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Multi-stage evolution of single- and multi-objective MCLP

Successive placement of charging stations

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Abstract Maximal covering location problems have efficiently been solved using evolutionary computation. The multi-stage placement of charging stations for electric cars is an instance of this problem which is addressed in this study. It is particularly challenging, because a final solution is constructed in multiple steps, stations cannot be relocated easily and intermediate solutions should be optimal with respect to certain objectives. This paper is an extended version of work published in Spieker et al. (Innovations in intelligent systems and applications (INISTA), 2015 international symposium on. IEEE, pp 1–7, 2015). In this work, it was shown that through problem decomposition, an incremental genetic algorithm benefits from having multiple intermediate stages. On the other hand, a decremental strategy does not profit from reduced computational complexity. We extend our previous work by including multi-objective optimization of multi-stage charging station placement, allowing us to not only optimize toward (weighted) demand location coverage, but also to include a second objective, taking into account traffic density. It is shown that the reachable part of the full Pareto front at each stage is bound by the solution that was chosen from the respective previous front. By careful choice of the selection strategy, a particular focus can be set. This can be exploited to comply with concrete implementation goals and to adjust the evolved strategy to both static and dynamic changes in requirements.

Keywords Genetic algorithm · Optimization · Maximal covering location problem · Multi-stage · Single-objective · Multi-objective · Electric mobility

1 Introduction

Maximal covering location problems (MCLP) arise when resources need to be distributed around certain fixed locations. Recently the problem of charging station placement for electric vehicles has become increasingly important since European governments decided to support a shift toward non-fossil fuel-based transportation (BMVI 2011). A distinct feature of this task is its temporal dimension. Due to economic reasons, charging station infrastructure cannot be deployed in a single step. First stages have to encourage the commuters transition while in later stages economic factors will dominate. In both cases, coverage plays a key role. To complicate matters, multiple factors can be taken into account to define the objective function.

In this paper, we present an evolutionary approach to solve this multi-stage multi-objective MCLP. A target area within the region of Bonn and Rhein-Sieg-Kreis serves as an example (cf. Fig. 1). This work is an extension of a first study (Spieker et al. 2015), which was supported by the respective municipalities and local energy suppliers.

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Local politics in the meantime has decided to start building infrastructure based on recommendations derived from that study.

The multi-stage *maximal covering location problem* (MCLP) (Church and ReVelle 1974), in which a fixed number of demand locations need to be optimally covered by a fixed number of supply stations over a fixed number of stages, is an NP-hard problem (Church et al. 1996). Dynamic programming or branch-and-bound algorithms are commonly used (Berman and Krass 2002) to solve it. However, those exact approaches suffer from exponential complexity. In the presented example case, the exact solution thus becomes intractable, since the number of demand locations (*points of interest*) amounts to 5062 and up to 935 charging locations need to be placed. The latter number is derived from projected figures for the year 2020 on the necessary total number of charging stations (Elektromobilität 2012), total car stock in Germany (Kraftfahrt-Bundesamt 2015) and total car stock in the Bonn-Rhein-Sieg region (MBWSV-NRW 2013).

The target area is subdivided into so-called traffic cells which underlie municipal traffic planning (cf. Fig. 1). Figure 1 also shows *points of interest* (POI) such as airports, public transportation transitions, museums and parking lots that were selected based on an expected length of stay, allowing batteries to be charged up to at least 80 %. For the sake of clarity, results will be presented only for a subregion of the target area, depicted in Fig. 1. The subregion consists of multiple municipal cores as well as large low-density, rural areas.

We use *genetic algorithms* (GA) to approximate near-optimal solutions. Two objectives will be taken into account to determine a solution's fitness, POI coverage and coverage of traffic flow. Using the NSGA-II algorithm, both objectives will be maximized simultaneously resulting in a Pareto front of non-dominated solutions. Results will be compared to a single-objective case using weighted POI coverage as a single-objective.

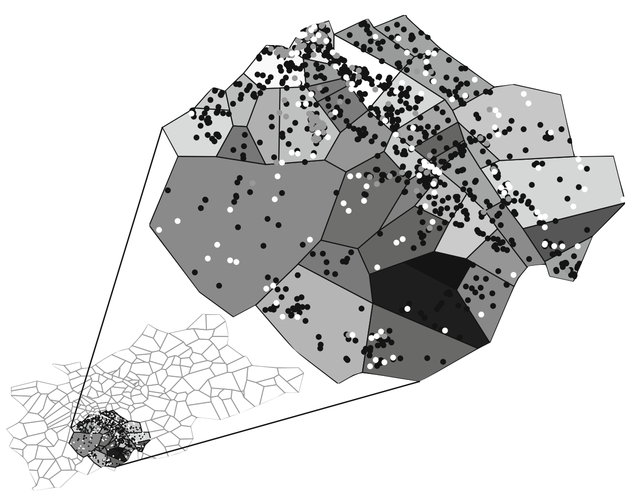

Fig. 1 Target area within the original region with POI. *Lighter colors* indicate a higher demand. POI are shown as points and the traffic flow is shown per traffic cell. *Lighter colors* indicate higher traffic volume. The area includes high-density city regions (Bonn city, *upper left* of reduced area) as well as rural areas (northeast and southwest)

Multi-stage MCLP can be optimized in two ways. Either every stage is optimized sequentially, taking the result of the last stage as a starting point for the optimization of the next. Alternatively, the final stage can be optimized and then gradually reduced toward the first stage by removing charging stations from the previous solution. We examine the final as well as intermediate results and compare the results of both strategies to independently calculated solutions.

In the next section, we provide more details about requirements that need to be fulfilled.

2 Problem description

The target of the optimization of this multi-objective, multi-stage MCLP, placing charging stations in a mixed urban-rural region, is a maximization of POI coverage to increase public visibility as well as covering as many high-density traffic routes as possible, encouraging the usage of charging stations.

Economic costs cannot be taken into account due to data unavailability, and this project does not aim to produce exact placement locations but much rather approximate ideal locations. We can thus produce an ideal distribution which serves as a basis for further planning steps.

Only public POI locations are taken into consideration so only Mode II (up to 22 kW BMVI 2014) charging stations will be placed, as slower charging stations are not suitable for public locations, where parking space and time are scarce. Mode III stations are unavailable due to power network capacity constraints.

In the single-objective use case, only the maximal coverage of POI, taking into account the weighted demand based on the German government's projections, has been taken into account. Instead of traffic density, five demand categories with attached weights (1–5) are defined, reweighing the importance of every POI, based on expected traffic density (Infas Institut für angewandte Sozialwissenschaft Gmbh 2009).

As currently neither demand nor necessary resources are available to deploy all planned charging stations at once, a successive, multi-stage deployment from 2016 to 2020 is planned, with a final total of 935 charging stations. This staggered deployment needs to be reflected in the placement process of the charging stations. More important regions need to be covered earlier, which is reflected in POI importance weights. Maximizing the coverage is an important goal for all stages of the roll out.

