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Electric Vehicle Charging Stations Deployment Optimization using Genetic Algorithms

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Abstract
The incorporation of electric vehicles to the transportation system is considered to be imperative in order to mitigate the environmental impact of fossil fuel use and alleviate the current energy crisis. For that reason, it is of critical importance to establish methods for determining the location of the charging infrastructure in an optimal way. This study uses Genetic Algorithms to develop an optimization model that determines the optimal locations to place the charging stations and the number of stations that need to be deployed. This is implemented by combing into a linear objective function the goals of maximizing the electric vehicle user satisfaction (minimum travel distance) and minimizing the construction, operational, and maintenance cost for the charging stations deployment, while considering the user charging demand and the service area. The model has been applied to a simple project consisting of a 200-EV fleet and is tested for various scenarios in order to provide insight regarding the effectiveness of the algorithm by examining the quality of the solution and the required computation time. These scenarios assess the model efficiency in finding either the coordinates of the stations or both the required number of stations and their exact locations, while investigating how different initial solutions, in terms of number and distribution of the charging stations, affect the optimization outcome. Evaluating results indicate that the proposed model can effectively approximate the optimal solution in all cases.

Keywords
Electric vehicles, Electric vehicle charging stations, Charging station placement problem, Genetic algorithms, Multi-objective optimization

1. Introduction

In December 2019, the European Union decided on its Green Deal for Europe, with the aim of becoming carbon neutral by 2050. This target has set turning to e-mobility as one of the EU's top priorities as a way to mitigate the environmental impact of fossil fuel use, achieve future goals to reduce air pollution and alleviate the current energy crisis. Electric vehicles (EVs) promise high efficiency, energy savings, low noises and zero emissions, however, the lack of supporting charging infrastructure is holding back their prompt, widespread adoption. For that reason, it is imperative to deploy an extended network of charging stations for attracting private vehicle drivers to use EVs. This has as a prerequisite to solve efficiently the facility allocation problem, meaning that the number and the location of the charging stations composing the respective network should be firstly optimized, while considering certain constraints (budget limitation, charging station capacity, dispersion of the charging demand etc.).

Existing research has developed a variety of methods and algorithms in order to solve the charging station placement and sizing problem. (Huang & Kockelman, 2020) utilize genetic algorithms to solve the fast-charging station location-and-sizing problem to maximize EV charging stations owner profits across a region for BEV owners who wish to charge en route, taking into consideration elastic demand, station congestion, and network equilibrium. Genetic Algorithms have also been employed by (Akbari et al., 2018), (Efthymiou et al., 2017), (Tao et al., 2018) to calculate the necessary number of charging stations and best positions to locate them to satisfy the clients demand, with (Efthymiou et al., 2017) and (Tao et al., 2018) using origin – destination (OD) data of conventional vehicles in

Thessaloniki (Greece) and real-world driving data of 196 battery electric vehicles in Wuhan (China) respectively, for the purposes of their analyses.

(Yi et al., 2019) develop a model based on artificial immune algorithm to identify the optimal solution considering user's comprehensive satisfaction: charging convenience, charging cost and charging time. (J. He et al., 2018) develop a bi-level mathematical model to optimize the location of charging stations for EVs with the consideration of driving range. The upper-level is to maximize the flows served by charging stations, while the lower-level depicts the route choice behavior given the location of charging station. (Erbaş et al., 2018) apply a geographic information system (GIS)-based Multi Criteria Decision Analysis using the analytical hierarchy process (AHP) to address the electric vehicle charging station site selection in light of 15 environmental, economic and urbanity criteria. A hierarchical optimization model, integrating three levels of analysis, is also chosen by (Kong et al., 2017) to assist city planners for charging station location selection and system design. (Zhang et al., 2019) establish a GIS-based Multi-objective Particle Swarm optimization model aiming to both minimise the total cost of the charging stations investment and maximise the service coverage. (Bai et al., 2021) solve the siting and sizing problem by combining the hybrid particle swarm optimization (HPSO) algorithm with the entropy-based technique for order preference by similarity to ideal solution (ETOPSIS) method. (S. Y. He et al., 2016) present a case study on planning the locations of public electric vehicle charging stations in Beijing, China, where they apply and test the effectiveness of three different classic facility location models (the set covering model, the maximal covering location model, and the p-median model). (Liu et al., 2018) use an intelligent multi-objective optimization method to handle this problem by integrating a multi-objective particle swarm optimization (MOPSO) process to obtain a set of Pareto optimal solutions and an entropy weight method-based evaluation processto select the final solution from Pareto optimal solutions.

