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Evaluation of optimal charging station location for electric vehicles: an Italian case-study

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Abstract Electric vehicles are accelerating the world transition to sustainable energy. Nevertheless, the lack of a proper charging station infrastructure in many real implementations still represents an obstacle for the spread of such a technology. In this paper, we present a real-case application of optimization techniques in order to solve the location problem of electric charging stations in the district of Biella, Italy. The plan is composed by several progressive installations and the decision makers pursue several objectives that might conflict each other. For this reason, we present an innovative framework based on the comparison of several ad-hoc Key Performance Indicators (KPIs) for evaluating many different location aspects.

Keywords Electric vehicles · Charging stations · Optimal Location · KPIs

1 Introduction

With the increasing pressure on the environment and resource shortage, energy saving has become a global concern. However, this issue is particularly critical in the field of transportation for freight and people. In fact, it has been estimated that motorized vehicles are responsible for 40% of carbon dioxide

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emissions and 70% of other greenhouse gas emissions in urban areas [12]. This has led to the consideration of alternatives to the current mobility and, due to the technology development, electric vehicles (EVs) have become a clean and sustainable alternative to traditional fuel ones. However, one of the barriers that still limits the desirable expansion of EVs industry is the lack of a proper infrastructure for re-charging the vehicles or, more in general, of a structured guideline for the administrations to decide where to locate the available charging stations so to optimize the quality of the service.

In this context, the company *Ener.bit S.r.l.*[1] and the *Dipartimento di Automatica e Informatica (Control and Computer Engineering Department)* of the Politecnico di Torino (Polytecnic University of Turin, Italy) have recently developed a project for the sustainability of electric mobility in the district of Biella, Piedmont (Italy). The project goal was to plan the type, number, and location of the charging stations over a horizon of about 10 years (2019-2030). According to PNire[2], i.e. the Italian infrastructural plan for EV charge, the possible infrastructures that can be build are slow charging (up to 7kW), quick charging (between 7 and 22 kW), fast charging (between 22 and 50 kW), and very fast charging (more than 50 kW) stations. Several strategic areas characterized by different capacity as well as different stopping time (parking areas, shopping centers, railway stations, etc.) have been identified as possible places where to locate the charging stations. It is worthwhile noticing that the number of stations to locate depends on an economical analysis of the decision process over the time horizon, whereas the type of charging stations mainly depends on the features of the selected location and on the analysis of the traffic flow (see [10], [9] and [11]).

For example, a charging station near working centers can have a slow charging system (because workers are assumed to park their vehicle during the working hours, almost eight), whereas a charging station near shopping centers must be faster (cars must be recharged during the shopping time, up to two hours). Therefore, the actual operational problem faced by our project team was to identify an optimal location of the different charging stations in the various municipalities of the district.

The good results obtained in this project have fostered a wider and deeper analysis of the problem of locating charging stations for electric vehicles (see the first results in [7]). In fact, location problems still attract great attention from the research community (see, e.g., [3] and [16]).

Usually, the real decision maker despite defining a single objective (such as cost minimization or gain maximization) are interested in several aspects of the solution. Thus, it is not rare to evaluate the solution with respect to several criteria not explicitly considered in the objective function (see, e.g., [6] and [8]). In particular, location problems may consider several different (and possibly conflicting) objectives, e.g., achieving a level of service proportional

[1] Official website: `http://www.enerbit.it/`, last accessed: 2020-01-29.

[2] `https:http://www.governo.it/sites/governo.it/files/PNire.pdf`, last accessed: 2020-01-29.

to the importance of the location, reducing the worst-case service level, and maximizing the average service level. Considering all those objectives in the same mathematical problem may end up with a huge amount of solutions that can confuse the decision maker instead of providing help. For this reason, our study provides an innovative analysis based on the comparison of several different aspects of a location solution through the use of a battery of Key Performance Indicators (KPIs). Moreover, since charging infrastructures are commonly supposed to be located through several progressive interventions over a defined time-horizon, we also analyze the trend of the provided KPIs over the interventions to generate long-term managerial insights.