An *independent* placement strategy consists of independently optimizing every stage, not taking into account the placement of the previous or next stage. An *incremental* strategy is defined to be stagewise, with every stage taking the solution of the previous as a fixed part of the solution. The placement of another batch of charging stations added to this fixed solution then is optimized. Vice versa, a *decremental* placement strategy starts with an optimized final solution. A subset of the final placements is then removed to arrive at the solution for the former stage.

As the accompanying cost for station relocation is not possible due to the aforementioned lack of data, the use of an independent placement strategy is prohibited, as an intermediate solution set is not an actual subset of the next stage's solution. Each successive stage takes the solution from the former stage as fixed.

3 Related work

Church and ReVelle (1974) first introduced the MCLP, which has since been broadly discussed in the literature. A recent review of the problem and available approaches can be found in Berman et al. (2010) and Farahani et al. (2012).

GA, a class of optimization algorithms inspired by natural and evolutionary concepts, were first presented by Holland (1975). The main idea is to gradually improve a set of initially random solutions (a population consisting of several individuals) measured by a performance index. In each generation, individuals are selected as parents to create new solutions, children, via recombination and mutation. A value is assigned to each child, representing how well the solution solves the problem, according to a predetermined objective or fitness function. This fitness value is then taken into account to derive a new generation, consisting of individuals with an average fitness that is often higher than the last.

Classical GAs typically optimize a solution with respect to a single-objective, but for some applications it is necessary to simultaneously optimize multiple conflicting objectives. To efficiently handle multi-objective optimization problems, multi-objective genetic algorithms (MOGA) have been proposed (see Deb and Wiley 2006), such as NSGA-II (Deb et al. 2002), which we will employ in the presented multi-objective scenarios. These algorithms group individuals into Pareto fronts according to their dominance in a fitness or objective space. An individual is said to dominate another individual if it has better fitness on at least one objective and the same or better fitness on all other objectives. The set of individuals which are non-dominated form the first Pareto front of the population are the most fit according to the objectives.

GAs have been used to optimize the placement of charging stations by other authors. Lim and Kuby (2010) applied a GA for the flow-refueling location model, which optimizes placement to minimize traffic flow interruption and give individual drivers the possibility to charge on route when needed—in contrast to the MCLP used in this paper, which tries to optimize the availability of charging opportunities for parked vehicles. Hess et al. (2012) combined a GA with a traffic simulator to evaluate each individual according to a traffic model, targeting traffic flow optimization. A cost-focused approach regarding the construction costs of the charging infrastructure was described by Jin et al. (2013). This approach does not apply to our concrete problem, as is mentioned in Sect. 2.

The application of multi-objective GAs to variations of covering problems, such as MCLP, has been published by other authors as well. For example, Attea et al. (2014) recently described the applicability of NSGA-II for the coverage of mobile networks and Badri et al. (1998) made use of a GA to optimize the location of fire stations based on the travel times and distances from the stations to the areas of possible demand.

The concrete application of GAs to optimize MCLP was discussed by Zarandi et al. (2011) in which they presented a customized GA for a large-scale MCLP with 2500 nodes. This approach was based on a discretized problem and does not work in an incremental way.

An important aspect for charging station placement planning is multi-stage optimization, where the final placement plan is reached over intermediate stages. This is a common problem decomposition method in applications where it is unreasonable or not possible to realize the optimal solution immediately. Reininger et al. (1999) discussed this problem in the context of planning mobile radio networks on discrete sets of fixed possible locations. Their solution was based on GAs, and they evaluated various approaches to reach the maximum stage. Their solutions did, however, allow stations to be moved in intermediate stages, an option explicitly prohibited in our problem. Furthermore, Canel et al. (2001) present a branch-and-bound algorithm for a dynamic multi-stage facility location problem and Albareda-Sambola et al. (2009) further formulate it as a multi-period incremental service facility location problem (MISFLP) for which they present a Lagrangian formula. Chung (2012) analyzed a multi-period planning problem of charging station placement for Korean expressways, also based on a flow-refueling location model. The three latter approaches can be excluded by us, as we solve a static problem and do not take into account queue times or station blocking.

In the following section, we will present different strategies that cater to the explicit multi-stage continuous and multi-objective character of the placement strategy at hand.

4 Methods

Successive multi-stage planning yields a set of charging station placements for each stage, where later stages include all charging stations of earlier, smaller stages. This is either achievable by planning forward from smaller to larger stages or backward from larger to smaller ones. These two strategies, which were used in the previous study as well (Spieker et al. 2015) are called *incremental*, respectively, *decremental*. They, as well as a third strategy, which is used for comparison, are summarized in the following.

4.1 Incremental strategy

An incremental strategy to successive charging station placement is to first optimize for a smaller stage and then add additional charging stations for each subsequent stage. All formerly placed charging stations are fixed and part of subsequent solutions.

This strategy works in chronological order and first places charging stations, which would also be built first, while giving latter stages freedom to find uncovered, but important places for charging stations. At each stage also a small number of additional charging stations can and has to be optimized, resulting in a problem decomposition effect. Nevertheless, choices at an early stage are fixed and can also keep solutions stuck at local optima.

4.2 Decremental strategy

On the contrary, a decremental strategy starts from an optimized larger stage and places only the most important charging stations at each preceding stage. Afterward, it works backwards and places at each preceding stage only the most important stations.

An optimized solution at a final stage ensures good coverage at the end of the charging station placement process, because it can freely optimize without constraints. Each stage's solution restricts possible locations for charging stations at smaller stages, as it has only a discrete set of possible locations available.

From a computational perspective, this allows to switch from continuous placements to a combinatorial problem of discrete placement possibilities.

4.3 Independent strategy

As a third strategy, each stage is calculated independently of former or latter stages. In an practical realization, this would require to move existing charging stations in subsequent stages, which is not allowed by problem constraints.

Because it has no restrictions on possible placements, it can evolve freely and is used for comparison, as it is unlikely that all optimal solutions are subsets of former or latter optimal solutions.

4.4 Optimization goals

Two different optimization objectives are considered throughout all experiments. The first objective is to cover a maximum number of POI, where each POI has a certain demand weight attributed.

The second objective is to place charging stations close to points of high traffic, increasing visibility and usage. Traffic flow figures (one static value per traffic cell, see Fig. 1) provide information about the importance of each prospective charging station placement for the actual traffic.

POI only need to be covered by one charging station. Multiple coverage is neither necessary nor restricted, but does not count toward the optimization goal, both for POI and for traffic demand. Nevertheless, in future planning steps it is advisable to consider whether the demand at a specific placement requires more than one charging station, too. This aspect is not part of this study.

It follows that charging stations should be placed at highly frequented and highly weighted POI.