Existing studies generally attempt to solve this problem by creating models which use a predefined list of candidate locations for charging stations to be deployed, as well as a predefined number of stations to allocate. The objective of this study is to develop an optimization model that determines freely the optimal locations to place the charging stations within an area of interest and the number of stations that should be allocated, with the goal to maximize the electric vehicle user satisfaction (minimum travel distance), while considering the construction, operational, and maintenance cost for the charging stations deployment.

2. Proposed model

The electric vehicle charging stations deployment problem is a large combinatorial problem based on the optimization model of facility location problem. This analysis is positioned among the approaches of minimizing total charging station network cost and maximizing user satisfaction by reducing travelling distance, as the goals of the main infrastructure placement choice, while considering EV fleet assignment as a second level of the problem. The analysis aims to search for the most efficient locations for positioning the charging stations within the area of interest and provide suggestions on the number of EVs that can make use of the charging station daily, so as to ensure that the solution meets the charging demand per day.

The objective function of the proposed model represents the total cost that needs to be minimized and is formulated as the sum of the costs of all optimization objectives. In the present paper, two objective goals have been proposed and evaluated for their efficiency in approaching the global optimum and in minimizing computational time, which incorporate:

- The cost for deploying a network of charging stations (CSc), representing the sum of costs for land acquisition, construction, operation and maintenance.
- The cost of travelling distance (Dc), representing the sum of units traveled by the users from their charging demand point to the nearest charging station.

The above parameters can be incorporated in a linear objective function of the following form:

$$minF = w1 * CS_C + w2 * Dc \tag{2}$$

where *wi* is the corresponding unit cost value, defined by the user based on the problem characteristics.

The following assumptions and constrains are considered in the development of the optimization model:

- The optimization analysis is performed after the user provides the margins of the area of interest in the form of coordinates.

- The optimization analysis is performed after the user provides the desired number of charging stations that will compile the charging network, and for which the model will provide the optimal placement within a given area. Alternatively, the number of charging stations is considered as part of the optimization problem.
- The potential charging deployment sites are not predefined by the user in the form of candidate locations but are determined through the genetic algorithm employment.

The present analysis has used evolutionary algorithms, and more specifically Genetic Algorithms, to approximate the optimal solution as it is a classical method, suited for this type of optimization problems, where the exact solution is unknown or computationally expensive to obtain. The proposed model has been implemented in an Ms-Excel spreadsheet and the optimization is performed via a commercial optimization software (Palisade Evolver 8.1) which works as an Excel add-in. The Genetic Algorithm that has been employed to search for optimal solutions uses 50 chromosomes to form the initial population with crossover and mutation rate 0.5 and 0.1 respectively. An iterative procedure of 200,000 trials or 60 minutes of runtime is used for all the scenarios that have been tested.

3. Results

A case study with a simple project consisting of a 200-EV fleet is considered in order to illustrate the algorithm application. The number of EVs (charging demand), the number of stations compiling the charging network, the cost per station, the coordinates of the charging station location and the total travel distance covered by users to satisfy their charging needs are shown in Table 1, representing the initial scenario tested in which all stations have initially been placed at coordinates (0, 0). Alternatively, one can start the optimization with either predetermined initial locations for placing the charging stations or randomly allocated stations within the area of interest. Figure 1 graphically presents the respective demand scatter diagram and charging station deployment for the initial solution of the case study.

Based on budget limitations, various scenarios have been tested where a maximum number of deployment sites is defined by the user. More specifically, 25 different scenarios have been examined where the charging station network was composed of 1 to 25 stations respectively, aiming to achieve a balanced trade-off between the two optimization objectives described in Section 2 and depicted in Equation (1). Table 2 presents the optimal solution of each scenario and provides the average improvement of the objective function which was achieved by applying the proposed model. The objective function values are calculated by equation (1) with $w1$=1, $w2$=10, CSc equal to 1000 times the number of stations and Dc=7,157. Fig.2 indicatively presents the charging station allocation for the case of employing 12 such stations. This scenario leads to the overall best solution (lowest total cost after optimization) among all scenarios for the existing demand size and origin.

