

Multiobjective electric vehicle charging station locations in a city scale area: Malaga study case

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Abstract. This article presents a multiobjective variation of the problem of locating electric vehicle charging stations (EVCS) in a city known as the Multiobjective Electric Vehicle Charging Stations Locations (MO-EVCS-L) problem. MO-EVCS-L considers two conflicting objectives: maximizing the quality of service of the charging station network and minimizing the deployment cost when installing different types of charging stations. Two multiobjective metaheuristics are proposed to address MO-EVCS-L: the Non-dominated Sorting Genetic Algorithm, version II (NSGA-II) and the Strength Pareto Evolutionary Algorithm, version 2 (SPEA2). The experimental analysis is performed on a real-world case study defined in Malaga, Spain, and it compares the proposed approaches with a baseline algorithm. Results show that the SPEA2 computes the most competitive solutions, even though both metaheuristics found an accurate set of solutions that provide different trade-offs between the quality of service and the installation costs.

Keywords: Electric vehicles · Infrastructure location · Sustainable mobility · Multiobjective optimization · NSGA-II · SPEA2

1 Introduction

In recent years, sustainability has become a major goal for industry, academia, and society as a whole. Society has steadily moved towards ecological awareness, adapting their lifestyles to promote environmental initiatives, cleaner means of production, and environmentally friendly energy sources. One of the most critical changes in current activities concerns urban mobility, where an effective transition towards inclusive, efficient, and low-carbon means of transport is being experienced [6]. Electric mobility provides citizens with a cleaner and safer way of getting around without gas emissions.

Electric vehicles (i.e., electric cars, scooters, and motorbikes) are powered by an electric motor charged using energy from the electricity grid. They have shown rapid and sudden growth and expansion, as they are preferred mobility options for the younger generation. Consequently, electric vehicles have a relevant socio-economic impact [14]. In addition, electric vehicles have a higher overall efficiency than combustion engines vehicles. They save (on average) 40% of energy while contributing to reducing gas emissions, when the electricity used to charge the vehicles is obtained from green sources [12].

When considering the deployment of electric vehicles in large cities, a relevant logistical problem arises, similar to other location problems related to public services in the context of smart cities [9, 17, 22]. One of the most relevant sub-problems is the effective and efficient location of charging points for electric vehicles [10]. The main objective of this problem is to provide a good quality of service to citizens while keeping costs reasonable for the city administration.

Different authors have tried to address this siting problem from different perspectives. One of the common ways in the literature is to address the location of charging stations as ILP or MILP problems. The researchers usually used these methods to maximize the economic profits of installing new charging stations [1, 2, 15], minimizing the total walking distance according to parking patterns estimated using realistic urban data [3], or maximizing coverage to improve demand [11, 25]. Some authors have relied on open data to improve the quality of service offered to citizens by taking into consideration the energetic constraints of the area [4, 21]. The cited articles work with a mono-objective view of the problem. However, in the real world, the location of charging stations have different objectives.

This article presents a new multiobjective variation of the problem of locating electric vehicle charging stations (EVCS) in a city known as the Multiobjective Electric Vehicle Charging Stations Locations (MO-EVCS-L) problem. Two objectives are considered: maximizing the quality of service of the charging station network to the citizens, and minimizing the deployment and installation cost of the new stations. Both objectives need data about different aspects of a city: locations of neighborhoods, streets, etc., energy data such as types of charging stations or energetic capability of electrical substations, and economic data such as installation costs. To obtain this data, different open data sources were used. This research uses a realistic case study defined in the city of Malaga, Spain.

The main contributions of this article are: *a)* defining and formulating a new realistic multiobjective problem for locating electric vehicle charging station on a city scale, taking into account the quality of service, power restrictions, and deployment costs; *b)* proposing two multiobjective metaheuristics to address the proposed problem; *c)* devising specific evolutionary operators; and *d)* addressing the problem on a realistic instance defined using real-world data.

The rest of the article is organized as follows: Section 2 presents the problem addressed in this study. Section 3 describes the algorithms used in the experimentation as well the operators designed for the problem. The experimental setup and evaluation are reported in Sections 4 and 5 Finally, Section 6 presents the conclusions and formulates the main lines for future work.

2 The multiobjective electric vehicle charging stations location problem

The problem considered in this paper aims to select the best locations of EVCSs to maximize the quality of service provided to users and simultaneously take into account the infrastructure deployment costs. Different types of EVCS are

considered. The kind of EVCSs determines the number of users that can be served per unit of time, the charging time, and the installation costs.

