

# A clustering based bi-objective optimization of the location of electric charging stations in Tunis

**Abstract**—With the increasing adoption of electric vehicles (EVs) in urban areas like Tunis, the strategic placement of charging stations is paramount. This paper presents a novel approach to optimize the placement of EV chargers in Tunis using a clustering-based bi-objective evolutionary algorithm. This algorithm simultaneously minimizes two objectives which may be conflicting: the costs of the chargers installation and the coverage of the charging infrastructure. By considering these objectives concurrently, the proposed method aims to strike a balance between minimizing the deployment costs and ensuring a sufficient coverage to meet the users demands. Through simulations conducted on a benchmark example in Tunis, we assess the algorithm’s effectiveness in generating Pareto-optimal solutions that offer trade-offs between cost and coverage. The findings underscore the potential of the bi-objective algorithm in proposing new interesting solutions for the placement of EV chargers, thereby contributing to the development of a sustainable transportation infrastructure in Tunis.

**Index Terms**—Location problem, charging stations, bi-objective model, K-means, evolutionary algorithm.

## I. INTRODUCTION

Many countries have defined their specific Nationally Determined Contribution (NDC) as part of global efforts to combat global warming [1]. They have therefore begun to integrate electric transport systems into their intelligent urbanisation initiatives to ensure environmental sustainability [2]. In this context, Tunisia has set itself the ambitious target of reducing its carbon intensity by 41% by 2030, as compared with 2010 levels [3]. As a result, the number of electric vehicles circulating in Tunisia is set to increase considerably. However, a widespread adoption of electric vehicles requires the effective deployment of enough public electric charging stations to ease their use by electric vehicle owners, especially for users who do not benefit from a charging option at home or at the workplace [4]. This is exactly the case of Tunisia. The development and operation of a charging infrastructure requires a collaborative effort between various stakeholders including the charging stations owners and operators who are responsible for its installation and maintenance. The purpose of this paper is to aid these stakeholders to decide where to locate the future charging stations in the city of Tunis, for maximising their usage while minimizing their investment costs. Therefore, we propose a bi-objective evolutionary algorithm which aims to optimize the location of electric vehicle charging stations (EVCS) and test its performance on an example of the literature in the city of Tunis. The remainder of this paper is structured as follows. In section 2, a short literature review on the EVCS placement problem is presented. This problem is then described and

formulated as a bi-objective model in section 3. Section 4 presents the different steps of the bi-objective evolutionary algorithm. In Section 5, the results of the case study are analysed and discussed. Finally, conclusions and prospects for future researches are drawn in Section 6.

## II. RELATED WORKS

The optimal deployment of Electric Vehicle Charging Stations (EVCS) is a well-known NP-hard problem [5], extensively studied through various optimization models. Among the most prominent are node-based models such as the Set Covering Location Problem (SCLP) [6], the Maximal Covering Location Problem (MCLP) [7], and the P-Median problem [8]. These models address different aspects of the location problem [9], focusing on minimizing infrastructure costs, maximizing demand coverage, or minimizing user access distances.

Several resolution techniques have been proposed to solve these models, ranging from exact approaches to metaheuristics [10]. Genetic Algorithms (GA) [11], [12] and their multi-objective variants like NSGA-II have proven particularly effective in exploring Pareto-optimal trade-offs between conflicting objectives, such as cost and coverage [13], [14]. These methods benefit from population-based search, but often suffer from issues such as poor diversity in the initial population and the use of generic genetic operators not tailored to the spatial structure of EVCS deployment.

To address these gaps, our work introduces a novel Clustering-Based Evolutionary Algorithm (CBEA) that integrates k-means clustering during population initialization to ensure spatial consistency. This aligns with the recommendations of recent works advocating for more data-driven and geographically-aware heuristics [7], [15]. Additionally, we propose problem-specific crossover and mutation operators, improving convergence and maintaining feasibility under real-world constraints.