For attaining a more quantitative assessment of the degree of convergence to the absolutely best value, further specific test cases were designed and implemented. In particular, a couple of scenarios considered the demand concentrated in specific points of the study area with the number of points being equal to or lower than the number of stations. In particular, the demand was allocated in eight points (randomly placed in the search area) and a number of eight or ten charging stations were alternatively assumed (initially all placed at coordinates (0, 0)). In both cases, the model allocated one station exactly at each demand spot (i.e., the transportation cost was zero) leaving the two unnecessary stations in the second case unmoved.

Table 35. Project data for the initial placement of stations in the application example

EVs (charging demand)	Number of stations	Cost per station (in units)	Station coordinates	Travelling distance (in units)
200	i=1,2,...,25	1,000	(0,0)	7,157

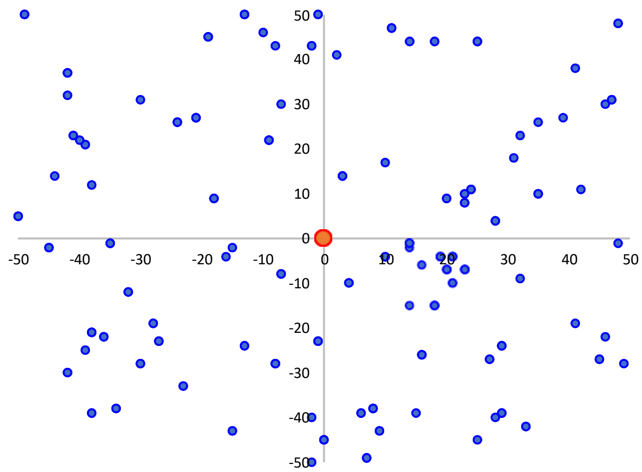

Fig. 1. Demand scatter diagram (blue color) and charging station deployment (orange color) for the initial solution of the case study

Table 2. Optimal results for the application examples

EVs (charging demand)	Number of stations (and scenario number)	Objective function before optimization	Objective function after optimization	Average improvement (%)
200	1	72,569	72,047	0.72
200	2	73,569	55,543	24.50
200	3	74,569	44,265	40.64
200	4	75,569	38,563	48.97
200	5	76,569	34,314	55.19
200	6	77,569	32,690	57.86
200	7	78,569	31,068	60.46
200	8	79,569	30,568	61.58
200	9	80,569	29,614	63.24
200	10	81,569	29,200	64.20
200	11	82,569	28,788	65.13
200	12	83,569	28,341	66.09
200	13	84,569	28,510	66.29
200	14	85,569	28,643	66.53
200	15	86,569	29,016	66.48
200	16	87,569	29,176	66.68
200	17	88,569	29,993	66.14
200	18	89,569	30,254	66.22
200	19	90,569	30,497	66.33
200	20	91,569	30,994	66.22
200	21	92,569	31,574	65.89
200	22	93,569	32,325	65.45
200	23	94,569	32,677	65.45
200	24	95,569	33,221	65.24
200	25	96,569	33,791	65.01

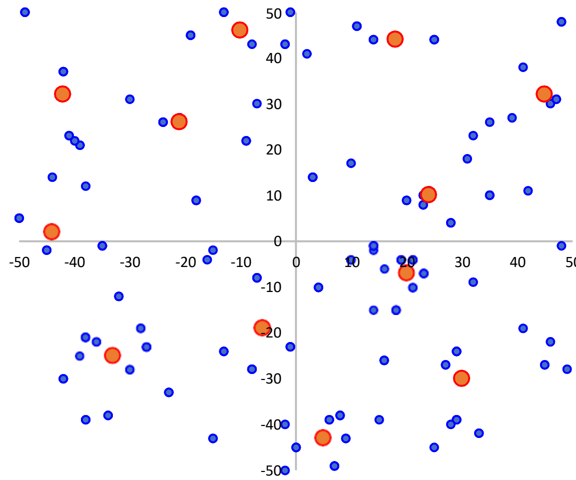

Fig. 2. Demand scatter diagram (blue color) and charging station deployment (orange color) for Scenario 12 of the case study