The quality of service is evaluated according to the users that can be served (each EVCS may attend the users that live within a defined *service distance*), the charging time, and the citizens that any charging station does not serve. The deployment cost has two main components: *i*) the infrastructure installation expenses for the required charging equipment and the construction of a new station and *ii*) the cost of connecting the installed station to the power grid.

The two discussed objectives (quality of service and deployment costs) are in conflict, because installing charging stations close to the residences of all tentative clients would require a significant investment, which in turn may not produce in adequate expected revenues for the institutions in charge of the management of the electric vehicle charging system. Thus, in order to assist the decision-makers, the main research outcome of the addressed problem is to provide solutions (i.e., EVCS locations) that properly samples the different trade-offs between these problem objectives.

2.1 Mathematical formulation

The mathematical formulation of the addressed optimization problem is defined considering the following elements:

- A set $S = \{s_1, \dots, s_M\}$ of candidate road segments for installing EVCSs. Each road segment s_i can be the location of only one charging station.
- A set $C = \{c_1, \dots, c_N\}$ of the locations of the tentative users. Nearby locations are grouped in clusters, as usual in the related literature. The number of clients to serve at each cluster c is u_c . The distance from the cluster c to the charging station $s \in S$ is $dc_{c,s}$. A cluster of clients c is served by the charging station located in s if the $dc_{c,s}$ distance is lower or equal to the Ds_s *service distance*, i.e., $dc_{c,s} \leq Ds_s$. $C_s \subseteq C$ represents the set of clusters of clients served by station installed in s , and $NC \subseteq C$ defines the set of clusters not served by any charging station.
- A set $E = \{e_1, \dots, e_T\}$ of electrical substations that supply the power to the charging stations. Due to the power distribution restrictions, each electrical substation e can serve electricity only to a given subset of candidate road segments enclosed in a given city area A_e , named electrical substation influence area. In turn, the maximum power allocated for EVCSs, i.e., the electricity distributed by substation e that can be used to feed the electric vehicle charging stations limited by MP_e .
- A set $J = \{j_1, \dots, j_H\}$ of EVCS types. Each type has its own charging time ct_j , equipment and building cost cc_j , connection to the grid cost cg_j , and required electric power from the electrical substations ep_j . By convention, the model assumes $cc_0 = cg_0 = 0$ and $ct_0 = \infty$ to characterize segments where no charging station is located.

Eq. 3–7 describe the proposed optimization model, using the following variables: x_s is an integer variable, $x_s = j_i$ when a charging station of type $j_i \in J$ is

installed in segment s , and $x_s = 0$ otherwise; and $y_{e,s}$ is a binary variable, $y_{e,s} = 1$ if the electrical substation e is feeding the charging station located in s and 0 otherwise.

The quality of service provided by the deployed infrastructure is defined in Eq. (3) as the sum of the service provided by each charging station installed in $s \in S$ to the subset C_s of clusters within its *service distance* minus the number of clients in clusters not served by any charging station NC . NC , defined in Eq. (5), is the complementary set of the set of all clusters served by all charging stations, see Eq. (1). The service provided by the EVCS deployed in s is proportional to the number of citizens in the cluster u_c and inversely proportional to the time required to charge an electric vehicle ct_{x_s} . The quality of service is proposed to be maximized.

$$SC = \bigcup_{s \in S} C_s \quad \forall s \in S : x_s \neq 0 \quad (1) \qquad NC = C \setminus SC \quad (2)$$

The installation cost of a EVCS considers the sum of the infrastructure cost cc_{x_s} and the cost of connecting the station to its electrical substation, defined in Eq. (4). The budget required to connect the charging station to the electrical substation is proportional to the distance between them $d_{e,s}$ and the cost of wiring cg_{x_s} . The cost is proposed to be minimized.

$$\max \sum_{s \in S} \left(\sum_{c \in C_s} \frac{u_c}{ct_{x_s}} \right) - \sum_{nc \in NC} u_{nc} \quad (3)$$

$$\min \sum_{c \in C} \sum_{s \in S} (d_{e,s} \cdot cg_{x_s} + cc_{x_s}) \quad (4)$$

subject to

$$NC = C \setminus SC \quad (5)$$

$$d_{c,s} \cdot y_{e,s} \leq De \quad \forall e \in E, s \in S \quad (6)$$

$$\sum_{s \in S} y_{e,s} \cdot ep_{x_s} \leq MP_e \quad \forall e \in E \quad (7)$$

Regarding the problem constraints, Eq. (6) imposes that the distance between an electrical substation and any charging station it feeds is lower than De , i.e., the charging station in s is in the A_e of the electrical substation e . In turn, the constraint in Eq. (7) guarantees that the total power consumption of all charging stations that are fed by a given electrical substation is lower or equal than MP_e .