To define the problem more precisely, the following optimization objectives are used. The notations are similar to the ones used in (Farahani et al. 2012, p. 375):

$$\text{POI Coverage: Maximize} \sum_{i=1}^{L} c_i v_i$$

$$\text{Traffic Coverage: Maximize} \sum_{k=1}^{N} \sum_{j=1}^{M} a_{jk} w_j$$

where i is the POI index, j traffic zone index, k charging station index, c_i binary variable is 1 if POI i is covered, else 0, v_i demand weight of POI i, a_{jk} binary variable indicating if charging station k is placed in j or not, w_j traffic weight of traffic zone j, L number of POI, M number of traffic zones, and, N number of charging stations to be placed.

4.5 Selection of base solutions

In a successive placement strategy, a subsequent or preceding stage is based upon an former solution, except for the first and final stage, respectively. This selection is simple for single-objective optimization, where the fittest individual is chosen as a base solution.

However, in multi-objective optimization a Pareto set of non-dominated solutions is calculated, which can contain more than one solution. In this case, a selection strategy has to be defined that is used to decide which solution becomes

Table 1 Incremental/independent genotype

Station #	1	2	3
x	3.6	0.5	8.6
y	4.2	11.1	5.5

Table 2 Decremental genotype: four of seven charging stations are placed

Station #	1	2	3	4	5	6	7
Active	1	0	1	1	0	0	1

Table 3 Discrete genotype: seven charging stations are placed at fixed POI locations

Station #	1	2	3	4	5	6	7
POI ID	1015	10	17	800	30	120	470

the base solution. Two strategies to select the solution which serves as a base for the next step are considered.

In a first selection strategy, a base solution could be formed by those stations which are most frequently placed throughout the final Pareto front. However, during experimentation this resulted in worse solutions, because of interactions between overlapping charging stations when combining genes from each solution.

A second possibility is to choose one specific solution from the set of solutions based on a heuristic. This allows us to guide the development over multiple stages. We can choose a solution according to the Pareto principle with respect to POI. For example, from the best 80 % w.r.t. POI coverage, take the solution that has the highest traffic coverage. It is possible to change the criterion over time, if it is favored to have a more traffic-focused development in the earlier stages and than shift focus to a POI-centered optimization in later stages. In the experiments presented in Sect. 5.2, two selection heuristics are presented and applied.

4.6 Parametrization

Both the incremental and decremental strategies will be evaluated in single- and multi-objective optimization scenarios. Single-objective optimization is included to show general feasibility of successive placement by the incremental and decremental strategies.

4.6.1 Single-objective optimization

The single-objective case has a best performing, near-optimal solution after each stage. This solution is taken as the base solution for the next successive stage. Therefore, no additional selection strategy for subsequent stages is necessary, which makes it simpler to discuss differences in the aforementioned strategies. A weighted POI coverage is used as a fitness metric.

A standard genetic algorithm is applied, where each individual's representation and recombination operators depend on the used strategy.

When using an incremental strategy, each charging station is represented by its *x*/*y* coordinates (see Table 1), which are continuous and constrained by the target area's boundaries.

Individuals are recombined via fitness-weighted uniform crossover. When mutating, a charging station is randomly moved in the target area with distances drawn from a Gaussian distribution. The mutation distance has a standard deviation of 3500 m, which was chosen experimentally. The overall target area has a range of approximately 25 km in each direction.

For the decremental strategy, possible placement locations are given by the larger base solution. Each individual is therefore described by a binary vector (see Table 2), indicating whether a station is placed.

GA parameters were chosen identically as for the incremental strategy, except for mutation parameters due to the different representation. Mutation distance was changed to 1 station (i.e., flipping 1 bit), and mutation probability was reduced to 10 %. Due to the discrete solution space, it is possible to calculate the covered POI of each possible placement upfront and store them in a lookup table. The actual fitness evaluation can then be reduced to simple matrix operations, which are computationally faster.

4.6.2 Multi-objective optimization

Multi-objective optimization extends the single-objective optimization and considers both traffic and POI coverage as separate objectives. The selection strategy for base solutions of each stage depends on the actual scenario.

Computation time prohibited using continuous placements. Stations were therefore only placed on POI locations (see Table 3), turning the problem into a discrete MCLP. Pareto fronts were computed using the NSGA-II algorithm (Deb et al. 2002). Parameters in the incremental and decremental strategies are consistent with those of the single-objective, decremental case. Mutation consists of randomly moving one charging station to a random POI.

An overview of all parameters used is presented in Table 4. They were experimentally chosen for the representative target region used in the evaluation.

5 Evaluation

At first, single-objective scenarios are discussed to understand effects of successive multi-stage evolution in simpler

Table 4 Genetic algorithm parameters

Parameter	Incremental/independent	Decremental/multi-objective
Population size	90	90
Selection	Tournament	Tournament
Selection pressure	2	2
Crossover probability	95 %	95 %
Mutation probability	**25 %**	**10 %**
Mutation distance	**3500 m**	**1 station**
Prob. of new individual	5 %	5 %

Bold values indicate differences between both columns

Table 5 Scenario overview

Scenario	Strategy	Objective (s)	Initial stage	Intermediate stages	Final stage
One-step	Incremental	POI	50	./.	100
	Decremental	POI	100	./.	50
Two-step	Incremental	POI	50	./.	75
	Decremental	POI	100	./.	75
	Incremental	POI + traffic	50	./.	75
	Decremental	POI + traffic	100	./.	75
Multi-stage	Incremental	POI	20	40, 60, 80	100
	Decremental	POI	100	80, 60, 40	20
	Independent	POI	20	40, 60, 80	100
	Incremental	POI + traffic	20	40, 60, 80	100
	Decremental	POI + traffic	100	80, 60, 40	20

cases. Afterward, these results are extended by multi-objective optimization results. All scenarios are listed in Table 5. Initial stages are always calculated via the independent strategy without any restrictions on possible placements.

One main aspect is to see how results from the presented multi-stage strategies differ, measured by the fitness in each stage as well as of the final solution, and later on how the selection criteria in the multi-objective scenarios influence the evolution of successive stages.

Evaluation is based on a representative part of the actual target area and its characteristics, having both high and low POI density areas (see Fig. 1), instead of using synthetic examples. Scenarios are derived from the original project, but proportionally reduced to fit to the reduced target area, which leads to a final stage of 100 charging stations, whereas originally up to 935 charging stations were placed. The sum of the importance weight values of all 1230 POI in the reduced target area is 1678. For comparability and statistical relevance, all results are averaged over 32 runs. Each run was stopped after 1000 generations, as they by then all reach 98 % of the maximum fitness after 4000 generations (see Fig. 2).

A discussion of results consists of comparing absolute fitness number, spatial distribution of placements in the target area and the composition of overall fitness.