According to the results presented above, the travel distance decreases with the increase in the number of charging stations being deployed. However, the number of charging stations should be determined and kept under certain limitations based on the charging demand, the size of the area of interest/coverage service as well as the restrictions in budget availability. Figure 3 portrays the classical trade-off diagram between the charging station number and the travelling distance. This diagram shows the impact of a change in each attribute to the other attribute and how this may affect the decision making, minding the special characteristics and constraints of the problem. For example, if the main goal is to keep the travelling distance for the drivers under 2,000, the optimal number of charging stations is 10, providing that the available budget is over 10,000. In case that the budget is limited to 8000 then 8 charging stations may be constructed in order to approximate the initial goal of the travelling distance (2,222). It can be seen in Table 2 that a considerable minimization improvement is being achieved in most of the optimization cases compared to the initial solution. By applying the proposed model, the decrease in the objective function ranges from 0.72% to 66.68% with an average level of 59.83%. An exception to these results is Scenario 1, which has a very limited solution space size and alternatives to search for the optimal placement, as the network comprises of one charging station and therefore has not much room for improvement. Figure 4 portrays the relative convergence function rate indicatively for four indicative scenarios. The function convergence diagram is formed using the following function:

$$C=(F(i)-F_{optimal}) / (F_{initial} - F_{optimal}) \qquad (2)$$

where i is the optimization iteration and $F(i)$ the value of the objective function in i^{th} iteration. Among the presented results in Figure 4, Scenario 10 presents the fastest rate of convergence and is reaching its optimal solution after approximately 110 seconds of runtime, while Scenarios 15, 20 and 25 are developing the optimal solution after 250, 500 and 650 seconds respectively. This is expected since the higher the number of stations, the more computationally difficult to place them in an optimal way.

Additionally, Scenario X - built upon Scenario 12 (representing the case study best solution) - has been used to examine whether a different initial charging station allocation setting could be a parameter that affect the model efficiency. For this optimization, an initial station allocation setting in the form of “X” was selected, as depicted in Figure 5. In this setting, four charging stations have been placed at point (0, 0) while the other eight stations have been distributed symmetrically in the four quadrants. The optimization results (CSc = 12,000, Dc = 1,634, Objective function = 28,341) indicate that the algorithm converges to the same solution of Scenario 12 (see Fig. 2 above) regardless of the initial station placement.

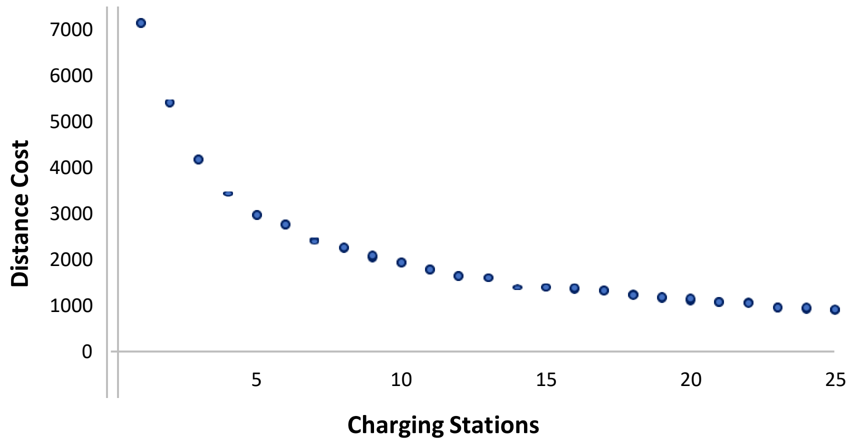

Fig. 3. Trade-off diagram between the distance cost and the number of charging stations