3 Algorithms

Two state-of-the-art MOEAs are applied in this study to address MO-EVCS-L *Non-dominated Sorting Genetic Algorithm, version II* (NSGA-II) [8] and *Strength Pareto Evolutionary Algorithm, version 2* (SPEA2) [26]. NSGA-II and SPEA-2 have been successfully applied in many problems in different application areas in smart cities [17, 18, 20, 22, 23]. This section presents their main features and describes the specific operators applied in this research.

3.1 NSGA-2

The evolutionary search applied by NSGA-II uses a non-dominated elitist ordering to mitigate the complexity of the dominance check, a crowding technique to keep solutions diversity, and a fitness assignment method that takes into account dominance ranks and crowding distance values. Algorithm 1 presents the pseudo-code of NSGA-II evolving a population P (size N).

Algorithm 1 Pseudo-code of the NSGA-II algorithm

```

1:  $t \leftarrow 0$  ▷ generation counter
2: offspring  $\leftarrow \emptyset$ 
3: initialize( $P(0)$ ) ▷ population initialization
4: while not stopping_criterion do
5:   evaluate( $P(t)$ ) ▷ population evaluation
6:    $R \leftarrow P(t) \cup \text{offspring}$ 
7:   fronts  $\leftarrow$  non-dominated sorting( $R$ )
8:    $P(t+1) \leftarrow \emptyset$ ;  $i \leftarrow 1$ 
9:   while  $|P(t+1)| + |\text{fronts}(i)| \leq N$  do
10:    crowding distance(fronts( $i$ ))
11:     $P(t+1) \leftarrow P(t+1) \cup \text{fronts}(i)$ 
12:     $i \leftarrow i+1$ 
13:   end while
14:   sorting by distance (fronts( $i$ ))
15:    $P(t+1) \leftarrow P(t+1) \cup \text{fronts}(i)[1:(N - |P(t+1)|)]$ 
16:   selected  $\leftarrow$  selection( $P(t+1)$ )
17:   offspring  $\leftarrow$  evolutionary operators(selected)
18:    $t \leftarrow t + 1$ 
19: end while
20: return computed Pareto front

```

3.2 SPEA-2

SPEA2 was an evolution of the SPEA algorithm. SPEA2 is distinct from other MOEAs because it applies the *strength* concept on the fitness computation, which is based on both Pareto dominance and diversity. Thus, the *strength* measures how many solutions dominate (and are dominated by) each candidate solution. In turn, a density estimation is also considered for fitness assignment. Furthermore, an elite population is defined to store the non-dominated individuals found during the search to apply elitism.

SPEA2 working on a population P (size N) is shown in Algorithm 2. The $elitePop$ parameter represents the elite population, which has $eliteSize$ size. The most similar individuals are removed by a pruning method to assure that the size of the elite population is always $eliteSize$ when the elite population is full.

Algorithm 2 Schema of the SPEA2 algorithm.

```

1:  $t \leftarrow 0$ ;
2: elitePop  $\leftarrow \emptyset$ 
3: initialize( $P(0)$ )
4: while not stopcriterion do
5:   evaluate( $P(t)$ )
6:    $R \leftarrow P(t) \cup elitePop$ 
7:   for  $s_i \in R$  do
8:      $s_{i_{raw}} \leftarrow computeRawFitness(s_i, R)$ 
9:      $s_{i_{density}} \leftarrow computeDensity(s_i, R)$ 
10:     $s_{i_{fitness}} \leftarrow s_{i_{raw}} + s_{i_{density}}$ 
11:   end for
12:   elitePop  $\leftarrow nonDominated(R)$ 
13:   if size(elitePop) > eliteSize then
14:     elitePop  $\leftarrow removeMostSimilar(elitePop)$ 
15:   end if
16:   selected  $\leftarrow selection(R)$ 
17:   offspring  $\leftarrow variationOperators(selected)$ 
18:    $t \leftarrow t + 1$ 
19: end while
20: return computed Pareto front

```

3.3 Main operators

The proposed NSGA-II and SPEA2 for the locating the electric vehicle charging stations include the main following features:

Solution encoding . Solutions are encoded as a vector of integers in the range $[0, |J|]$. Each position in the vector represent a possible location for the charging station (i.e., indexed by s_1, \dots, s_M), and the corresponding integer value on index s_k represents one of the possible electric vehicle charging type, i.e., $j_i \in J$. The special value '0' is used to represent the situation where no charging station is installed in the segment s_k . Fig. 1 presents an example of solution encoding for a sample scenario with eight tentative locations $\{1, \dots, 8\}$ and two types of charging stations $\{1, 2\}$.