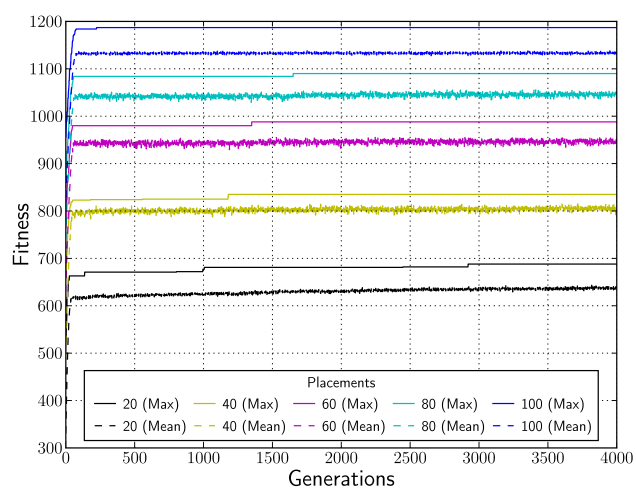

Fig. 2 First 4000 steps of independent runs for different numbers of placements. All leading to an approximate convergence time of 1000 generations, reaching 98 % of the respective final fitness values after 4000 runs

5.1 Single-objective placements

5.1.1 One-step comparison

This scenario shows the basic behavior of a single step per successive strategy and how the subsequent results are

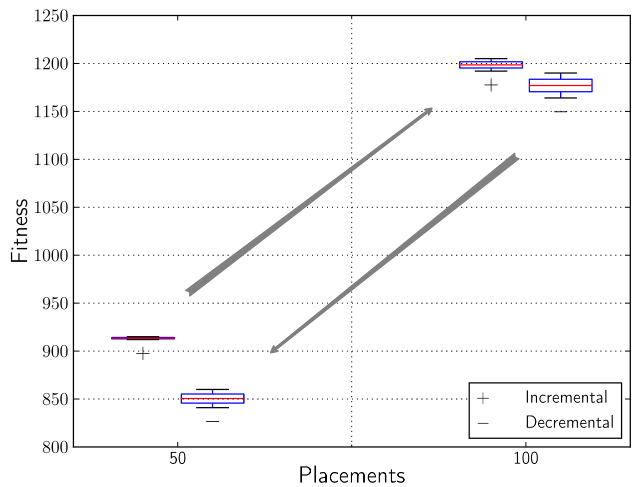

Fig. 3 Fitness values based on a single step, allowing the comparison of both strategies with an independent calculation. A 50 placement increment and decrement are shown. Starting conditions for both strategies are determined by independent solutions for 50 and 100 placements, respectively

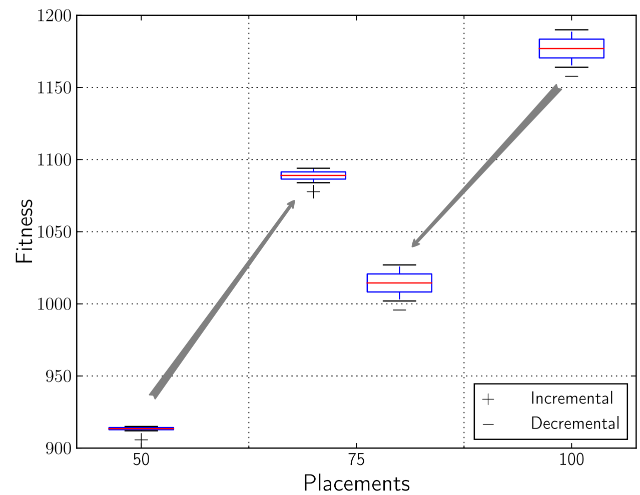

Fig. 4 Comparison of fitness values based on a single target stage with 75 placements, allowing a direct comparison with similar starting conditions, which are determined by the independent strategy

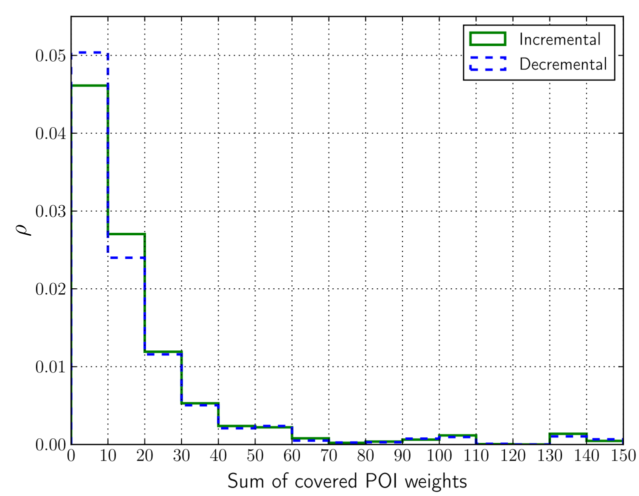

Fig. 5 Density histogram comparison between incremental and decremental strategy at intermediate stage with 75 charging stations

restricted by it. It is shown how the incremental and the decremental strategies differ, because of problem decomposition. The results of both successive calculations are compared to independently calculated solutions for each stage.

Figure 3 shows significantly better result for the incremental than for the independent strategy. This might be explained by the fact that the latter optimizes all 100 placements at once and is therefore more prone to run into a local optimum. Furthermore, independent solutions are generally better than decremental solutions, because the upper bound for the latter is set by the precedingly chosen solution. The upper bound will only be reached in certain unique cases, with equally distributed POI, and in general, decremental will perform worse.

5.1.2 Two-step comparison

Figure 4 shows a direct comparison of the incremental and decremental strategies, where the actual problem is simplified to a single intermediate target stage of 75 charging stations, with fixed initial solutions for both algorithms. The incremental strategy's fixed solution, marked with + in the lower left corner, was calculated by using the independent strategy for 50 charging stations. The initial solution for the decremental strategy, marked with − in the upper right corner, was calculated for 100 charging stations also by the independent strategy.

As both strategies successively move to the same number of charging stations placed, in an optimal solution those solutions should not differ greatly. However, Fig. 4 shows that the chosen strategy and its properties limit the evolution of successive stages.

At the intermediate stage, the incremental strategy reached a significantly higher fitness than the decremental strategy. Both results differ in their variance. The incremental strategy, which generally has more freedom in the solution space, shows a smaller variance than the decremental strategy. This indicates that the incremental strategy's runs tend to find a certain optimum for 75 placements, whereas the subset of the decremental strategy's initial solution includes a certain range of possible placements leading to similar, but varying fitness values.

