Multi-objective, multimodal passenger transportation network design: robustness analysis

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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. In this research we focus on the integration of transportation networks of cars, public transport (PT, which includes bus, tram, metro and train) and bicycles as a cost effective solution to alleviate these problems.

When infrastructure is planned by decision makers, the current practice is to design a few alternatives, have these alternatives assessed by a transportation model and choose the best performing alternative. However, the alternative is still likely to have room for improvement. This is the reason for applying optimization techniques in this context, to find the best possible transportation network, within certain constraints. Furthermore, a multi-objective approach is adopted, because of the complex context of competing sustainability interests, like accessibility, livability, environmental impact and costs. In this multi-objective approach, objectives are not translated into a single objective by using weights for each objective, because the weights as well as the normalization of the different objectives are arbitrary. Instead, tradeoffs between objectives / criteria can are identified by studying the set of possibly optimal solutions, denoted as the Pareto optimal set, see (Coello et al. 2006). This modeling framework was earlier described in and presented at the BIVEC conference in Luxembourg (Brands and Berkum 2013).

The scores on the criteria of the transportation network designs in the Pareto set is based on a range of uncertainties, like transportation demand, choice parameters, model structure and general parameters like oil prices. Effects of these uncertain aspects on the transportation model results has received considerable attention in the literature, see the review in (Rasouli and Timmermans 2012). However, in the same paper numerous undiscovered areas of research are identified. Since the transportation model results determine the scores on criteria, the effect of uncertainties on the scores is of interest.

Besides the effect on the scores, another issue is the effect of uncertainties on the physical transportation network designs: the question is whether the resulting Pareto set (i.e. the decisions to be made) is sensitive to these uncertain assumptions / external developments. This paper gives a method to analyze these uncertainties in more detail. 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 a robust Pareto set with respect to an uncertain future or not.

Another way to look at robustness, is the robustness of transportation networks: 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. In the literature, the robustness of transportation networks in a multimodal context is still lacking (Van Nes et al. 2007). Nevertheless, in situations where private and public modes are alternatives for each other, as is the case in most areas of the Netherlands, especially in disruptive circumstances it is likely that travelers will be more willing to choose alternative travel options than in a regular situation. Long term developments, like higher environmental awareness, might cause behavioral shifts in regular situations as well.

In the literature, robustness is defined in various ways. There are a few examples of multi-objective network design studies that include robustness. Santos (Santos et al. 2009) defines robustness as one of the objective values in terms of reserve capacity in the network. Sharma (Sharma et al. 2009) defines variance of the total travel time as one of the objective functions to represent robustness. Another possibility is described in (Ukkusuri and Patil 2009), where a flexible investment scheme is introduced as an answer to demand uncertainty. The concept of designing strategies instead of single solutions is also called Dynamic Adaptive Policy Pathway (Haasnoot et al. 2013), 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. (Kasprzyk et al. 2013) integrate 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. This may result in the selection of different solutions than a selection purely based on the most likely or average objective values.

Following the latter line of thought, in this paper robustness is tested after optimization, as a first step to incorporate robustness into the design of transportation networks in a multimodal and multi-objective context. Additional attention is given to the long computation times involved with the problem at hand. This results in testing 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 demand assumptions.

1 Optimization problem

In this section, the optimization problem is described, including network definition, decision variables, objective functions, solution algorithm for the upper level and the multimodal transportation model in the lower level. This section ends with a description of the practical case study where this optimization framework is applied. In the next section, the robustness analysis with respect to this optimization framework is described.

1.1 Bi-level problem

The transportation network design problem is often solved as a bi-level optimization problem (for example (dell'Olio et al. 2006)). The upper level represents a network authority that wants to optimize system objectives. In the lower level the travelers minimize their own generalized costs in the multimodal network, which results in a stochastic user equilibrium. This equilibrium is a constraint for the upper level problem.

1.2 Pareto-optimality

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 strongly dominate (or simply dominate) S_2 if $z_i(S_1) < z_i(S_2)$ for all *i*. All solutions that are not dominated by another known solution are possibly optimal for the decision maker: these solutions form the Pareto set (also called Pareto-optimal set or Pareto front). The set *X* is defined as all solutions that are calculated during the optimization process. The set of solutions $X^* = \{S_1^*,..,S_n^*\}$ is defined as the Pareto set, so it includes all solutions for which the corresponding objectives cannot be improved for any objective without degradation of another, with respect to all solutions in *X*. This is the outcome of our optimization problem: an approximation of the Pareto-optimal set.