Initialization . The population is initialized by applying a random procedure that creates feasible solutions. The initialization process iterates over the areas of influence of each electrical power station A_e . For each A_e , it randomly selects a tentative location s_i and adds a randomly chosen EVCS j_k to it. If the power consumption restriction in Eq. 7 is met, it selects another location in A_e to install a new EVCS. This process is repeated while power consumption restriction is fulfilled.

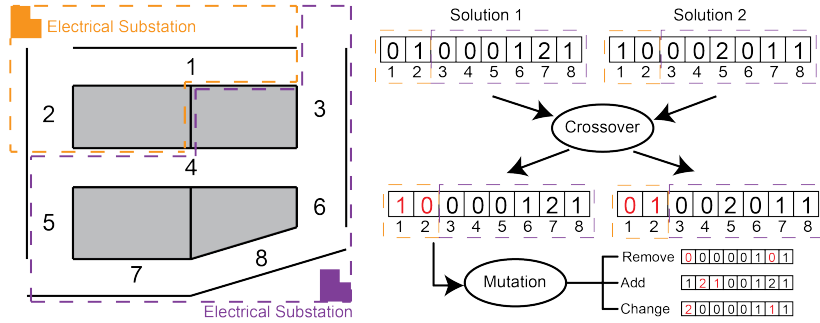


Fig. 1: Example of solution encoding of an scenario with eight possible locations for EVCS and two types of stations, and the evolutionary operators.

Selection, replacement, and fitness assignment . NSGA-II applies the $(\mu+\lambda)$ evolution model. Tournament selection is applied, with tournament size of two individuals. The tournament criteria is based on dominance, and if the two compared individuals are non-dominated, the selection is made based on crowding distance. Fitness assignment is performed considering Pareto dominance rank and crowding distance values.

Evolutionary operators . The recombination operator applied is a variation of the standard n-point crossover applied over two selected individuals specifically devised to address MO-EVCS-L named k electrical substation influence area crossover (k -A_eX). That randomly exchange the deployment configuration of the electrical areas of influence of k power stations (A_e defined in Section 2). This operator works as follows: given two parents (individuals), k -A_eX randomly selects k A_e and exchanges between parents the information of the selected A_e to create two offspring (see Fig 1). The mutation operator is based on randomly modifying specific attribute of a randomly selected segment in the A_e of a given individual (i.e., x_s). There are three different potential changes shown in Fig 1: *i*) if there is a charging station (i.e., $x_s \neq 0$), the charging station can either *removed*; *ii*) if there is no any charging station (i.e., $x_s = 0$), a randomly chosen charging station is selected to *add* it in the represented segment (i.e., x_s is replaced by an integer value uniformly selected in the range $[0, Z-1]$); and *iii*) the values of two different attributes x_s and $x_{s'}$ are *changed* with each other regardless of their values. Te recombination and mutation operators are applied with probability p_C and p_M , respectively. Fig. 1 represents both evolutionary operators.

Solution feasibility . The restriction defined in Eq. 7 may not be met after the application of evolutionary operators, i.e., the total power consumption of all charging stations in A_e could be higher than MP_e . Thus an operator is applied to randomly remove charging stations installed in A_e until the restriction is fulfilled.

4 Experimental Setup

This section summarizes the methodology applied for the experimental analysis of the proposed MOEAs to address MO-EVCS-L.

4.1 Problem Instance

The experimentation is performed over a realistic scenario defined on the city of Malaga, Spain. Around 567,953 citizens spread over 363 neighborhoods live in this city. The road map is composed by 33,550 road segments. Each road can be selected for the placement of a EVCS (see Fig. 2). The city’s electric power is supplied by 14 electrical substations. These electrical substations limits the number of stations that we can install in a specific area. When we install a EVCS we can choose between different types of stations according to the different charging speed. In this article, we consider two different types of charging stations to be installed: fast charging stations (type 1) and super-fast charging stations (type 2). Each one have different energy consumption requirements, installation (equipment/building and connection) costs, and also times for fully charging a standard electric vehicle. Table 1 summarizes the main characteristics of both electric vehicle charging station types.

Table 1: Main features of the considered charging stations.

type (j)	ct_j	ep_j	cc_j	cg_j
fast (1)	120 minutes	7.4 kW	13,915 €	1.15€
super-fast (2)	15 minutes	50.0 kW	39,930€	1.35€

All the information about the city is obtained by open data sources as Open Street Maps [19] or the electrical company itself. With this scenario we test our algorithms in a real urban area.