Unlike traditional binary encodings commonly used in GA-based approaches [14], [16], our method encodes both the location and the number of chargers per site, enabling more realistic and flexible modeling of deployment scenarios. This hybrid encoding also facilitates fine-grained control over investment levels and service availability, two key concerns in public EV infrastructure planning.

We validate our method on a realistic case study in the city of Tunis, and benchmark it against the exact ILP formulation presented by Bouguerra and Layeb [17]. The CBEA demonstrates strong performance in both solution quality and

diversity, and offers decision-makers a range of trade-off solutions adaptable to different radius and budget constraints.

In summary, this work includes:

- A k-means-based initialization strategy for spatial coherence;
- A hybrid chromosome encoding incorporating the quantity of chargers;
- Tailored genetic operators for EVCS configuration;
- A robust comparison to exact methods on a real-world Tunisian case.

### III. PROBLEM FORMULATION

#### A. Problem description

As the popularity of electric vehicles continues to grow, the need to extend the existing charging infrastructure is becoming increasingly evident. Finding the optimal locations for these charging facilities is a pressing concern. The objective of this paper is to develop a bi-objective optimization model for determining the optimal deployment of EVCSs.

#### B. Bi-objective location model

In our model, we define  $I = \{1, \dots, n\}$  as the set of potential charging stations locations which may contain  $n_i$  chargers, and  $J = \{1, \dots, m\}$  as the set of demand points representing points of interest (amenities, shopping malls, workplaces, hotels, banks) and residential buildings.

- $f_i$  : Fixed cost of opening a charging station  $i$
- $a_j$  : Demand for community  $j$
- $u_i$  : Cost of installing a charger in location  $i$
- $x_i$  : Binary decision variable for installing a charger in location  $i$

$$\text{Minimize } F_1 = \sum_{i=1}^V (f_i x_i + u_i n_i) \quad (1)$$

$$\text{Maximize } F_2 = \sum_{j \in J} a_j y_j \quad (2)$$

This approach aims to minimise the total cost of the charging station network (Eq. 1), while maximizing the coverage of the total EV charging demand (Eq. 2). The first objective function was proposed by Bouguerra and Layeb in their work [17] for minimizing the infrastructure opening costs and the chargers installation costs.

The second objective function is the one of a classical Maximal Covering Location Problem (MCLP). The additional notations used in the MCLP in the context of an EV charging station are explicitly detailed in [18].

The problem is subject to a specific set of constraints. For instance, if a station is selected, it is imperative that at least one charger is installed there, while ensuring that the number of chargers does not exceed the station's capacity. Another constraint ensures that if some demands are covered at node  $i$ , then at least one charging station must be positioned within its coverage range.

### IV. A BI-OBJECTIVE CLUSTERING BASED EVOLUTIONARY ALGORITHM

To tackle the bi-objective formulation of the electric charging stations location problem, we used a bi-objective evolutionary method particularly adapted to multi-objective problems, since its population-based nature leads to a set of optimal solutions corresponding to the Pareto front.

The proposed method is called Clustering Based Evolutionary Algorithm (CBEA) because it starts by generating an initial population with a heuristic based on the k-means clustering algorithm. The genetic operators are then performed as well as archiving and ranking routines to provide Pareto optimal solutions. The general structure of the proposed algorithm is illustrated in Figure 1.

