is formulated as Z_3 , rather than as a budget constraint, to provide explicit insight in the relation between costs and other objectives. Cost parameters follow from Dutch PT operating practice. CO₂ emissions represent climate impact (Z_4). All 4 objectives are to be minimized.

2.6 Study area

The case study area covers the Amsterdam Metropolitan Area in The Netherlands (Figure 2). This area has an extensive multimodal network with pedestrian, bicycle, car and transit infrastructure. Transit consists of 586 bus lines, 42 tram and metro lines and 128 train lines, which include local trains, regional trains and intercity trains. Bicycles can be parked at most bus stops and at all train stations. A selection of transit stops facilitates park-and-ride transfers. Origins and destinations are aggregated into 102 transportation zones. Important commercial areas are the city centres of Amsterdam and Haarlem, the business district in the southern part of Amsterdam, the harbour area and airport Schiphol. Other areas are mainly residential, but still small or medium scale commercial activities can be found.



Figure 2: Map of the study area, showing transportation zones, railways, roads.

2.7 Decision variables

In the network of the study area, 37 decision variables are defined related to transfer facilities or to PT facilities. The decision variables are based on regional policy documents and on interviews with policy makers in the study area. For every potential network development, a decision variable y_v is defined in advance (see table 1). Opening / closure of train stations, intercity status of train stations and opening / closure of park and ride (P&R) facilities are represented by binary variables. For transit line frequency, a discrete set of choice options is predefined, depending on the expected load for that transit line. Network developments are only included as a candidate location if spatial and capacity constraints are met. For example, a P&R facility is only potentially opened if the corresponding station is served by PT. The characteristics of links, lines and stops that are not candidate locations are fixed at one value. Furthermore, the car and bicycle networks are assumed to be fixed. In this case, the feasible region Y contains approximately $7 \cdot 10^{10}$ possible decision vectors.

Decision variable index v	Possible values of y_v	Represents real value	Description
1-6	$\{0,1\}$	Existence	Opening / closure of train stations
7-9	$\{0,1\}$	Existence	Intercity status of train stations
10-16	$\{0,1\}$	Existence	Opening / closure of P&R facilities
17,21,22,24	$\{0, \frac{1}{3}, \frac{2}{3}, 1\}$	$\{0, 4, 8, 12\}$	Frequency of bus lines
18,19,20,23	$\{0, \frac{1}{3}, \frac{2}{3}, 1\}$	$\{0, 2, 4, 6\}$	Frequency of bus lines
25-32,34,36	$\{0, \frac{1}{3}\}$	$\{0, 2\}$	Frequency of local train lines
33,35	$\{0, \frac{1}{3}, \frac{2}{3}, 1\}$	$\{0, 2, 4, 6\}$	Frequency of local train lines
37	$\{0,1\}$	Existence	Extension of a tram line

Table 1: Overview of decision variables in the multimodal network design problem.

2.8 Transportation demand forecasts

In this case study, a demand forecast for 2030 is used as the reference situation. This forecast is based on a scenario study on the expected spatial developments in the Netherlands [12]. This paper tests the differences between Pareto sets, resulting from solving the network design problem using three realistic different demand scenarios. Besides this 2030 demand forecast, these scenarios involve the 2020 demand forecast and a Transit-Oriented Development (TOD) demand forecast. The 2020 demand forecast is based on the same scenario study and represents a situation with smaller growth due to the economic crisis. The TOD demand forecast contains the same level of economic growth as the 2030 demand forecast, but all growth (like new jobs and new houses) takes place in the vicinity of a train station, instead of spread out throughout the whole region. Realizing such a situation would require a strong and consistent policy and is difficult to realize [13]. However, in this demand scenario these developments are assumed.

2.9 Lower level model

The lower level model calculates the network flows through the multimodal network. Therefore, transportation demand is assumed to be fixed, but mode choice and route choice of travelers is flexible. As defined in the previous section, the decision variables typically involve multimodal trip making, for example a park and ride facility involves combining car and PT to a park and ride trip and a new train station may involve combining bicycle and PT

to a bike and ride trip. To correctly take into account these effects, combinations of different access and egress modes are defined in mode chains. These mode chains are seen as separate modes in the mode choice model, which comprises a nested logit model with choice between car and PT in the main nest and choice between mode chains in the PT subnest. More details of this model can be found in [14].