4.2 Evaluated Metrics

Three relevant multiobjective optimization metrics were considered for results evaluation: generational distance (GD), inverted generational distance (IGD), and relative hypervolume.

GD measures the average distance from the solutions computed by the MOEA to their closest solution in the *Pareto-front* [24]. Let us assume the points found by the MOEA are the objective vector set $Sol = \{s_1, s_2, \dots, s_{|Sol|}\}$ and the reference points set (*Pareto-front*) is $P = \{p_1, p_2, \dots, p_{|P|}\}$. Then, the GD is computed according to Eq. (8), where d_i represents the distance from s_i to its nearest reference point in P (when $n = 2$ the Euclidian distance is used). In turn, we evaluated the generational distance plus (GD⁺) proposed by Ishibushi et. al. [13]. GD⁺ is evaluated according to Eq. (9), where for minimization problems the modified distance between s_i and the nearest point in P is computed as $d_i^+ = \max\{s_i - p_i, 0\}$.

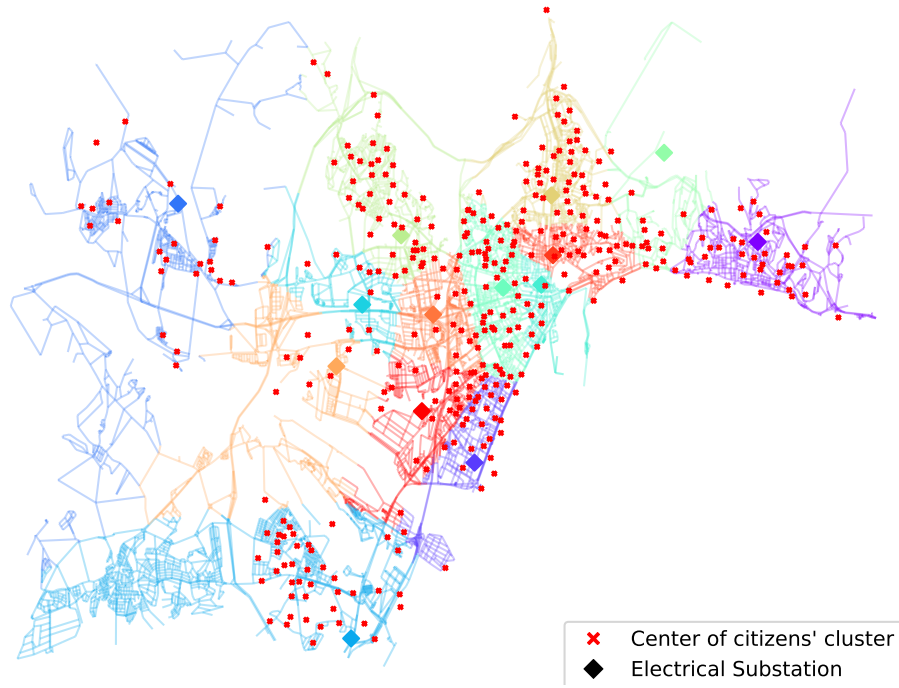


Fig. 2: Citizen' clusters, electrical substations, and road map of Malaga, Spain. Each edge represent a street segment associated with a substation.

$$GD(Sol) = \frac{1}{|Sol|} \cdot \left(\sum_{i=1}^{|Sol|} d_i^n \right)^{\frac{1}{n}} \quad (8) \quad GD^+(Sol) = \frac{1}{|Sol|} \cdot \left(\sum_{i=1}^{|Sol|} d_i^{+2} \right)^{\frac{1}{2}} \quad (9)$$

IGD performance indicator inverts the GD and measures the distance from any point in P to the closest point in Sol [5]. Eq. (10) presents the IGD computation, where \hat{d}_i represents the distance from p_i to the closest reference solution in Sol . Besides, the inverted generational distance plus (IGD⁺) [13] was considered in the experimental analysis. The IGD⁺ performance metric is weakly Pareto compliant whereas the original IGD is not. The IGD⁺ metric is computed as it is shown in Eq. (11), where for minimization problems the modified distance between p_i and the nearest reference point in Sol is computed as $d_i^+ = \max\{s_i - p_i, 0\}$.

$$IGD(Sol) = \frac{1}{|P|} \cdot \left(\sum_{i=1}^{|P|} \hat{d}_i^n \right)^{\frac{1}{n}} \quad (10) \quad IGD^+(Sol) = \frac{1}{|P|} \cdot \left(\sum_{i=1}^{|P|} \hat{d}_i^{+2} \right)^{\frac{1}{2}} \quad (11)$$