1.3 Network, demand and decision variables

The network is defined as a directed graph *G(N,A)*. For each link *A* one or more modes are defined. These modes can traverse that link with a certain speed and capacity. Transportation zones $z \in Z$ are a subset of node set *N* and act as origins and destinations. Total fixed transportation demand *D* is given in a matrix with size $|Z|\times|Z|$. Transit service lines are defined as ordered subsets A_l within *A* and can be stop services or express services and have a frequency *f*. Transit stations or stops $s \in S$ are defined as a subset within *N*. Consequently, a line *l* traverses several stops. Access / egress modes and public transport (PT) are only connected through these stops. Whether a line calls at a stop or not, and whether exchange between car and PT is possible (park and ride) is indicated by stop properties, that are also decision variables (see table 1).

Table 1: Definition of decision variables

Decision variable	*Formu-lation*	*Explanation*
Park and Ride facility at stop *s*	$p_s \in \{0,1\}$	This binary variable indicates whether it is possible to park cars at a stop *s* (i.e. exchange between the car network to the PT network). At existing stops with park and ride facility, this variable is fixed to 1. At candidate locations, this variable can take values 0 and 1.
Existence of stop *s*	$t_s \in \{0,1\}$	This binary variable indicates whether transit vehicles call at stop *s* or not (i.e. exchange between the walk and bicycle networks and the PT network). At existing stops this variable is fixed to 1, at candidate locations this variable can take values 0 and 1.
Express status of stop *s*	$e_s \in \{0,1\}$	This binary variable indicates whether transit vehicles of express lines call at stop *s* or not. At existing express stops this variable is fixed to 1, at candidate locations this variable can take values 0 and 1.
Frequency of PT service line *l*	$f_l \in F_l$	F_l contains possible values for the frequency of PT service line l. Existing lines can either be fixed (F_l contains only 1 element) or free (F_l contains 2 or more elements and $l \in L_f$). In the latter case 0 may also be included.

1.4 Objective functions

In this paper we consider multiple policy objectives related to sustainability: maximization of accessibility, minimization of the urban space used by parking and minimization of the climate impact of the transport system. Maximization of cost efficiency is added as a fourth objective to give insight in the marginal costs of achievements in the other objectives, rather than setting a budget constraint. In general, the result of a multi objective optimization is not one single solution, but a set of solutions: the Pareto set. This Pareto set contains all non-dominated solutions, i.e. there are no two solutions in the set for which one solution is better for all objectives.

The values of the objective functions are calculated based on loads and costs in the network, which are stored in link characteristics and in $|Z|\times|Z|$ matrices. The objectives are operationalized as follows. Total travel time in the network represents accessibility, which is possible because total demand is fixed. 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. In less urban and rural areas this is considered to be irrelevant, because space is less scarce at those locations. Alternative urban land uses can for example be residential area, greenery or pedestrian zone. Implicit assumption here is that car ownership is gradually adapted as a result of less car trips. CO_2 emissions operationalize climate impact. The emissions are calculated using the ARTEMIS traffic situation based emission model, where emission factors depend on link speed and volume / capacity ratio (INFRAS 2007). Finally, operating deficit represents cost efficiency and includes operating costs of PT and Park and Ride (including depreciation of investments), from which PT revenues are subtracted. The PT operating costs and fares are taken from Dutch practice and the operating costs for Park and Ride are taken from (Van Ommeren and Wentink 2012). This includes all costs from the perspective of the regional authority, which is responsible for operating public transport. From the other decision variables, new train stations and tram line extensions involve investment costs, but these are disregarded in this case, because these investments in the Netherlands are usually paid by the national government. All four objectives are to be minimized