2.10 Solution method

The optimization problem defined in equation 1 is solved using the evolutionary algorithm ε -NSGAII [15]. This method was earlier shown to outperform the well-known predecessor of the algorithm NSGAII [16] when applied to the problem at hand in [17], especially when limited function evaluations are possible due to high computation time. A more detailed description of the algorithm can be found in the same paper.

3 METHOD FOR ROBUSTNESS ANALYSIS

As stated in the introduction, in this paper the robustness of the optimization framework is tested by investigating the sensitivity of the resulting Pareto set with respect to transportation demand input. This is done by assessing the extent to which the optimization result (i.e. the Pareto set) still performs Pareto optimal under different demand input, by comparing the set with the Pareto set that was optimized using that demand. Because the solution method is stochastic in the nature the optimization process is executed twice for each transportation demand, resulting in 6 Pareto sets being calculated. In this section first the notation is formalized. Next, indicators are defined that are used to identify similarities and differences between sets of solutions.

3.1 Notation

The set of N^j solutions $P^j = \{\underline{y}_1^j, \underline{y}_2^j, \dots, \underline{y}_{N^j}^j\}$ is defined as the Pareto set resulting from process j , which includes all non-dominated solutions with respect to all calculated solutions. P^j is the j -th outcome of our multi-objective optimization problem (eq. 1): one approximation of the Pareto-optimal set. The j -th execution of the algorithm is also denoted as run j . Each run j has a corresponding transportation demand q^* for which that Pareto set was optimized. In addition, for each run j the objective values are calculated for other demands q , resulting in Q objective vectors $\underline{Z}^q(\underline{y}_i^j)$ calculated for every element or solution \underline{y}_i^j . These objective vectors consist of W objective functions, denoted by index w : $\underline{Z}^q(\underline{y}_i^j) = \{Z_1^q(\underline{y}_i^j), \dots, Z_w^q(\underline{y}_i^j), \dots, Z_W^q(\underline{y}_i^j)\}$. The Pareto set optimized for demand q^* , calculated for another demand q is denoted as $P_{q^*,q}^j$.

3.2 Indicators

A main distinction to be made is to determine the differences between sets of solutions in objective space and in decision space. When focusing on the objective space, the main question to be answered is whether Pareto solutions optimized for one demand scenario, still perform Pareto optimal under different demand scenario, or at least perform reasonably well. When focusing on the decision space, the main question to be answered is whether different decision variables perform optimal under different demand scenarios. Earlier work paid more attention to these two types of indicators [2], a detailed description can be found there. Here, we provide a brief description of the indicators used. The first three indicators (minimum value per objective, hypervolume and set coverage) relate to objective values. It is expected that Pareto sets that are optimized us-

ing a certain demand q , perform better on these indicators than Pareto sets that are optimized using a different demand q' , and are evaluated using demand q . The last three indicators are used to indicate differences between decision vectors of Pareto sets. This provides insight to the extent to which a different demand leads to different Pareto solutions to be found.

Minimum values per objective value

The minimum objective value attained by Pareto set j for every objective function indicates the extent to which set j covers the entire Pareto front for every objective dimension. Eq. 2 results in w values per Pareto set: the best values per objective.

$$MIN_w(P^j) = \min_{\underline{y}^j \in P^j} Z_w(\underline{y}^j) \quad \forall w \tag{2}$$

Hypervolume

Hypervolume is also called space coverage or S-metric, denoted as $SSC(P^j)$. It is implemented as in [18]. In the 2-dimensional case it determines the area that is covered by the Pareto set with respect to a reference point (the star in figure 3). The reference point is defined such that it is dominated by all solutions in the Pareto set. Because the maximum values of the objective functions are not known, we choose a conservative point, based on the evaluated solutions. In the 3-dimensional case area is replaced by volume, and in the more dimensional case by hypervolume. The higher the hypervolume value, the better, since the problem at hand is a minimization problem.