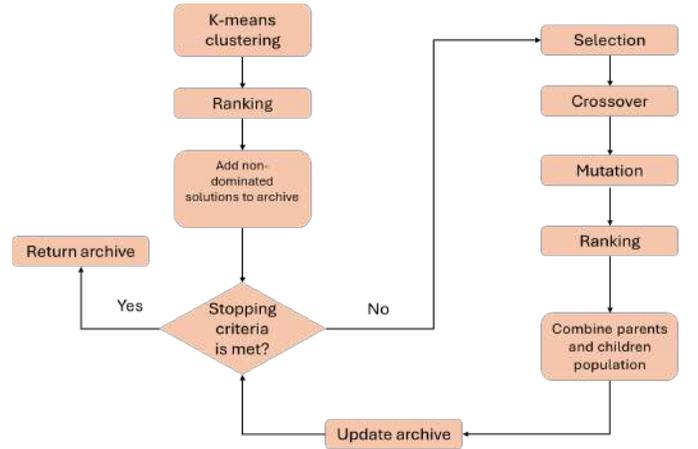


Fig. 1: Overview of the Clustering Based Evolutionary Algorithm

#### A. Chromosome encoding

The initial step in developing a genetic algorithm for a specific problem is to design an appropriate representation scheme. In our approach, a solution is represented as an array which consists of the locations of the charging stations, identified by their ID numbers, along with the number of chargers to be installed at each location. Each charging station can accommodate either 0, 1, or 2 chargers. If a charging station counts 0 charger, it means that it is inactive, see Fig 2. All the solutions within the population have the same length, denoted by  $P$ , which represents the number of potential charging stations.

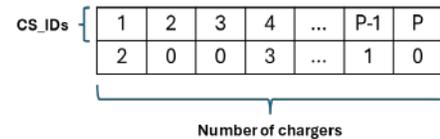


Fig. 2: Representation of a solution

### B. Generation of the initial population

In this work, a clustering approach is used to build the initial population of solutions. The first step involves clustering the demand points using the k-means algorithm. Once the demand points have been clustered, the next step consists in assigning the charging stations to the k clusters. For each cluster, the closest station to the cluster centroid is selected. For the next step, this solution must be transformed into a meaningful solution for the algorithm in order to apply the algorithm's operators and build the next generations. Figure 3 illustrates

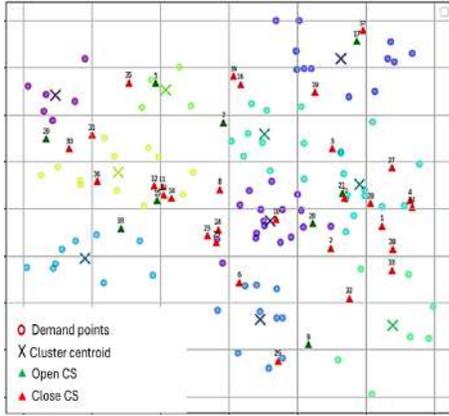


Fig. 3: Example of a solution obtained using the k-means algorithm with  $k=10$ .

an example of initialization. We considered  $k=10$ , therefore, we obtained 10 clusters of demand points, each in a different color. Then a heuristic was used for assigning each cluster to a single charging station (represented by a green triangle in the figure) which can satisfy its demand. In the CBEA algorithm, we used different values of  $k$  and applied the k-means algorithm to generate a sufficient number of solutions for the initial population.

### C. Parents Selection

In the CBEA, we choose to use an elitist selection method. It begins by examining the first Pareto front, which contains the best-performing solutions. If this first front contains several solutions, the method checks whether it is feasible to select all these solutions while maintaining an even total number of parents. If so, all the solutions on the front are selected as the future parents. However, if including all the solutions of the front results in an odd number of parents, the method selects all but one of the solutions of the front, thus guaranteeing an even number of parents. If the first front contains only one solution, this single solution is automatically designated as the parent.

The selection method then moves on to the next Pareto front and repeats the same selection process to maintain an even number of parents, until the required number of parents is reached. This elitist approach favors the best solutions while ensuring that the number of parents selected remains even, which is essential for the genetic operators.

### D. Crossover operator

The effectiveness of an evolutionary algorithm is heavily influenced by the choice and implementation of its operators. The crossover is performed between two parents at a time, iteratively, until all the parents have been considered. Applying a pairwise crossover aims to further diversify the new offspring generated, by exploring different combinations between parents. The crossover operator used in the CBEA is illustrated in Fig 4. This crossover operator is subject to the following rules:

- If the gene at a given position is identical for both parents, it is directly transmitted to the child. This corresponds to a white color in the figure.
- Otherwise, when the gene of the two parents are different, the child has a probability  $p$  of inheriting the gene from parent 1, and a probability  $(1-p)$  of inheriting the gene from parent 2.