Figure 5 shows the density distribution for both strategies. This distribution categorizes the charging stations with respect to their fitness share. We can conclude that the incremental strategy is generally better at avoiding placing charging stations that have hardly any effect on the total fitness. This can be derived from the fact that the amount of

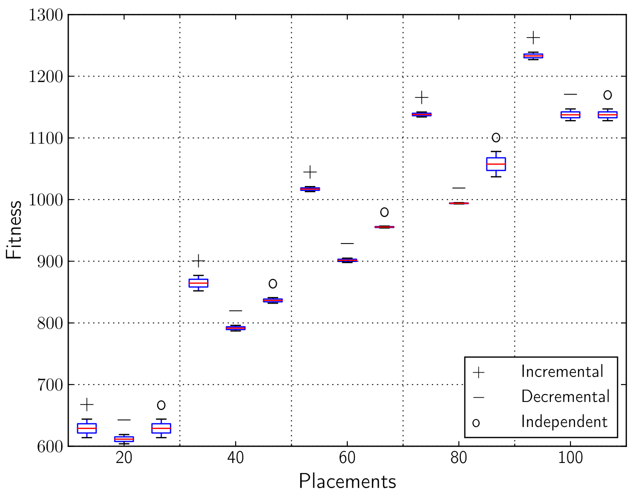

Fig. 6 Comparison of fitness values per strategy over five stages

charging stations in the leftmost bin is significantly lower for the incremental strategy. A significant number of placements is moved from the first to the second bin. On the other hand, the decremental strategy is confined to a mere subselection of placements from the final stage. Which strategy was chosen does not seem to have any visible influence on the solutions' variance, which only holds true for large numbers of charging stations.

5.1.3 Multi-stage comparison

Besides of the comparison of single steps, the development of results for a number of subsequent stages is investigated. The scenario for this evaluation is based on a successive placement strategy with five stages and a final number of 100 placements in the target area (see Table 5).

Figure 6 displays the average fitness values for each strategy at each stage. It should be noted that for the first stages, i.e., 20 placements for the incremental and 100 placements for the decremental strategy, the fitness values of the successive strategies are equal to the independent strategy, because the successive strategies start based on the independent results of their initial stages. The results show that the incremental strategy can utilize problem decomposition as it has to place only a small number of 20 charging stations on top of the existing solution. This seems to work well regarding the dynamics of the GA and results in the best overall fitness at each stage.

On the other hand, the decremental strategy is constrained by the fixed set of options, which hinder the dynamics of the GA, resulting in less fit results at all stages. The difference to the incremental results is especially visible between the incremental results at stage 60 and the decremental results at stage 80, where the placement results of more stations are less optimal than the smaller placement.

For the smallest stage of 20 placements, it can be observed that the fitness values of the different solutions are very similar, even for the reduced decremental strategy, indicating a local optimum found by both GA implementations.

Further differences between the strategies and their successive placement behavior are depicted by the fitness differences between each subsequent stage. These differences get smaller for each step of the incremental strategy as the most valuable points are covered at an early stage and later stages further optimize the result in small additional steps. This is opposed to the decremental strategy, where the fitness difference per stage is neither steadily increasing nor decreasing, but changing. From 100 to 80 placements and from 40 to 20 placements, the fitness difference for the decremental results is significantly larger than between the intermediate stages, because of the way the initial solution was built. The independent strategy directly places all 100 charging stations for the initial stage. That can lead to a state where the complete construction is necessary for the fitness result and is less robust compared to the incremental strategy, which is based on partial high fitness building blocks.

The multi-stage comparison shows the ability of the incremental strategy to better adapt to the problem by gradual improvement as well as producing stages containing high fitness placements in earlier stages, fulfilling the requirement of placing important charging stations earlier on.

In Fig. 7, it is shown for one exemplary run how the different strategies affect the distribution of charging stations. The visualization directly represents which charging station is placed at which stage. For the incremental and decremental strategies (see Fig. 7a, b), this corresponds to the stage when a charging station is added or removed. The longer a station exists, i.e., the earlier it is placed or the later it is removed, the brighter its color. For the independent strategy, all placed charging stations are displayed at all stages. It can be seen that it mostly covers the same, high valuable regions and then further spreads out over the target region to place the additional stations at larger stages.

Variation in placements of charging stations in rural areas is quite high, but the main placement clusters are similar and according to the POI density distribution (see Fig. 1). However, the independent placements (see Fig. 7c) also show a similar distribution pattern, where some regions are always covered, regardless of the number of placements, which gives the impression of the region to be an important part of a high fitness solution.

5.2 Multi-objective placements

Former experiments showed basic effects for a single-objective, multi-stage evolution. In practical applications, multiple factors than only POI influence decisions on charg-

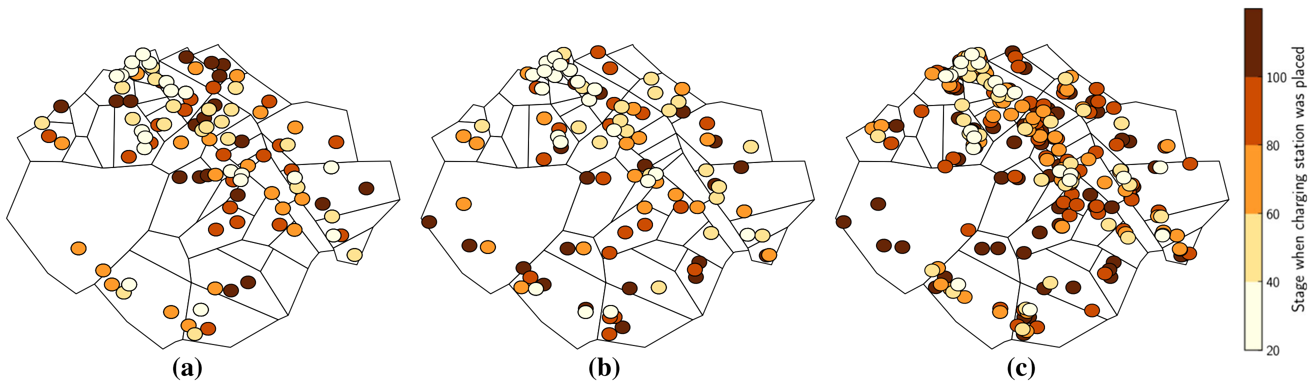

Fig. 7 Exemplary actual charging station placements; the *colors* depict at which stage a charging station is added or removed, except for the independent where at each stage all charging stations are shown. For the independent placements, the *color* shows at which stage a charging station was placed. **a** Incremental placements, **b** decremental placements, **c** independent placements (color figure online)

ing station placement. Therefore, further scenarios in a multi-objective problem space are introduced.

Instead of focusing on the single-objective of POI coverage, traffic flow coverage is added as a separate second objective. Maximizing traffic flow coverage guides the algorithm to positions where there is both a high POI demand and a high traffic, making the overall solution more accurate to actual needs.

5.2.1 Spatial distribution of charging stations

In the following, it is described how spatial distribution of charging stations differs between single-objective and multi-objective problem instances in general, without considering multiple stages. Each subfigure of Fig. 8 shows how often a charging station placement was present in the final solution of 30 runs. For single-objective runs, the final solution is one solution of 100 placements, and for multi-objective runs it is a Pareto front of non-dominated solutions, each with 100 placements. The colors indicate the percentage of final solutions in which a charging station was placed at a specific POI.