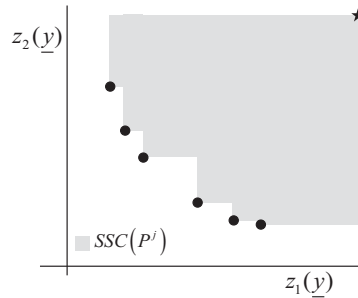


Figure 3: hypervolume 2-D visualisation.

Set coverage

The set coverage or C-metric, see equation XX that is taken from [19], indicates the level in which the solutions in $P^{j'}$ are weakly dominated by at least one solution in set P^j , so a higher value indicates a better set coverage of P^j over $P^{j'}$.

$$CTS(P^j, P^{j'}) = \frac{\left| \left\{ \underline{y}^{j'} \in P^{j'} ; \exists \underline{y}^j \in P^j : \underline{y}^j \preceq \underline{y}^{j'} \right\} \right|}{N^{j'}} \tag{3}$$

This indicator is usually used to compare two Pareto sets. However, in this paper the set that is compared with (set $P^{j'}$ or set 2) is not necessarily a Pareto set (i.e. not all solutions in the set perform Pareto optimal with respect to each other), since its solution were optimized for a different demand q^* . Figure 4 shows the relations between pairs of solutions that may exist in the 2-dimensional case, where set 2 contains solutions that are dominated by a solution in its own set. For set 2, this results in three different types

of solutions: the solution dominates a solution in set 1, it is dominated by a solution in set 1, or neither of the two. In the latter case, note that the solution in set 2 performs Pareto optimal with respect to set 1. For set 1, this results in four different types of solutions: as additional type it is possible that a solution is dominated by a solution in set 2 and at the same time dominates another solution in set 2 (the triangle in figure 4). The set coverage $CTS(set1,set2)$ equals the fraction of solutions in set 2 that is dominated by at least 1 solution in set 1 (indicated by the open squares in figure 4), but in this paper all types of solutions are presented in the results section. When it comes to a robust performance of the optimization framework, it would be good if a lot of solutions in set 2 are within the type ‘star’, since that implies Pareto optimality without dominating a solution in set 1 (that was optimized for that specific demand).

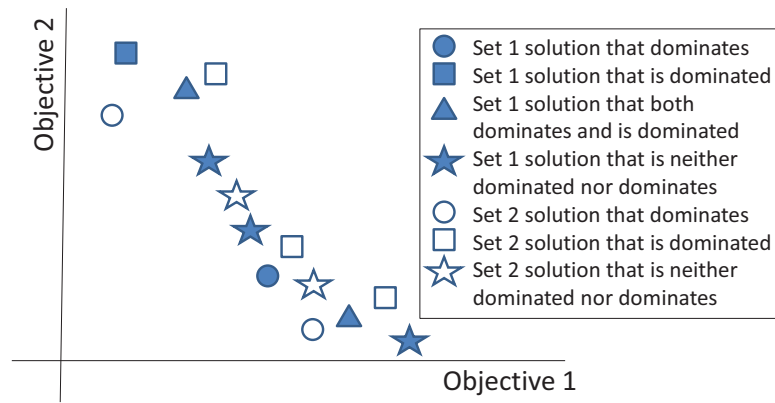


Figure 4: different types of solutions that can be distinguished concerning set coverage.