Hypervolume (HV) is the most popular quality indicators to evaluate MOEAs. The HV value of Sol is the volume of the area that is dominated by objective vectors in Sol and bounded by the reference point q as it is shown in Eq. (12), where the function *volume* is the Lebesgue measure [27]. A large HV value indicates that Sol approximates the Pareto front well in terms of both convergence and diversity. The RHV metric is computed as the relative value of HV to the maximal hypervolume of the *Pareto front*.

$$HV(Sol) = volume \left(\bigcup_{s \in Sol} [s_1, q_1] \times \dots \times [s_n, q_n] \right) \quad (12)$$

In turn, the solutions provided are evaluated in terms of split ted quality of service. Thus, two metrics are defined: a) sum of service provided by each station, defined in Eq. 13, and b) sum disconnected users, defined in Eq. 14, which represents the number of inhabitants not served by any charging station.

$$QoS = \sum_{s \in S} \left(\sum_{c \in C_s} \frac{u_c}{ct_{x_s}} \right) \quad (13) \quad du = \sum_{nc \in NC} u_{nc} \quad (14)$$

4.3 Parameter Settings and Execution Platform

A set of parametric setting experiments were performed to determine the best parameter values for the proposed MOEAs. The parameter setting analysis were made over the proposed scenario. Both MOEAs apply the same initialization, crossover, and mutation operators. The population size ($\#p$) and the maximum number of generations ($\#g$) were calibrated in preliminary experiments. The analysis confirmed that using $\#p = 20$ and $\#g = 500$ provided a good exploration pattern for both MOEAs. In SPEA-2, the size of the elite population was set to 5 individuals, following rules-of-thumb from the related literature [26].

For p_C and p_M , candidate values were $p_C \in \{0.5, 0.7, 0.9\}$ and $p_M \in \{1/14, 4/14, 7/14\}$ (we have 14 zones in or scenario). Each configuration was evaluated over 30 independent executions performed for the proposed MOEAs. The distribution of the relative hypervolume results obtained using each configuration were analyzed by applying the non-parametric Kruskal-Wallis statistical test to determine the configuration that allowed computing the best results. Thus, for NSGA-II, the most competitive results were achieved with $p_C = 0.5$ and $p_M = 1/14$, and for SPEA2, with $p_C = 0.5$ and $p_M = 4/14$.

We perform 30 independent executions of each algorithm. Each one was run on a machine with a Intel Xeon Gold 6240R with two processors, 48 cores at 2.40 GHz and 220 GB. The cluster was managed by HTCondor 8.2.7, which allowed us to perform parallel independent executions to reduce the overall experimentation time. The algorithms are written in python 3.8 using the library DEAP [7] and the source code is available at <https://github.com/cintrano/EV-CSL/releases/tag/EvoApps2022>.

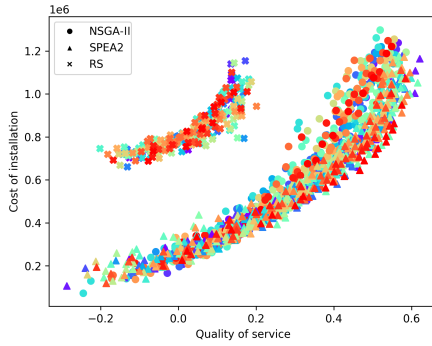


Fig. 3: All computed solutions.

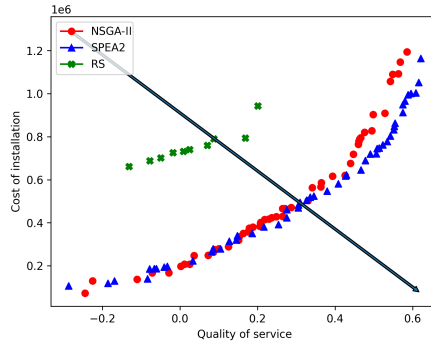


Fig. 4: Pareto fronts.

4.4 Baseline Method

In order to test the effectiveness of our algorithms, an intelligent Random Search (RS) method to get a baseline of solutions is defined. RS generates feasible solutions using the same constructive method applied to generate the initial population in NSGA-II and SPEA2. The method keeps all non-dominated solutions generated during the process. RS iterates generating new solutions until a stop criteria is reached. In this case, it stops after ruining the maximum execution time of the two MOEAs analyzed here.

5 Experimental Evaluation

This section reports the experimental analysis of the proposed MOEAs to address the real-world case study of MO-EVCS-L.