With the POI objective only (see Fig. 8a), the algorithm frequently places charging stations in the urban region of Bonn City, which is situated in the center north part of the region. However, it does not always focus on the same POI, as the highest repetitive occurrence of a POI in the solutions is around 30 %. This can be explained by both the coverage radius of a POI and the area's dense POI distribution. Due to this, most charging stations cover multiple POI, thus increasing the fitness by more than a single POI's fitness. This introduces higher solution variance—multiple different solutions can cover the same amount of POIs, whereas the sparsely distributed POI in the rural area do not show the same effect. Generally, the solution achieves a good spatial distribution of charging stations in the whole target area and focuses on some important areas rather than directly on specific important POI.

The solutions that consider the traffic objective (see Fig. 8b), on the other hand, reflect the traffic structure of the target area (see Fig. 1). Up to 80 % of placements occur in the high traffic area of Bonn City. Accordingly, rural areas with little traffic and population are neglected (middle left area).

Multi-objective solutions reflect both single-objective results as shown in Fig. 8c. As this figure shows the placement frequency over all fronts of 30 runs, it depicts the evenly spread diversity of the solutions, also visible in Fig. 9. In conclusion, the objectives do not contradict each other and allow a smooth transition between the two extreme, single-objective solutions.

5.2.2 Successive placements

Subsequently, the next step is to examine how a multi-objective approach is applicable in the formerly discussed multi-stage optimization process. As the multi-objective optimization does not provide one single solution, but instead a set of solutions, it raises the question, which current solution should serve as a base for the next optimization step (see Sect. 4.5). It will be shown how the selection criterion plays a crucial role, as it restricts the set of feasible solutions.

In the following two-step comparison, the solution that maximizes POI coverage is chosen from the top 90 % w.r.t traffic coverage. In the multi-step comparison, the criterion was shifted from a more traffic-centered choice in the first stage toward a more POI-centered one in the end. This is motivated by the need to build only few stations in the beginning covering as much traffic as possible rather than providing a charging opportunity at every interesting place. This strategy is implemented by choosing the best solution (w.r.t. POI) from the top 20, 40, 60 and 80 % in the incremental case and in reverse order in the decremental case.

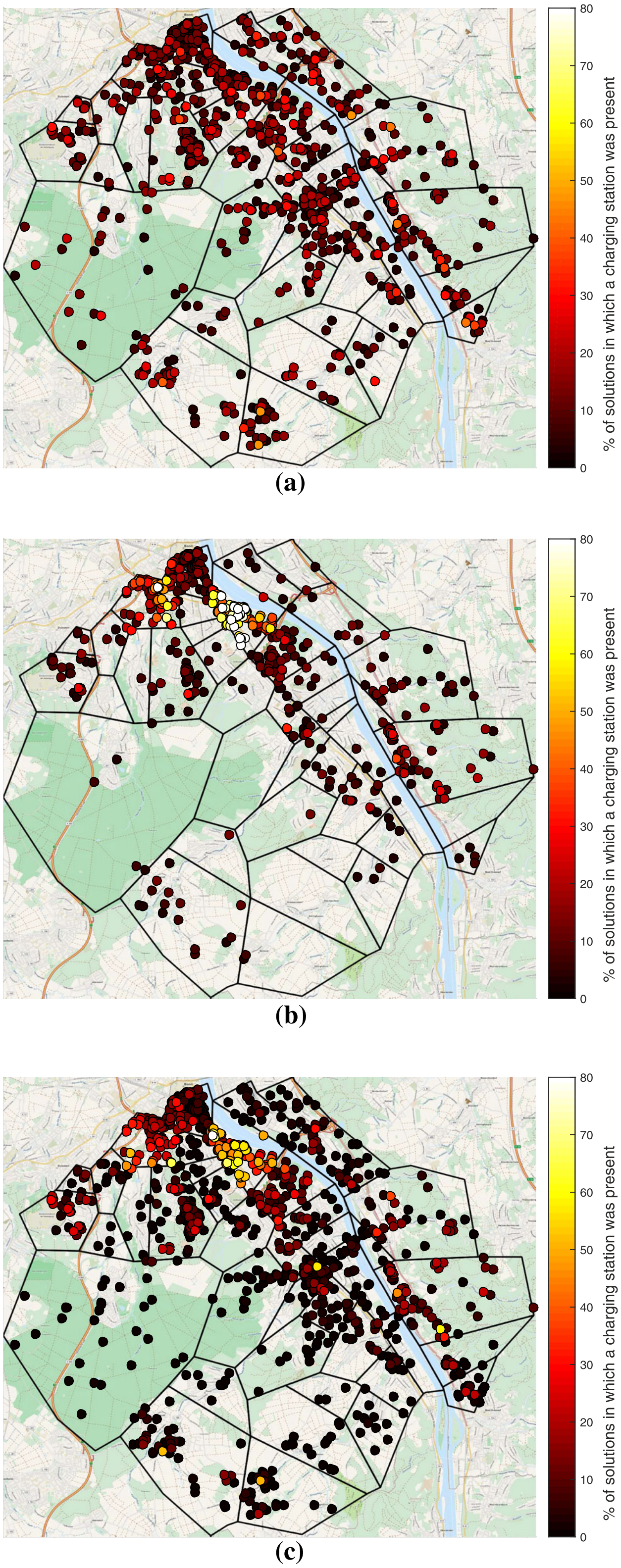

Fig. 8 Actual charging station placements; the *colors* depict how frequent a specific placement was present in the solutions over 30 runs. Map data © OpenStreetMap.org contributors. **a** POI, **b** traffic, **c** POI + traffic

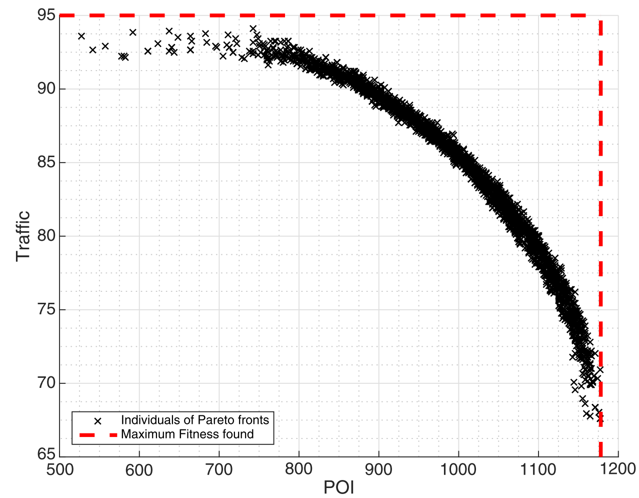

Fig. 9 Cumulative Pareto fronts of 30 runs with 100 placements; the *dashed lines* show the maximum fitness found in evaluation runs