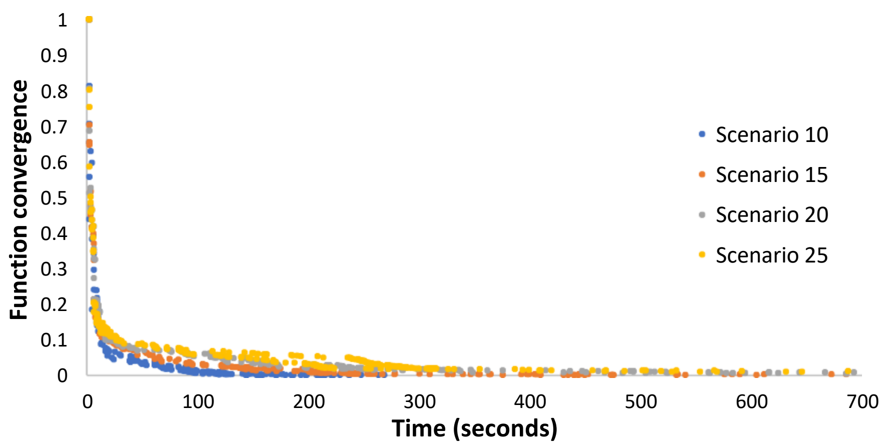

Fig. 4. Optimization convergence curves for different scenarios.

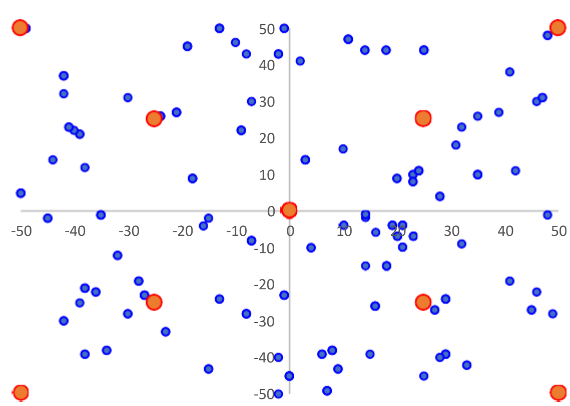

Fig. 5. Demand scatter diagram (blue color) and charging station deployment (orange color) for Scenario X of the case study

In the second direction of analysis, the number of charging stations was considered as a decision parameter in addition to the optimal station placement (Scenario N). More specifically, the algorithm was redeveloped to identify both the number and the location of the charging stations. Several tests were performed considering an initial number of stations ranging from 15 to 25 and being initially placed at coordinates (0, 0). In general, the model presented a convergence to a solution consisting of 12 stations while small deviations in the objective function were observed, ranging from 28,341 to 28,370. The minimum value solution was found to coincide with those of Scenarios 12 and X.

For the case that the demand was considered as concentrated in eight points (randomly placed within the study area) and starting with ten charging stations, the algorithm eliminated the two excessive stations (to avoid the deployment cost) and allocated the remaining eight stations exactly upon the points of the demand existence to fully eliminate the transportation cost.

4. Discussion

This study proposes a model which utilizes Genetic Algorithms to formulate a flexible tool for planning the location of charging stations infrastructure. This analysis can be extended to include additional factors/constraints that could affect the optimization outcome, such as the physical-geographical condition and topography of the area of interest and the difference in charging station capacities, based on the grid tolerance. Also, within the area of interest, different zones could be considered to indicate variations in station deployment costs, either for land acquisition, construction or operation and maintenance.

In regard to the selected algorithm, it should be highlighted that due to meta-heuristic algorithm special characteristics, the obtained solution may not necessarily be the optimal one in every single run (especially as the problem grows up in size). To improve the success rate (i.e., to minimize the degree of error between the obtained and the optimal solution), the algorithm was run repetitively so that, considering the stochastic nature of it, to obtain more viable solutions. Different optimization criteria were tested in order to identify the one that better suits the individual problem objectives, limitations and characteristics. By exploring more alternatives, it is much likely to find a solution with higher generalized impact, than by focusing only on the optimization of a single sub-goal.

5. Conclusions

The electric vehicle charging stations placement problem is one of the most challenging optimization problems in transportation sector and in the field of infrastructure management. In this context, the objective of this research is to propose a solution for optimal EV charging infrastructure deployment, based on Genetic Algorithms which are considered as an effective tool used to handle large combinatorial optimization problems. The present study has delivered a model to optimize the number and the location of charging stations for EVs. The variables composing the objective function were the driving distance required for the fleet of EVs to reach the charging station and the construction, operational and maintenance costs of the charging network deployment. The presented case studies (varying in terms of parameters tested and initial station network allocation) have demonstrated that the proposed method can attain the reasonable planning of the EV charging stations, including both the number and location of the stations, considering the priorities and individual objectives in every tested scenario.

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