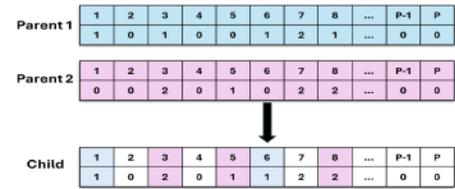


Fig. 4: Illustration of the proposed crossover

This process is repeated for each position in the array representing each individual, ensuring that each child retains some of its parents' characteristics while exploring new genetic combinations.

### E. Mutation operator

After applying the crossover operator, we proceed to a mutation process on the resulting chromosomes. This mutation consists in randomly modifying certain genes on the chromosome. More specifically, the mutation works as follows:

- We randomly select a charging station that is currently open, and close it.
- At the same time, we randomly select a charging station that is currently closed, and open it.
- During these changes (opening/closing), we ensure that the total number of installed chargers remains the same.

After this mutation process, we apply a repair procedure to the mutated solution. The aim of this operation is to ensure that the solution remains feasible and respects all the constraints defined for the problem. This combination of mutation and repair processes allows to explore new regions of the search space while maintaining the feasibility of the solutions.

### F. Archive

In multi-objective evolutionary algorithms, using an archive is essential to maintain the best solutions and ensure their quality and diversity. This improves the convergence and stability of the algorithm, while helping decision-makers to

analyse the trade-offs between different objectives. The archive is a valuable tool for understanding trade-offs and finding solutions tailored to the specific needs of the decision-makers. Updating the archive consists in adding a solution when it is not dominated by any existing solution in the archive. Additionally, solutions in the archive that are dominated must be removed.

### G. Ranking

In this work, the solutions are ranked by the Hierarchical Non-Dominated Sorting (HNDS). This is an advanced algorithm designed to improve the efficiency of non-dominated sorting in multi-objective optimisation problems. Unlike traditional methods, the HNDS uses a hierarchical approach to determine non-dominated solutions, which significantly reduces the number of comparisons required. Therefore, the solutions are sorted according to the value of their first objective and non-dominated solutions are systematically identified step by step. The method is explained in depth in the work [19].

## V. CASE STUDY

The practical implementation of the proposed method is validated by a case study carried out in the city of Tunis, including 39 potential sites for the location of charging stations, corresponding to parking lots and gas stations. The required information about the potential stations can be found in detail in Bouguerra and Layeb's study [17]. In their work, the authors chose to consider a fixed demand for all the charging stations linked with a predefined number of electric vehicles to be served. However, for our study, we chose to adopt a more realistic approach by representing each of the 100 demand points by its geographical coordinates and an associated demand, calculated using a normal distribution. This is closer to the reality of electric vehicle charging infrastructure deployment. The demand points are points of interest such as workplaces, shopping malls and a variety of public and private establishments in high dense and congested areas of the Tunisian capital. Figure 5 illustrates the case study area with the charging stations sites and the demand points.

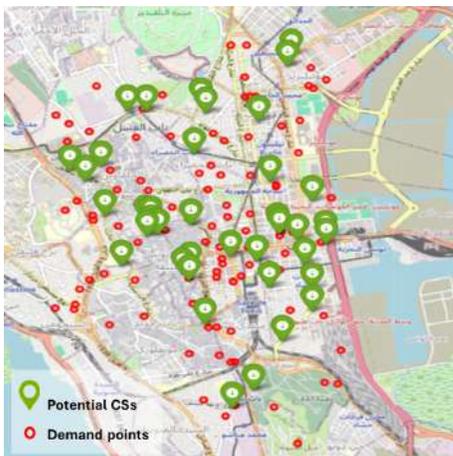


Fig. 5: Geographical illustration of the studied area.