Average distance between Pareto solutions

The average distance (in the decision space) between the solutions in two Pareto sets P^j and $P^{j'}$ (where j may also be equal to j'), see eq. 4.

$$AD(P^j, P^{j'}) = \frac{1}{N_j} \frac{1}{N_{j'}} \sum_{i=1}^{N_j} \sum_{i'=1}^{N_{j'}} d(\underline{y}_i^j, \underline{y}_{i'}^{j'}) \quad (4)$$

This indicator uses a distance function, which can be any distance function defined for two solutions as $d(\underline{y}_i^j, \underline{y}_{i'}^{j'})$. In this paper the distance function is defined as in eq. 5.

$$d(\underline{y}_i^j, \underline{y}_{i'}^{j'}) = \sum_{v=1}^V |y_{iv}^j - y_{i'v}^{j'}| \quad (5)$$

Average distance to the closest Pareto solution

The distance of an element in P^j to the closest element (i.e. most similar in decision space) in Pareto set $P^{j'}$, averaged over all elements P^j , see eq. 6. A low value indicates higher similarity (the extreme case $AND(P^j, P^j) = 0$ holds). The same distance function is used (see eq. 5).

$$AND(P^j, P^{j'}) = \frac{1}{N_j} \sum_{i=1}^{N_j} \min_{i' \in \{1..N_{j'}\}} d(\underline{y}_i^j, \underline{y}_{i'}^{j'}) \quad (6)$$

Average difference of nonzero decision variables fraction

This indicator compares the fractions of nonzero decision variables in two sets (eq. 7). The fraction ρ_v^j of solutions in Pareto set j that has a positive value for decision variable y_v characterizes the values of that decision variable of the solutions in the set: decision variable y_v represents the existence of a measure in the transportation network, so a higher fraction for variable y_v implies a larger ability to attain (Pareto) optimal solutions by implementing that measure. The κ -function defines the nonzero relation. To indicate the difference between Pareto set j and j' , the absolute difference between these fractions is calculated, averaged over all V decision variables. The closer this value is to 0 for two Pareto sets, the more similar the sets are. If this value is equal to 0, both sets contain all decision variables to the same extend. With other words, in that case both sets assess the effectiveness of the decision variables in the problem at exactly the same level.

$$AFD(P^j, P^{j'}) = \frac{1}{V} \sum_{i=1}^V |\rho_v^j - \rho_v^{j'}|, \text{ where } \rho_v^j = \frac{1}{N^j} \sum_{i=1}^{N^j} \kappa(y_{iv}^j), \text{ where } \kappa(y_{iv}^j) = \begin{cases} 0 & \text{if } y_{iv}^j = 0 \\ 1 & \text{otherwise} \end{cases} \quad (7)$$

4 RESULTS

This section contains the optimization results using different demand forecasts. Firstly, the relation between 2020 demand objective values and 2030 demand objective values is given, to illustrate the impact of a different transportation demand on these objective values. Secondly, the objective values are compared by presenting the minimum values per objective, the hypervolume values and the set coverage for pairs of sets. For each of the three demand forecasts, two outcomes of the optimization process with a different random seed are presented (6 Pareto sets in total). Thirdly, the decision variables of Pareto sets that were optimized for a different demand are compared by using the defined indicators.

4.1 Relation between 2020 and 2030 demand objective function values

Figure 5 shows the relation between objective function values of the same network designs, calculated for two different demand scenarios (2020 demand and 2030 demand). It can be observed that operating deficit (Z_3) shows an almost linear relation, because operating costs do not depend on demand and operating revenue almost linearly increases with demand. On the other hand, travel time (Z_1) shows a scattered plot, indicating that travel time is highly non-linear, because of the complex network behavior of travelers. CO₂ emissions (Z_4) and urban space used by parking (Z_2) both show a comparable, approximately linear relation between 2020 demand values and 2030 demand values. Especially for travel time, the relation between 2020 demand values and 2030 demand values is unstructured, indicating that solutions optimized for one demand are probably not performing optimal any more when assessed using a different demand.