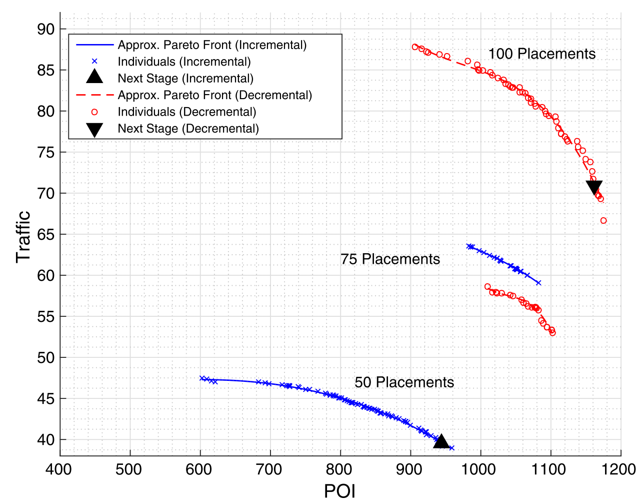

Fig. 10 Exemplary Pareto fronts for incremental and decremental runs. Both successive Pareto fronts are limited by the formerly selected solution and cannot reach the same spread and diversity

5.2.3 Two-step comparison

In a first evaluation, the two-step comparison (see Sect. 5.1.2) is repeated for the multi-objective algorithm. Only one instead of 30 runs was considered in the evaluation to show the basic applicability rather than to evaluate the actual performance. Both strategies, incremental and decremental, calculate an initial stage and one successive stage. The incremental strategy extends 50–75 stations, and the decremental strategy reduces 100–75 stations. The resulting Pareto fronts are shown in Fig. 10.

In the initial stages, both Pareto fronts are similar as they are wide spread and diverse, but after one successive step a

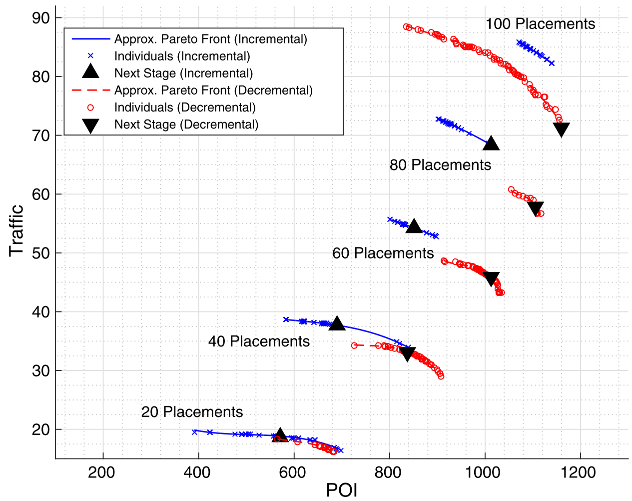

Fig. 11 Exemplary Pareto fronts over five stages. Especially the successive fronts of the incremental strategy are influenced by the selected individual of the former stage, as its fitness values form lower bounds on the new Pareto front in the following stage

different behavior results. Both Pareto fronts are less wide and, as there are fewer placements, have a lower fitness on both objectives. Because the chosen solutions are focused on a good POI fitness, the successive solutions are not able to evolve to high traffic fitness. In the incremental case, a lower bound for the exploration of solutions with high traffic fitness results from the chosen solution of the initial stage.

Nevertheless, the incremental case still evolves into better solutions as it has more freedom to place additional charging stations, whereas for the decremental solutions only a small set of possible placements exist.

5.2.4 Multi-stage comparison

In this comparison, not only one, but four successive steps are evolved to analyze effects over a longer period. Initially, 20 and 100 placements, respectively, are calculated independently to provide base solutions for later stages. The selection priority shifts from the traffic objective in stages with fewer placements to the POI objective in stages with more placements. Figure 11 shows the results of the comparison for an exemplary run.

Again, the selected base solution has a strong influence on the further stages of the incremental strategy. Over the whole multi-stage process, this effect continues and leads to an overall result similar to that seen in the single-objective comparison (see Sect. 5.1.3). The incremental strategy can evolve to a better solution than the initial decremental solution because it has an optimized base solution and only small optimization steps.

For the Pareto fronts of the decremental strategy, the successive evolution leads to a decreasing variety on the traffic objective with many solutions of similar traffic but different POI fitness.

By adjusting the selection on early stages, the evolutionary process can be guided into certain fitness regions and therefore adapt the set of available solutions in the end to the real-world needs of the problem, as will be shown in the next section.

5.2.5 Influence of selection criterion

The selection criterion influences the possible solutions of consecutive stages.

The selected solution builds a lower bound (in the incremental case) and an upper bound (in the decremental case), for the target space region in which the algorithm will search for the next stage. It therefore limits the expansion of the Pareto front. How the selection criterion influences the development of the Pareto front in the next stage is shown in Fig. 12. In Fig. 12a in the incremental case, the individual which has lowest fitness for objective X, but highest fitness for objective Y, is selected within the Pareto front. This means that all individuals on the next stage will have at least the same fitness values, which is satisfied by the complete exemplary next Pareto front. In this case, the complete next front can be reached. The same applies for the selection in the decremental case, if an individual with high X fitness and low Y fitness is chosen. In this case, an upper bound is set for the next solutions.

Two examples of how the selection can hinder the exploration of the whole next Pareto front are depicted in Fig. 12b. In the decremental case, the right part of the Pareto front, with solutions of higher values for objective X, is not reachable. Notably, the reachable solutions have a lower fitness on all objectives—there is no chance to improve on the lower level. In the incremental case, on the other hand, the left part is unreachable, but improvement on the objective X is possible.

Therefore, the choice of a strategy and selection criterion for multi-objective successive evolution can already limit the reachable target space. The characteristics of this limitation depend on the chosen strategy, incremental or decremental, the selection criterion, fixed position on the Pareto front or moving or totally random, and particularly on the shape of the Pareto front itself, as at each stage it sets the limits for the next stages.

Nevertheless, the effect that certain parts of the Pareto front are unreachable for the optimization process can be both helpful and problematic, dependent on the optimization goal. If a diverse spread of solutions is wanted, it is more feasible to choose a less limiting origin solution.