### A. Experimental setup

In this section, the performance of the proposed approach is compared with the results of the exact approach of Bouguerra and Layeb [17]. The algorithms were implemented in Python. The parameters adopted for running the algorithm are presented in Table I.

TABLE I: Parameters setting.

Number of clusters	[1..39]
Number of generations	100
Population size	30
Crossover probability	0.8

The charger's installation cost is considered pre-fixed and independent of the location where it has to be installed. As in [17], the cost  $u_i$  is set to \$56,000.

### B. Location results on the studied area

The CBEA provides solutions of the optimal locations for charging stations by minimizing the installation costs and maximizing the coverage of the demand. Several scenarios are generated by varying the radius  $R$  of coverage of a given charging station as shown in Figure 6. For example, with a radius of 0.2 km, we identify the need to install 27 stations, but only 79% of the coverage of the demand is ensured. On the other hand, with a radius of 1 km, only 8 stations are required to cover the entire studied area.

Increasing the radius  $R$  allows for a more efficient spatial distribution of the charging stations. With a larger radius, the stations are distributed over the whole territory, ensuring a more uniform coverage of the studied area. In this way, by extending the radius  $R$ , the spatial location becomes more efficient, ensuring a better accessibility and a satisfaction of the users' needs.

### C. Pareto optimal study

The proposed algorithm returns the Pareto optimal solutions that provide the best trade-offs between the coverage and the investment costs. This enables the decision maker to formulate informed decisions. Figure 7 illustrates Pareto optimal fronts corresponding to different values of the radius. We can see clearly that the number of solutions on the front depends strongly on the chosen radius. However, the fronts are well diversified, which reflects the good quality of the solutions provided by the evolutionary algorithm CBEA.

### D. Numerical results

Table II presents a comparison between the proposed CBEA and the exact approach proposed in [17]. Here we choose to retain, among Pareto optimal solutions, the best solution provided by the CBEA in terms of coverage. For both approaches, we report the investment cost, the number of opened stations  $N_s$  and the number of installed chargers  $N_c$ . For the CBEA, we also report the coverage, since the exact method assumes a coverage of 100%.

Increasing the radius of coverage of charging stations significantly improves the coverage of the served areas. At a

TABLE II: Impact of the coverage radius on the number of charging stations and chargers to be installed

R	CBEA				Exact approach		
	Cost	Ns	Nc	Cov.	Cost	Ns	Nc
0.2	\$1 733 369	27	30	79%	\$1 733 903	27	30
0.4	\$ 1 263 989	16	22	95%	\$1 265 553	17	22
0.6	\$1 034 275	13	19	98%	\$ 1 029 311	11	18
0.8	\$862 246	11	15	99%	\$971 475	10	17
1	\$912 042	8	16	100%	\$912 042	8	16

Ns: Number of opened stations, Nc: Number of installed chargers

radius of 0.2 km, the coverage is only 79%, but by increasing the radius to 0.4 km, the coverage rises to 95%. This trend continues with 98% coverage with a 0.6 km radius, 99% at a 0.8 km radius, and finally 100% coverage with a 1 km radius. Thus, a larger radius extends the area served by the charging stations, guaranteeing a more complete overall coverage. In addition, the efficiency is also improved, because at a radius of 1 km, only 8 stations and 16 chargers are needed to achieve a full 100% coverage. Extending the coverage radius therefore reduces the number of stations and chargers needed, which translates into lower investment costs.

By comparing CBEA with the exact method, we note that our approach outperforms the exact solution in terms of costs for radius of 0.2, 0.4, and 0.8, with very reasonable coverage of 79%, 95%, and 99%, respectively. Furthermore, the number of opened stations and installed chargers is almost the same, and in some cases, the CBEA leads to fewer stations and/or chargers. At a radius of 1 km, our approach is able to provide the same investment cost with a 100% coverage.