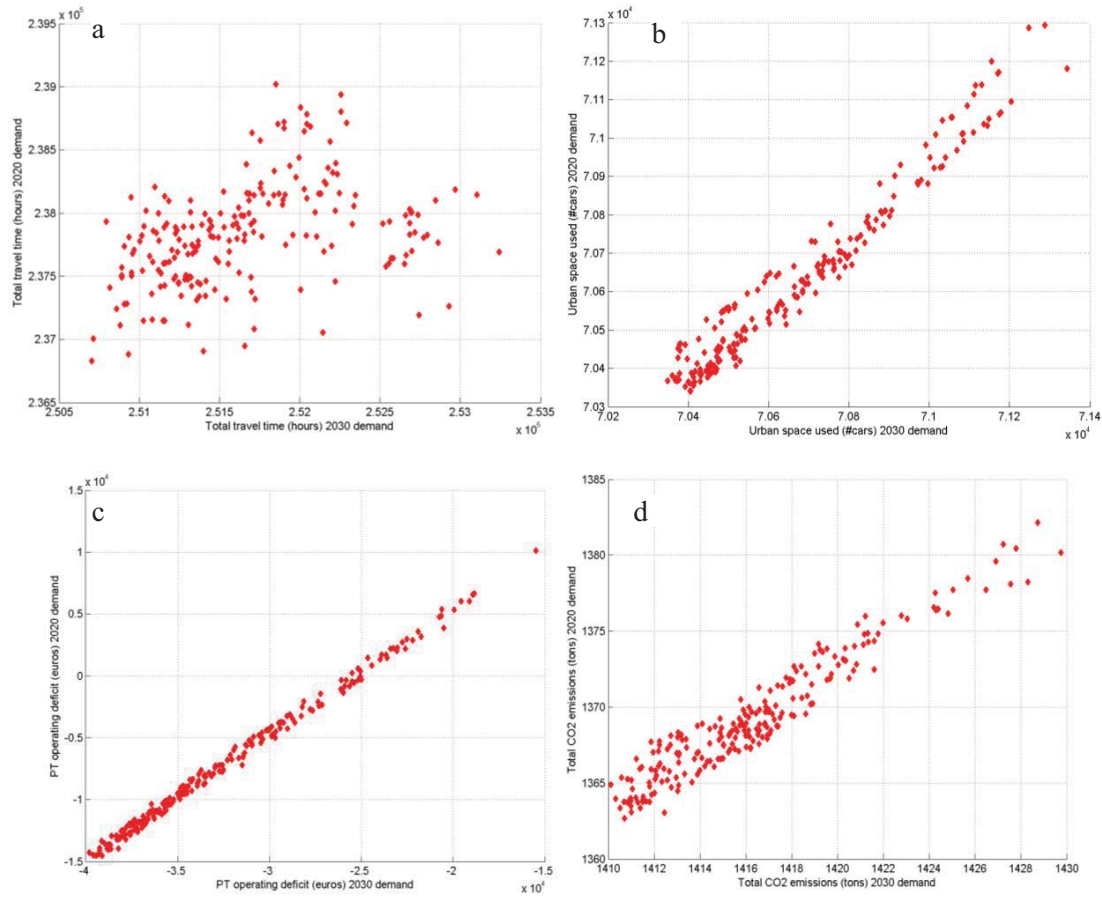


Figure 5: Relation between a) travel time b) urban space used by parking c) PT operating deficit d) CO₂ emissions calculated using 2020 demand (vertical axis) and 2030 demand (horizontal axis). Each dot in the figure represents one solution, i.e. one multimodal transportation network design.

4.2 Objective value comparison

Minimum values per objective

Table 2 shows the normalized minimum values per objective for each Pareto set $P_{q^*,q}^j$. This normalization is applied over all Pareto sets that are calculated for a certain demand q (over a column in table 2). It can be observed that for travel time, the best values occur in the sets that were optimized for the corresponding demand. This is in line with the observation in figure 5 that the travel time objective function is highly dependent on the demand input, so that optimizing for a different demand results in different optimal solutions to be found. For the other objectives, the best values also occur in sets that were not optimized for the corresponding demand. This is also in line with the observations in figure 5, since a solution that performs optimal using one demand is likely to perform similarly when a different demand is used. This can also be observed directly in table 2, especially for CO₂ emissions: the scores of the same Pareto set (in a row) are comparable for the three different demand results.