Table 2: Definition of objective functions and list of symbols

Policy objective	Measured by	Formulation
Accessi-bility	Total travel time	$z_1 = \sum_{(i,j)\in Z} \sum_{m\in M} T_{ijm} D_{ijm}$
Climate impact	CO_2 emissions	$z_2 = \sum_{a\in A} \sum_{b\in B} q_{ab} E_b^{CO_2}\left(v_a^0, \frac{q_a}{q_a^{\max}}\right) k_a$
Urban space used by parking	Number car trips to and from urban zones	$z_3 = \sum_{i\in Z_U} \sum_{j\in Z} \sum_{m\in M_O} D_{ijm} + \sum_{i\in Z} \sum_{j\in Z_U} \sum_{m\in M_D} D_{ijm}$
Cost efficiency	Operating deficit	$z_4 = \sum_{b\in B_{PT}} [C_b \sum_a q_{ab} t_{ab}] + C_{PR} \sum_{(i,j)\in Z} \sum_{m\in M_{PR}} D_{ijm} - \sum_{b\in B_{PT}} \sum_{l\in L} [\Delta_{bl} f_b \sum_{a\in A_l} k_a p_{la}]$
With:		

T_{ijm}	Travel time from origin *i* to destination *j* with mode or mode chain *m* (min)
D_{ijm}	Transportation demand from origin *i* to destination *j* with mode or mode chain *m*
q_{ab}	Flow on link *a* for vehicle type *b* (veh per hour)

$E_b^{CO_2}(v_a^0, \frac{q_a}{q_a^{\max}})$	CO_2 emission factor of vehicle type *b*, depending on free flow speed v_a^0 and volume / capacity ratio $\frac{q_a}{q_a^{\max}}$ of link *a* (grams/(veh*km)).
k_a	Length of link *a* (km)
Z_U	Set of highly urban zones. In the case study $Z_U = \{1,2,3,5,13,17,20,21,22,23,29\}$
M	Set of modes (including mode chains)
M_O	Set of modes (including mode chains) that start the trip with a car leg
M_D	Set of modes (including mode chains) that end the trip with a car leg
M_{PR}	Set of mode chains that contain the use of a Park and Ride facility
B	Set of vehicle types
B_{PT}	Set of vehicle types that are part of the PT system
A_l	Set of links that are traversed by line *l*
C_b	Operating costs for PT vehicle type *b* (euros per vehicle*hour)
C_{PR}	Operating costs of one Park and Ride space
t_{ab}	Travel time in link *a* for vehicle type *b*
Δ_{bl}	PT vehicle type indicator, equals 1 if line *l* is of vehicle type *b*, 0 otherwise
f_b	Fare for using PT of vehicle type *b* (euros per km)
p_{la}	Passenger flow in PT service line *l* on link *a* (passenger per hour)

1.5 Upper level

The problem is hard to solve and is computationally too expensive to be solved exactly, so we rely on heuristics. Literature provides different techniques to approximate the multi-objective optimization problem in the upper level (see for example (Deb 2001) for theory and (Fan and Machemehl 2006) for a practical application in transportation science). Examples of these are different forms of genetic algorithms, simulated annealing or tabu search. In this research the genetic algorithm NSGA-II (details see (Deb et al. 2002)) is used, since it was successfully applied by (Wismans et al. 2011). In short, this algorithm optimizes multiple objectives simultaneously, searching for a set of non-dominated solutions, i.e. the Pareto optimal set. It therefore sorts the set of known solutions based on their rank: Pareto optimal solutions receive rank 1. When solutions with rank 1 are removed from the set, the Pareto optimal solutions from the remaining set of solutions receive rank 2, etc. The higher the rank, the higher the fitness value of the solution. During optimization, the algorithm combines solutions in one generation to new solutions is the next generation (crossover using tournament selection), based on the principles of natural selection within evolution, where the solutions with a higher fitness value have a larger chance to survive over worse solutions. In the next generation, these enhanced solutions are recombined again, until no more progress is made or until the maximum number of iterations is reached. In this paper a population size of 80 solutions is used, with a maximum of 37 generations, since tests on a smaller case study showed that these parameter values are a good tradeoff between convergence in terms of hypervolume and calculation time (Brands and van Berkum 2013). In addition to this mating process, a random mutation operator is applied to a limited number of solutions from each generation, to promote the exploration of different regions in the solution space. In this paper, a mutation rate of 0.03 is used, implying that a fraction of 0.03 of the decision variables is randomly assigned a new value in every generation. In this paper, only one random seed is used for every optimization result, due to computational limitations. Issues considering different results due to different random seeds in the Monte Carlo simulations are discussed in (Brands and van Berkum 2013).