#### CONCLUSION AND PERSPECTIVES

The efficient deployment of a public network of charging stations is crucial and will play a key role in increasing the market share of electric vehicles in the future. With this in mind, we have proposed a bi-objective optimisation framework aimed at designing an optimal network of charging stations while minimising the overall investment costs and maximising the coverage of the demand. The proposed method was used to provide solutions to the electric charging station locations in the city of Tunis. The proposed Clustering-Based bi-objective Evolutionary Algorithm successfully generated well-distributed charging station locations to satisfy a maximum of demands and minimize investment costs. The optimal trade-offs provided by our algorithm allow decision-makers to choose the solution best suited to their needs and budget. Moreover, the proposed method was compared to an exact method focusing only on investment costs. The results reveal the good quality of our method in terms of convergence and diversity of the provided solutions. There are several ways in which this study can be improved. For instance, the socio-economic and environmental factors influencing the use of electric vehicles should be better assessed.

#### REFERENCES

[1] UN, "Nationally determined contribution," 2024. [Online]. Available: <https://www.un.org/en/climatechange/all-about-ndcs>

[2] D. Rezgui, H. Bouziri, W. Aggoune-Mtalaa, and J. C. Siala, "A hybrid evolutionary algorithm for smart freight delivery with electric modular vehicles," in *2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA)*. IEEE, 2018, pp. 1–8. [Online]. Available: <https://doi.org/10.1109/AICCSA.2018.8612861>

[3] I. Mehouchi, M. Trojette, and K. Grayaa, "Monna: Multi-objective neural network algorithm for the optimal location of electric vehicle charging infrastructure in tunis city," *Journal of Cleaner Production*, vol. 431, p. 139837, 2023.

[4] IEA, "Trends in charging infrastructure," 2024. [Online]. Available: <https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-vehicle-charging>

[5] A. Lam, Y.-W. Leung, and X. Chu, "Electric vehicle charging station placement: Formulation, complexity, and solutions," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2846–2856, 2014.

[6] S. G. A. Özşahin and B. Erdebilli, "Statistical-machine-learning-based intelligent relaxation for set-covering location models," *EURO Journal on Transportation and Logistics*, vol. 12, 2023.

[7] G. e. a. Dong, "Electric vehicle charging point placement optimisation by exploiting spatial statistics and maximal coverage location models," *Transportation Research Part D: Transport and Environment*, vol. 67, pp. 77–88, 2019.

[8] X. e. a. Meng, "Sequential construction planning of electric taxi charging stations considering the development of charging demand," *Journal of Cleaner Production*, vol. 259, p. 120794, 2020.

[9] M. Bennekrouf, W. Aggoune-Mtalaa, K. Benladghem, and H. O. Cherif, "A strategic approach for the optimal location of recycling bins in the city of boudjrida in algeria," in *2020 IEEE 13th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA)*, 2020, pp. 1–6.

[10] Y. Djenouri, Z. Habbas, and W. Aggoune-Mtalaa, "Bees swarm optimization metaheuristic guided by decomposition for solving max-sat," in *ICAART 2016 - Proceedings of the 8th International Conference on Agents and Artificial Intelligence*, vol. 2, 2016, pp. 472–479. [Online]. Available: <https://doi.org/10.5220/0005810004720479>

[11] S. Faye, F. Melakessou, W. Mtalaa, P. Gautier, N. AInaffakh, and D. Khadraoui, "Swam: A novel smart waste management approach for businesses using iot," in *TESCA'19: Proceedings of the 1st ACM International Workshop on Technology Enablers and Innovative Applications for Smart Cities and Communities*, 2019, pp. Pages–38. [Online]. Available: <https://doi.org/10.1145/3364544.3364824>

[12] S. Nasri, H. Bouziri, and W. Aggoune-Mtalaa, "An evolutionary descent algorithm for customer-oriented mobility-on-demand problems," *Sustainability*, vol. 14, no. 5, 2022. [Online]. Available: <https://www.mdpi.com/2071-1050/14/5/3020>

[13] G. e. a. Battapothula, "Multi-objective simultaneous optimal planning of electrical vehicle fast charging stations and dgs in distribution system," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 4, pp. 923–934, 2019.