		Total travel time			Space used by parking			Operating deficit			CO ₂ emissions		
q^*	j	q			q			q			q		
		2020	2030	TOD	2020	2030	TOD	2020	2030	TOD	2020	2030	TOD
2030	1	100.15	100.00	100.11	100.05	100.00	100.02	104.54	101.23	101.61	100.01	100.00	100.02
	2	100.20	100.04	100.16	100.03	100.00	100.02	102.22	100.20	100.28	100.01	100.00	100.05
2020	3	100.00	100.17	100.14	100.00	100.05	100.00	100.36	100.55	100.00	100.00	100.01	100.00
	4	100.06	100.08	100.18	100.02	100.05	100.03	104.14	101.58	101.86	100.01	100.00	100.00
TOD	5	100.15	100.04	100.00	100.03	100.02	100.03	100.00	101.07	100.09	100.04	100.03	100.02
	6	100.17	100.16	100.04	100.10	100.04	100.04	103.13	100.00	100.19	100.03	100.06	100.06

Table 2: normalized minimum values per objective, for each Pareto set $P_{q^*,q}^j$, that was optimized for demand q^* and for which the objective function values are calculated for demand q .

Hypervolume

Table 3 shows the normalized hypervolume values for each Pareto set $P_{q^*,q}^j$ and the number of solutions N_j in each Pareto set. This normalization is applied over all Pareto sets that are calculated for a certain demand q (over a column in table 3). In all cases the best performing Pareto set (per column) is the set that was optimized for the corresponding demand. In most cases this is also true for the second best performing Pareto set. However, one combination can be found where a Pareto set optimized for a different demand (run 5, TOD) outperforms the set optimized for the corresponding demand (run 4, 2020). In general, the hypervolume values of Pareto sets optimized for a different demand are only slightly lower.

q^*	j	N_j	q		
			2020	2030	TOD
2030	1	203	97.64	99.90	98.02
	2	229	98.15	100.00	98.17
2020	3	303	100.00	98.33	98.98
	4	197	98.50	98.63	97.41
TOD	5	226	98.63	99.27	100.00
	6	157	97.30	98.08	99.25

Table 3: the hypervolume values for each Pareto set $P_{q^*,q}^j$, that was optimized for demand q^* and for which the objective function values are calculated for demand q .

Set coverage

Figure 6 shows an example of a classification into the types of solutions that were defined in section 3.2, using the results of the case study for a 2-dimensional case, where the two objectives are urban space used by parking and operating deficit. In this example, set 1 is the Pareto set optimized for these 2 objectives and is shown in red. Set 2 is the set that was optimized for a different demand. Note, that this set contains solutions that are dominated by solutions in the set itself. Furthermore, it mainly contains solutions that are dominated by set 1, but it also contains a solution that dominates a set 1 solution.