5.1 Multiobjective Optimization Analysis

Fig. 3 shows the non-dominated solutions computed by each independent execution of the evaluated algorithms. The different marker colors indicate the each independent executions. In turn, Fig. 4 illustrates the three Pareto fronts computed by NSGA-II, SPEA2, and RS, i.e., all non-dominated solutions computed considering all the 30 independent executions performed by each method. The arrow indicates the direction of the *best* solutions.

Fig. 3 indicates that RS is the least competitive algorithm. The RS set of solutions represent charging covering shorter ranges of quality of service and deployment costs than the MOEAs. All solutions computed by NSGA-II and SPEA2 dominate the RS solutions, i.e., the RS solutions provide less quality of service while requiring higher deployment costs. In turn, NSGA-II and SPEA2 show robustness because the average dispersion of solutions for the same value of each problem objective was below 20% of each one of the independent runs.

Results in Fig. 4 show that the MOEAs are able to compute accurate solutions, properly sample the Pareto front of the problem, and demonstrate the practical applicability of the proposed approach. For deployment costs lower than 0.5×10^6 , both methods present solutions with close trade-offs between quality of service and deployment costs. However, for higher installation costs, SPEA2 is able to improve over the solutions computed by NSGA-II, i.e., SPEA2 solutions are able to provide a better quality of service at the same installation costs.

Regarding multiobjective optimization metrics, Table 2 reports relevant statistical values of the evaluated multiobjective metrics (i.e., minimum, maximum, mean, standard deviation, median and IQR) for the evaluated MOEAs.

Table 2: Statistics of multiobjective metrics for the executions of each algorithm.

algorithm	metric	minimum	mean±std	median	iqr	maximum
NSGA-II	RHV	0.74	0.82±0.03	0.83	0.05	0.88
	GD	6028.16	9777.69±2569.45	9174.03	2487.18	17151.89
	GD ⁺	0.07	1853.90±2396.43	986.55	3165.70	9132.95
	IGD	18213.75	29024.71±8099.82	27602.76	7603.97	57134.82
	IGD ⁺	0.17	13727.04±9850.17	12702.03	7333.46	44933.12
SPEA2	RHV	0.83	0.89±0.03	0.89	0.03	0.95
	GD	3738.85	7460.10±1472.98	7211.45	1496.41	10550.35
	GD ⁺	0.02	66.54±179.47	0.06	0.02	712.32
	IGD	13494.63	21287.26±5191.87	20642.87	6307.04	37576.88
	IGD ⁺	595.11	8327.67±6036.19	7301.21	7973.87	26004.91

According to the results in Table 2, SPEA2 is the most competitive method among the evaluated ones addressing MO-EVCS-L. SPEA2 present lower values for the distance-based metrics, i.e., GD, GD⁺, IGD, and IGD⁺ (see in bold in Table 2), which represents that SPEA2 computed solutions are closer to the Pareto front than the NSGA-II ones. The RHV results of SPEA2 are higher than the NSGA-II ones (see in bold in Table 2), which indicates that SPEA2 converged to more competitive solutions than NSGA-II.

Statistical analysis is performed to evaluate the statistical significance of these results. As the distribution of results follow a non-normal distribution, Kruskal-Wallis statistical test is applied. The results confirmed that SPEA2 outperforms NSGA-II with a confidence higher than 99%, i.e., p -values $\ll 0.001$ for all evaluated metrics. These results imply better convergence towards the Pareto front of the problem and a better coverage of the Pareto space by solutions computed by SPEA2

Table 3 reports the values of the multiobjective metrics evaluated for the Pareto front provided by NSGA-II and SPEA2. Results in Table 3 show that the Pareto front computed by SPEA2 provides the best values for each metric.

5.2 Computational Time Evaluation

This section discusses the execution time of the evaluated methods. Table 4 shows the relevant statistics of the execution time in minutes of NSGA-II and

Table 3: MOEAs metrics for the Pareto front computed by NSGA-II and SPEA2.

algorithm	RHV	GD	GD ⁺	IGD	IGD ⁺
NSGA-II	0.947	5790.885	590.648	10131.143	0.031
SPEA2	0.992	1175.294	0.009	2776.893	595.026

SPEA2 when addressing the proposed instance of MO-EVCS-L. RS is not included since its stop condition is set as running for the maximum running time of both MOEAs, i.e., 1515 seconds.

Table 4: NSGA-II and SPEA2 execution times (in seconds).

algorithm	minimum	mean±sd	median	iqr	maximum
NSGA-II	1214.37	1271.17 ±61.70	1242.04	61.86	1515.38
SPEA2	1214.25	1272.85 ±49.20	1260.53	47.11	1515.96

Results in Table 4 show that there are no significant differences between the execution time required by the evaluated MOEAs. The execution time is between 20 and 25 minutes, which entails a low computational cost.