[14] D. Eftymiou, K. Chrysostomou, M. Morfoulaki, and G. Ayfantopoulou, "Electric vehicles charging infrastructure location: a genetic algorithm approach," *European Transport Research Review*, vol. 9, 06 2017.

[15] R. Gopalakrishnan, A. Biswas, A. Lightwala, S. Vasudevan, P. Dutta, and A. Tripathi, "Demand prediction and placement optimization for electric vehicle charging stations," *arXiv preprint arXiv:1604.05472*, 2016.

[16] S. Chen, Y. Shi, X. Chen, and F. Qi, "Optimal location of electric vehicle charging stations using genetic algorithm," *2015 17th Asia-Pacific Network Operations and Management Symposium (APNOMS)*, pp. 372–375, 2015.

[17] S. Bouguerra and S. B. Layeb, "Determining optimal deployment of electric vehicles charging stations: Case of tunis city, tunisia," *Case Studies on Transport Policy*, vol. 7, no. 3, pp. 628–642, 2019.

[18] S. Y. He, Y.-H. Kuo, and D. Wu, "Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of beijing, china," *Transportation Research Part C: Emerging Technologies*, vol. 67, pp. 131–148, 2016.

[19] C. Bao, L. Xu, E. D. Goodman, and L. Cao, "A novel non-dominated sorting algorithm for evolutionary multi-objective optimization," *Journal of Computational Science*, vol. 23, pp. 31–43, 2017.