1.6 Lower level

To be able to assess a multimodal network in a suitable way, a multimodal traffic assignment model is applied in the lower level. This includes a nested logit mode choice model (Ben-Akiva and Bierlaire 1999) which has the car mode in one nest and trip chains with PT as a main mode in the other nest (walk – PT – walk, bicycle – PT – walk, car – PT – walk, walk – PT – bicycle, walk – PT – car). The car-only trips are assigned to the network using a standard capacity dependent user equilibrium assignment. The PT assignment method (including various access and egress modes) uses multiple routing based on the principles of optimal strategies, as developed by (Spiess and Florian 1989). The multimodal assignment algorithm is described in more detail in (Brands et al. 2013).

1.7 Case study

The case study area covers the Amsterdam Metropolitan Area in The Netherlands (Figure 1).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, that include local trains, regional trains and intercity trains. Bicycles can be parked at most stops and stations. A selection of transit stops facilitate 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.

The calculation time to assess one network design with the OmniTRANS transportation modeling software (multimodal traffic assignment and calculation of the objective values) takes approximately 6.5 minutes, using a computer with an Intel® Core™ i7 CPU 860 @ 2.8GHz and a 4 GB RAM. This implies that a full optimization of 37 generations of 80 solutions (in total 2960 solutions) takes around 2 weeks of computation time. Note that parallelization on one computer is not possible, since the multimodal assignment algorithm already uses parallel computing. However, parallelization on several computers would make it possible to decrease computation times.

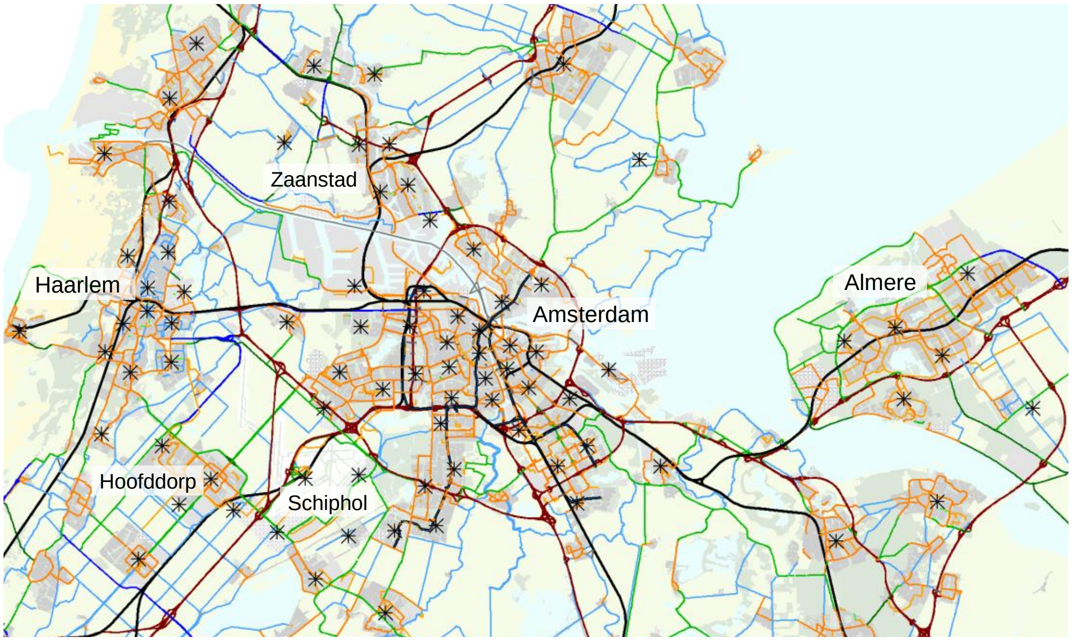

Fig. 1 Map of the study area, showing transportation zones, railways, roads

2 Robustness analysis

The result of the optimization framework described in section 1 is a set of possible optimal network designs (a Pareto set). From this set of possible networks, a decision maker may choose the final network design for implementation. An important question is whether the resulting set of network designs is subject to change when important assumptions in the model are set differently. In other words, it is important to assess the robustness of the set of network designs for changes in model assumptions. Further, it is of interest to identify network designs that appear multiple times under different circumstances. This would be an indication that these solutions may be optimal in several situations, which one could call a robust network design. The robustness could be tested with respect to the following input or mechanisms:

- A transportation demand matrix is taken as input. The robustness of the network designs with respect to higher, lower or differently distributed demand is of interest.
- Behavioral parameters in the model are set at certain values, that well represent the observed transportation demand. These parameters consider for example maximum walking and cycling distances to stops, line choice, sensitivity for mode travel costs, weights in the generalized costs calculation, mode specific utility constants. However, these behavioral rules may change in the future. For example, the maximum cycling distances might increase because the electric bicycle is introduced or a stronger preference for bicycle and PT may arise from a higher valuation of sustainability or health.
- Although the multimodal choice model is an appropriate choice in this type of network design problems, it would be interesting to see whether choosing another model type would strongly or weakly influence the results. Other models could for example include the bicycle as a separate

choice option, allow more multimodal trip chains, include elastic demand or include distribution effects.
- General parameters like income, variable costs of public transport and variable costs of car, dependent on policy (e.g. road pricing), or external influences (e.g. oil price, economic growth).

The ideal situation would be to taken robustness into account during optimization process as a separate objective function, by assessing the performance of every network design across a number of scenarios (i.e. varying model assumptions) resulting in assessing the robustness based on the performance across the scenarios. This robustness value determines, among other objectives, whether a solution in Pareto optimal or not, giving input to the NSGA-II algorithm for selecting solutions during the optimization process. Another very interesting option is to use a percentile value of the values across the scenarios for each objective, instead of just one observation per objective. However, as the calculation time of one optimization process is already 2 weeks in the situation with one single scenario, this approach is considered infeasible, since the calculation time would increase with a factor equal to the number of scenarios. Another possibility is to use parallel computing, which requires additional hardware facilities.

Therefore, 2 possible approaches are further developed to investigate the robustness of the network designs in the Pareto set. After that, first results for the second approach are presented.

2.1 Assessment of non-Pareto optimal solutions

This approach considers the results from one optimization process. First, the Pareto optimal and near-Pareto optimal solutions are selected, in the form of all solutions that received rank 1, 2 or 3 during Pareto ranking in NSGA-II (see section 1.4). This selection of solutions is assessed for 2 different scenarios by calculating the objective values. Since a Pareto set contains approximately 250 solutions, it is expected that this selection contains approximately 750 solutions. In case the set appears to be too big, only the solutions of rank 1 and 2 could be selected. This results in 2*750 solutions to be calculated (the empty cells in table 3), in addition to the 2960 solutions to be calculated during optimization, for the case of 3 scenarios (so 2 additional scenarios after the scenario used for optimization). This approach tests whether solutions that were not selected in the base scenario (the solutions with rank 2 or higher), are still dominated in the other scenarios, or are now Pareto optimal in another scenario. The two extreme cases that can occur are that all ranks are equal in the different scenarios, in case the Pareto set can be identified as robust, or that the non-dominated and dominated solutions have completely swapped in the different scenarios, in case the Pareto set can be identified as not robust.

Table 3: the relation between scenarios and solutions to be calculated

	Non-dominated solutions in scenario 1	*Dominated solutions in scenario 1*
Scenario 1	XX	XX
Scenario 2		
Scenario 3		

2.2 Various optimizations under different scenarios

In this approach the optimization algorithm is executed several times with several different scenarios, resulting in several Pareto sets of approximately 300 solutions each. After optimization, the Pareto sets are assessed based on the same scenarios (see table. 4 for the case of 3 scenarios). The Pareto sets on the diagonal are already assessed during optimization, so for each scenario 2 Pareto sets still have to be assessed (the empty cells in table 4), resulting in 2X3X250 = 1500 solutions that have to be calculated, in addition to the 3X2960 solutions to be calculated during optimization. This enables a comparison between the Pareto solutions produced for the corresponding scenario with the Pareto solutions that were produced for a different scenario. One would expect most Pareto solutions to be produced for that specific scenario. If in the extreme case no Pareto solutions are found if another scenario is optimized for, the method is not robust for the changes in that scenario. If in the other extreme case the same number of Pareto solutions is found independent of the demand scenario, the method is robust for demand, because with a different demand comparable Pareto solutions are found.