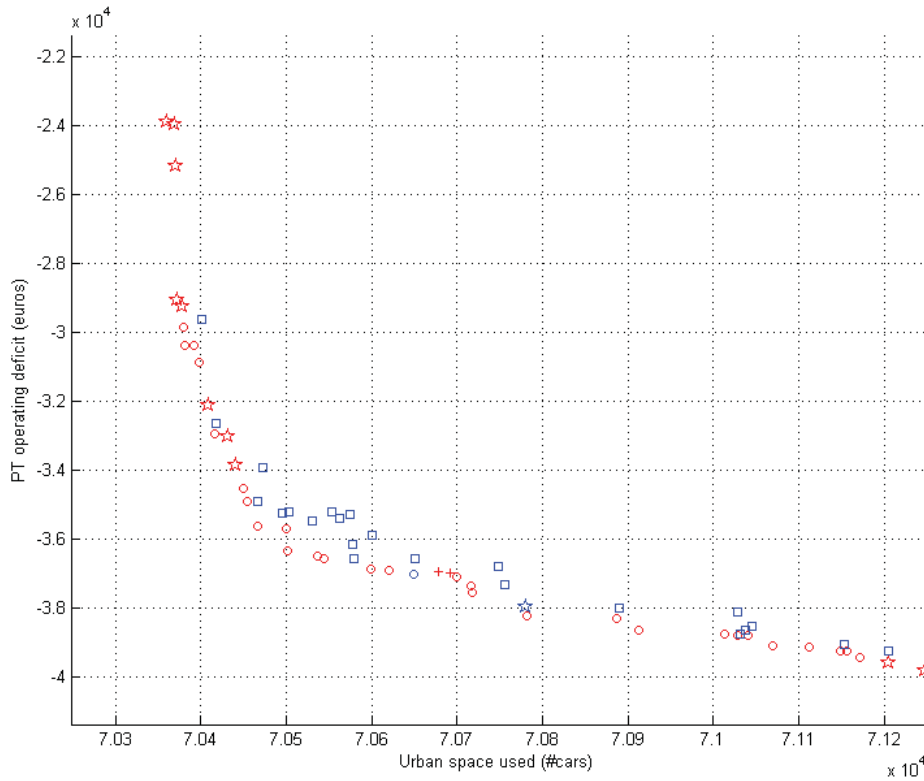


Figure 6: A 2-dimensional example plot showing the different types of solutions (set 1 in red, set 2 in blue, where the + symbol corresponds to the triangle in figure 4.

Table 4 shows the average values for the different type of solutions, where set 1 is the set optimized for the corresponding demand and set 2 is the set optimized for a different demand. The shapes (circle, star, triangle / +, square) correspond with the possible relations between solutions presented in figure 4. The results show that only 30% of the solutions still perform Pareto optimal under different demand circumstances (circle or star in set 2). On the other hand, it is good to see that only 12% of the set 1 solutions (that were optimized for that specific demand: triangle or square) is dominated by a solution that was optimized for a different demand. So a large difference can be observed in coverage between the two types of set, but as is indicated by figure 6 and by the hypervolume scores, the differences are small.

	circle	star	triangle	square
Set 1	70%	18%	9%	3%
Set 2	8%	22%	0%	70%

Table 4: set coverage values of different types.

4.3 Decision variable comparison

This section compares values of decision variables for solutions in the pairs of Pareto sets. A distinction is made between sets where $q^* = q^{*'}$ and sets where $q^* \neq q^{*'}$. In words, the first pairs of sets were optimized for the same transportation demand and differences between the sets are caused by the random nature of the solution algorithm. The second pairs of sets were optimized for different transportation demand, so these differences are both caused

by the random nature of the solution algorithm, as well as by this different demand input. The results for the three indicators defined in section 3.2 are shown in table 5. These numbers indicate that the resulting decision vectors only have slightly more differences when optimized for a different demand than differences that are caused by the random nature of the optimization (heuristic) algorithm.

	$q^* = q^{*'}$	$q^* \neq q^{*'}$
$AD(P_{q^*}^j, P_{q^{*'}}^{j'})$	9.4	9.6
$AND(P_{q^*}^j, P_{q^{*'}}^{j'})$	4.1	4.4
$AFD(P_{q^*}^j, P_{q^{*'}}^{j'})$	0.076	0.086

Table 5: Differences between sets concerning decision variables: comparison between pairs of sets optimized for the same transportation demand and pairs of sets optimized for a different transportation demand.

5 CONCLUSIONS

In the passenger transportation network design problem, the demand forecast used is an important assumption. Although demand forecasts are usually based on thorough models and methods, these forecasts always contain a certain amount of uncertainty. This paper showed the impact of a different demand assumption on the results of a multi-objective optimization of a multimodal transportation network.

It can be concluded that a different transportation demand has a strong influence on the Pareto optimal performance of solutions in the set: a majority of the solutions does not perform Pareto optimal any more if assessed using a different transportation demand. On the other hand, the loss in objective function values seems to be small: although performance is not optimal any more in most cases, loss in performance is limited.

The decision variables only show slightly more differences when optimized for a different demand than differences that are caused by the random nature of the used optimization heuristic. This indicates that the resulting decision variables are insensitive for transportation demand.

These two observations underpin that the exact demand forecast used is not very important, since its influence on the result is not big: the decisions to be taken are comparable, while the objective values achieved are not very much worse. In the context of policy measures that promote multimodal trip making, the measures that are optimal in one future situation, are near optimal in a different future situation.

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