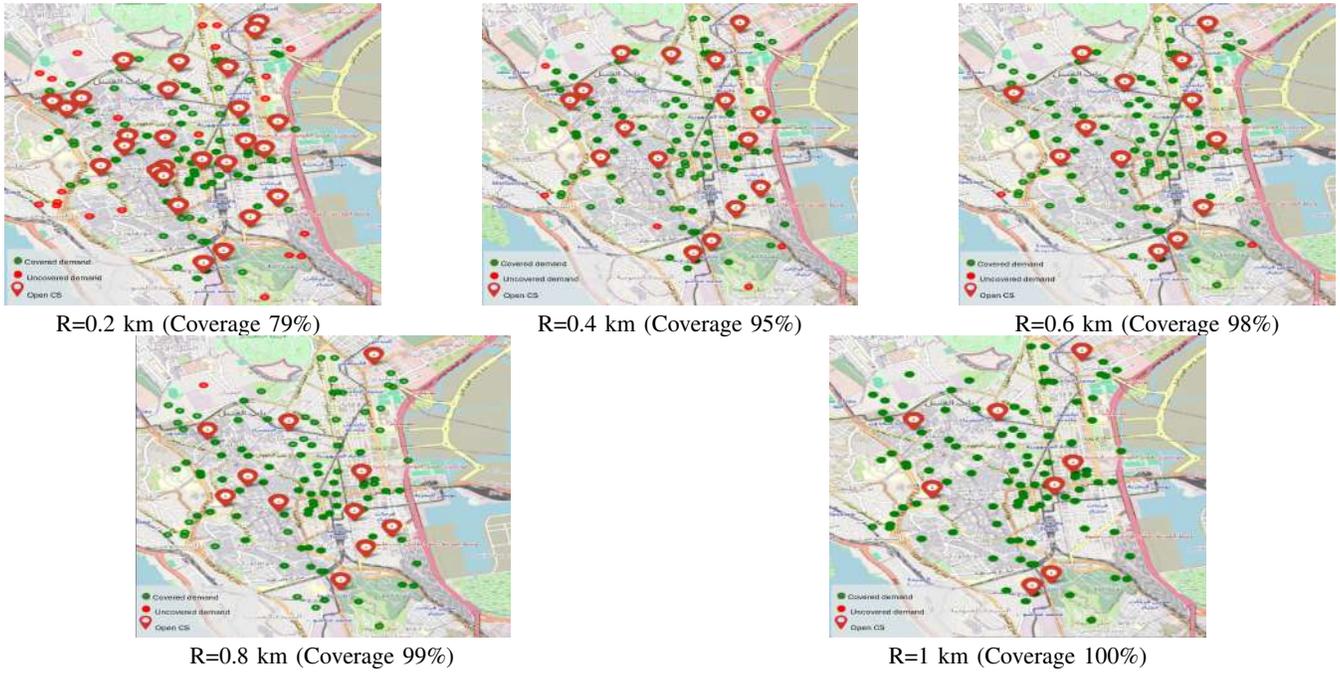


Fig. 6: Charging stations locations with different radius

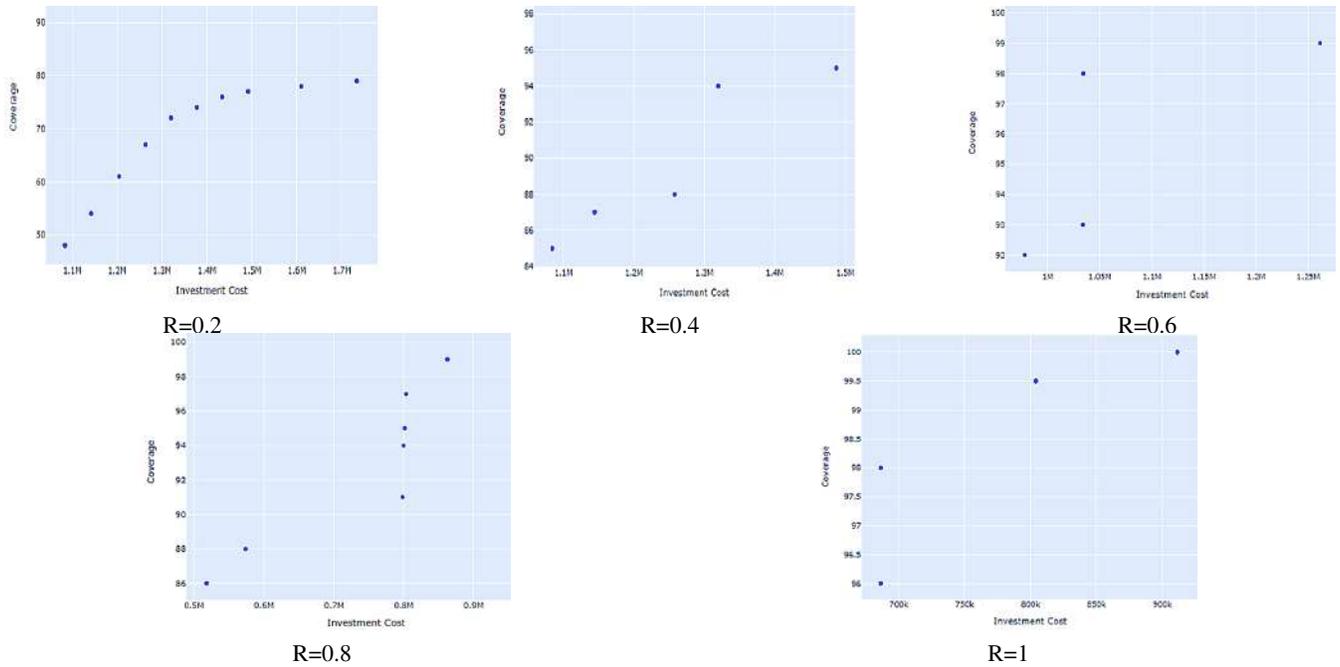


Fig. 7: Pareto optimal solutions with different radius