Table 4: the relation between scenarios and Pareto sets

	Pareto 1	*Pareto 2*	*Pareto 3*
Scenario 1	XX		
Scenario 2		XX	
Scenario 3			XX

2.3 Results

This section contains the results of two Pareto sets that are compared, based on the method in section 2.2. These Pareto sets are the result of the optimization processes, with one Pareto set with traffic demand expected for the year 2020 as input and the other Pareto set with traffic demand expected for 2030. More results are expected in future versions of this paper.

The sets are compared using the concept of dominance (as defined in section 1.2). Figure 2 explains the different types of solutions within each set that can be distinguished when two sets are compared. The first type includes solutions that dominate at least one solution in the other set. The second type includes solutions that are dominated by at least one solution in the other set. The third type includes solutions that are not dominated, but do not dominate solutions of the other set either. Note that the first and third type together are Pareto optimal solutions in the combined set.

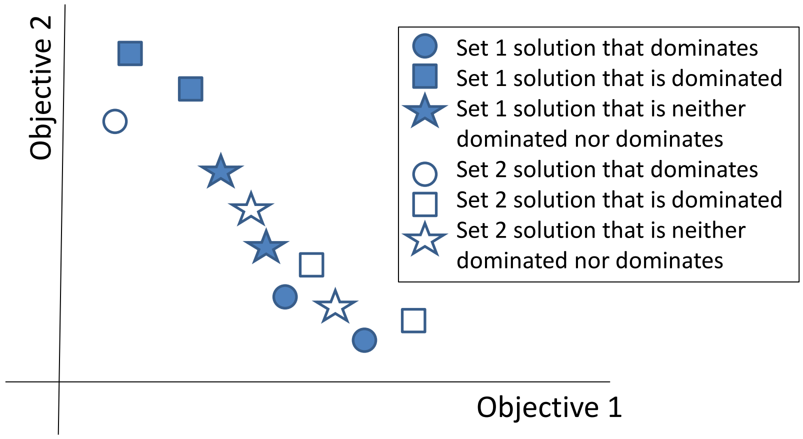

Fig 2: The relation between two Pareto sets, resulting in three types of solutions per set, depending on their dominance relation.

Table 5 contains the results for the case study. The Pareto set with 2020 demand as input contains 204 solutions, while the Pareto set with 2030 demand contains 213 solutions. It can be observed that the Pareto set optimized for 2020 demand performs considerably better than the solutions that were designed for 2030 demand, indicating that designing a transportation network for the 2030 demand will result in a suboptimal network in 2020. The other way around, the Pareto set that was optimized for 2030 demand still outperforms the solutions that were designed for 2020 demand (and assessed with 2030 demand), but the difference is small. This may be explained in two ways: it might indicate that the method is robust for a lower expected demand, since 75 solutions are still Pareto optimal when a different demand occurs. Another possible explanation is that the genetic algorithm is not very well capable of finding improvements within the available calculation time. Although genetic algorithms are repeatedly applied in the literature, every application is case depended, so one can never be sure that the algorithm converges to (close to) the real Pareto set.

Table 5: observed domination relations when Pareto sets are assessed based on a different demand from the demand used during optimization

Number of solutions in Pareto set:	2020 demand	2030 demand
That dominate at least one solution that was optimized for different demand	179	131
That are dominated by at least one solution that was optimized for different demand	9	60
That are neither dominated nor dominate another solution	16	22
Number of solutions that were optimized for a different demand:	2020 demand	2030 demand
That dominate at least one solution in the Pareto set	5	32
That are dominated by at least one solution in the Pareto set	160	129
That are neither dominated nor dominate another solution	48	43

2.4 Discussion

It is not feasible to assess all types of uncertainty, so a choice has to be made. In this paper, first results are presented for the robustness for the transportation demand. This will be extended with another demand scenario. Furthermore, there might be room for some additional analysis. This would be interesting to discuss during the conference in November. Another point of discussion is the number of scenarios to take into account. In this paper we chose to include 2 different scenarios, besides the base scenario. When approach 2 is used, for every scenario an optimization procedure has to be executed, resulting in longer computation times. In approach 1 the calculation time per scenario is smaller, since the analysis only takes place after optimization.

Another approach that may be interesting to operationalize robustness is the following. The availability of more travel options is valued by travelers (option value of infrastructure), which is already expressed in transportation modeling by the logsum concept. This flexibility from a network topology perspective might be operationalized by the number of alternative multimodal travel options that is available. Overlap between these options is an issue here.

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