5.3 Comparative Analysis

A few samples of computed solutions are compared in terms of two metrics of quality of service: the sum of the service provided by the stations (*QoS*) and the disconnected users (*du*). For a fair comparison, the solutions compared are the ones that require the same deployment cost. Three were selected according to a percentage over the maximum deployment cost computed: 50%, 75%, and 90%. Table 5 reports the results. Besides, it includes the number of stations of each type installed. Fig. 5 illustrates the solution with the 75% of the cost.

Table 5: Quality of service metrics for the selected run of each algorithm.

cost	algorithm	<i>QoS</i>	<i>du</i>	# stations type=1	# stations type=2
50%	NSGA-II	1204666	317563	21	9
	SPEA2	1413229	298201	19	10
75%	NSGA-II	1072286	280995	39	10
	SPEA2	1529501	275702	31	13
90%	NSGA-II	1502587	262766	43	13
	SPEA2	1619564	274091	40	14

According to the results in Table 5, SPEA2 provides the best QoS values for the three evaluated solutions. For the costs of 50% and 75%, SPEA2 leaves fewer users disconnected. However, NSGA-II has fewer citizens that are not served by any charging station for the cost of 90%. Finally, it can be seen that SPEA2 deployments have more EVCS of type 2 than NSGA-II, and NSGA-II installs more EVCS of type 1 than SPEA2.

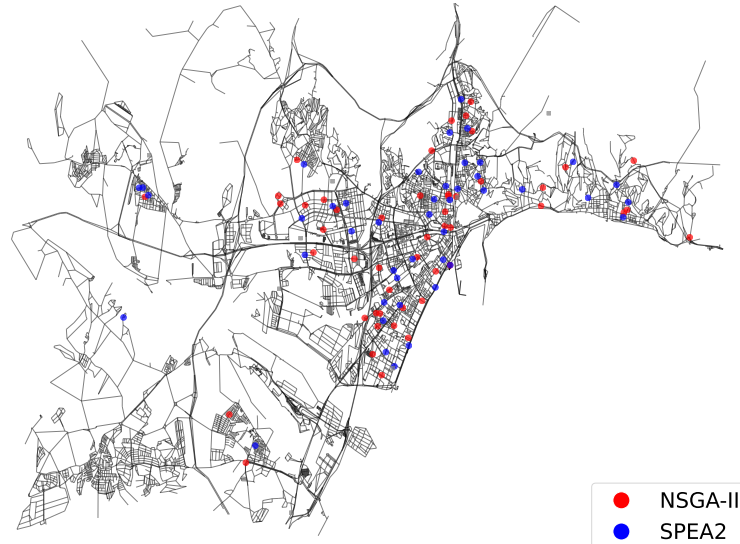


Fig. 5: Geographical locations of the solutions computed by NSGA-II and SPEA2 with a 75% of cost.

6 Conclusions and Future Work

This paper presents a multiobjective evolutionary approach to address the problem of locating electric vehicle charging stations in a city, a relevant challenge of the current sustainability and clean mobility concerns.

The multiobjective problem of locating electric vehicle charging stations studied considers two conflicting objectives: quality of service and deployment costs. The problem formulation is more realistic than previous approaches. On the one hand, it considers both kinds of users: citizens served by the stations and a long way to get to the nearest one. On the other hand, it explicitly models real energy supply constraints and deployment costs.

The proposed problem formulation as MO-EVCS-L is more realistic than previous approaches. On the one hand, it considers the two types of users: citizens served by the charging stations and those disconnected from the charging station network (i.e., not attended by any charging station). It is important considering the unserved users because this may make it difficult for these citizens to purchase electric vehicles. On the other hand, it explicitly models real energy supply constraints and deployment costs.

Two variations of MOEAs (NSGA-II and SPEA2) that apply specific evolutionary operators have been proposed to solve MO-EVCS-L. The problem has been solved over a real city-scale scenario, the city of Malaga (Spain). The results obtained show that the SPEA2 is the most competitive approach. However, both MOEAs provide accurate location plans to assist in making decisions on the

location of EVCSs taking into account the quality of service and the cost of installation.

The main lines for future work are related evaluating exact approaches such ILP variations to address this multiobjective optimization problem; devising other operators; applying a race-based method to configure the algorithms, e.g., irace [16]; increasing the realism of the model by considering general citizen's mobility behavior, the location of points of interest (i.e., hospitals, industrial areas, malls, etc.), or the vehicle fleet; and to the definition of real instances over other cities.

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