On the other hand, fitness bounds and the accompanying reduction in the target space can even increase the degree to which the optimization algorithm can explore the search

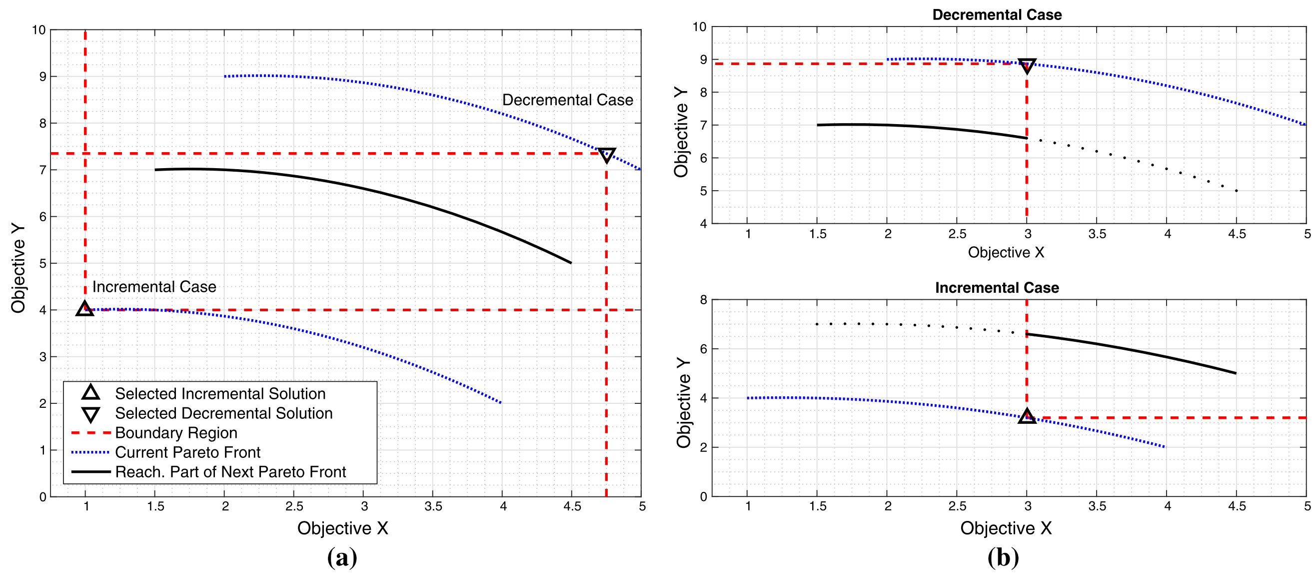

Fig. 12 Selected solution and the accompanying boundaries limit the discovery of certain regions of the Pareto front in subsequent stages. The degree of limitation depends on location and shape of the Pareto fronts. **a** No limitation, **b** limiting selection

space. In this case, the optimization benefits from the strong regulation, because the search is more concentrated on a smaller region, resulting in effects as shown in Fig. 11 where the incremental evolution achieves a more fit, but less diverse, Pareto front than the initial stage of the decremental strategy.

6 Conclusion

Optimization of a multi-stage MCLP based on a genetic algorithm using two different construction strategies for a successive multi-stage charging station placement is compared and evaluated, for both the single and multi-objective case. The incremental strategy begins with a small initial stage and builds iteratively upon this partial solution at each stage. The decremental strategy starts with an optimized final stage, with a subset of the former placements comprising each smaller stage. The strategies are compared in different scenarios with different numbers of intermediate stages and evaluation focuses. The initial solutions of both strategies are based on the same genetic algorithm used for the independent placement strategy. For the multi-objective case, this iterative approach must be adapted, as there are multiple non-dominated solutions produced at every stage, and solutions to act as bounds for successive stages must be selected.

For both the single and the multi-objective algorithms, it is clear that the decomposition of the placement problem into smaller stages fosters the evolution of an optimized solution. It can be concluded that the GA profits from small, successive optimization goals based on a fixed partial solution. This behavior, especially in the application of GA on single-objective MCLP, results from high fitness locations being covered first in every case, regardless of the total number of charging stations to be placed. These locations can yield a high share on the overall fitness with a single charging station placement, which aligns with our goal to place highest fitness stations as early as possible.

In later stages, the incremental strategy placed additional charging stations with the highest fitness, i.e., concentrating on high value regions first and later including missing parts of the target region. This is comparable to a greedy solution, which always places the charging station with the highest fitness gain next. The danger that an incremental strategy would settle into a local optimum at an early stage, and not achieve the same coverage as an unrestricted approach, failed to materialize in our case.

Furthermore, the maximum reachable fitness of the decremental strategy is constrained by the result of the independent strategy for the same stage, as the decremental strategy works on a discrete set of locations which are optimized for a larger stage. It can only achieve an optimal selection of the most valuable subset of these placements, but it lacks the chance to improve the result as it can not move any stations during optimization. In practice, this is only acceptable if it can be assured that the final result—i.e., the initial stage—is near the optimum and the project constraints focus more on the final than the intermediate results.

Within the multi-objective MCLP, the observed behavior is connected to the selection criterion, which determines which solution in the Pareto front will be used as a base.

Depending on the upper and lower bounds of the chosen solution, the Pareto front cannot evolve to solutions outside these bounds, but must remain in the bounded region of the fitness space.

The choice for a selection criterion can hinder the evolution process as important parts of the target space become unreachable, though it also allows for the exclusion of unimportant parts of the target space, assisting the optimization process. Adjustment of this selection criterion allows for tuning of the placement strategy's development over time.

We recommend an incremental strategy for charging station placement, not only for a successive, multi-stage placement strategy, but—especially for large-scale problems—to exploit the problem decomposition effect, and even to consider it as an alternative to an independent strategy for single-stage planning. If the problem has to handle multiple objectives, close attention should be paid to the choice of selection criterion. If computational constraints allow, choose multiple solutions at each stage and branch the optimization at these points. The selection criterion can be considered to be a possibility to control the strategy over time. Especially in complex decision processes, the criterion can be used to adjust a placement roll out when political, economical or environmental conditions change. The developed strategy is therefore more flexible and easier to implement.

The use of a decremental strategy did not lead to useful results. If it can start from an optimal initial solution and if it is acceptable for the intermediate results to be less than optimal it has the advantage of being less computationally expensive than the incremental strategy. However, this will usually not be the case for charging station placement strategies, except when a final solution is provided and the main task is to deconstruct it into smaller stages.

While this paper is based on a representative part of a real-world problem, we must consider how the strategies scale to larger problems, especially when additional intermediate stages are used to foster the problem decomposition effect. A comparison of this incremental evolutionary approach with a pure greedy solution should be considered, as the observed characteristics of the former show similarities with the latter. We solve a real-world problem where it is necessary to take into account further objectives, such as the charging station's distance to the power grid, grid capacity and demanded charging duration. A metric for spatial distribution to achieve more charging station coverage in certain rural areas or clustering of stations in high traffic regions should be considered.

For the multi-objective optimization problem, the effect of different selection criteria, especially when also considering further objectives, is an interesting issue. The selection criterion highly influences future stage diversity and strategic flexibility. A self-adjusting strategic solution to the MCLP problem would be very helpful in decision processes.

The application of other meta-heuristics than GAs, e.g., particle swarm optimization, would have to include the multi-stage aspect of the problem as well.

In this work, we presented approaches to the optimization of the multi-objective maximal covering location problem. While the task required the consideration of problems of theoretical interest, it should not be forgotten that the parameters and constraints of the problem were not contrived, but dictated by the demands of the real world. While the geography of our problem may be unique, the requirements, constraints, and benefits are not. Efficient placement of charging stations where they are most needed will ensure their use, and the success of efforts to move toward more sustainable modes of transportation will rely on rates of adoption of new technologies as much as on the development of the technologies themselves.

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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