The rest of this paper is organized as follows. In Section 2, a review of the literature regarding location of electric vehicle is given. In Section 3, the case study is presented. Section 4 is devoted to present the location model used in the project. In Section 5, we propose and discuss several different KPIs of interest for our application. In Section 6, we present the numerical results. Finally, conclusions are drawn in Section 7.

2 Literature review

A great number of applications in the field of electrical vehicles have appeared in the literature, and several aspects have been studied from the point of view of optimization. In particular, the computation of an optimal location of the charging stations seems of fundamental importance. In the following, we will review the most important and recent works related to this problem.

In [12] the authors present a study on the location of electric-vehicle charging stations for the city of Lisbon (Portugal), characterized by a strong concentration of population and employment. This type of area is appropriate for slow charging because vehicles remain parked for several hours within a 24h period. The methodology is based on a maximal covering model to optimize the demand covered within an acceptable level of service and to define the number and capacity of the stations to be installed. They proposed a complex model maximizing demand coverage, distinguishing between night-time and day-time demand.

In [1] and [19] the authors develop a complex model that optimally locates the charging stations by considering the travel patterns of individual vehicles. The model is applied to the city of Beijing (China) using vehicle trajectory data of 11,880 taxis over a period of three weeks. They use the taxi fleet as a case-study because public fleets are likely to be early adopters for electric vehicles. Similarly, in [15] the authors consider a bi-level programming model including electric vehicle driving range for finding an optimal location of charging stations. Similar approaches can be found in [17] and [23].

Considering a very similar setting, in [25] the authors formulate a multi-period optimization model based on a flow-refueling location model for strategic charging station location planning. They consider that, although it is expected that a sufficient number of charging stations will be eventually constructed, due to various practical reasons they may have to be introduced gradually over time. They simultaneously optimize the problem of where to locate the charging stations and how many chargers should be established in each charging station. By considering both decisions together, the complexity of the model increases, thus the authors propose a genetic algorithm-based method for solving the expanded model. Almost the same approach is followed by [2] for the city of Seattle (U.S.A.). In this paper, the authors consider a p-center problem enriched by the parking capacity problem. Other similar studies can be found in [21] and [24].

In [4], the authors propose a Mixed Integer Linear Programming (MILP) model to solve the plug-in hybrid electric vehicles (PHEV) charging infrastructure planning problem for organizations with thousands of people working within a defined geographic location and parking lots well-suited to charging station installations. Finally, [13] proposes a maximum covering model to locate a fixed number of charging stations in central urban areas to maximize the demand covered within a given distance, where the demand of each study area is determined by estimating the number of vehicles in the area.

As the reader can notice, the majority of the works define an ad-hoc optimization model describing some particular feature of the application. The goal of the present paper is to revert that paradigm: consider a standard model and measure the characteristic of the solution with respect to the performance indicator usually considered as goals. This approach, to the author knowledge, has been never considered in previous works.

3 An Italian case-study

The use-case considered deals with the location of electric charging stations in the district of Biella (Italy). In particular, the potential locations considered by the company are the 78 municipalities of the district. Thus, the main optimization problem is to decide in which municipalities to locate some charging stations. To do that, we first need to compute the total number of charging stations to be located, which is based on the expected number of electric vehicles.

From 2016 the registration of electric vehicles in the world (including electric cars, plug-in hybrids and electric fuel cells) is increasing, with over 750,000 sales globally. With a market share of 29%, Norway is confirmed as one of the leaders in the electric mobility revolution. It is followed by the Netherlands (6.4%) and Sweden (3.4%) and then by China, France, and the UK (1.5%). Despite promising estimates, there is strong uncertainty about the impact of electric mobility. In Italy, the uncertainty about battery life is the main barrier to the adoption of electric vehicles (35%), followed by the presence of charging stations (34%) and the low presence of fast charging stations (17%). Thus, the policies implemented by the regulator and the correct planning of the charging infrastructure are of fundamental importance for the development of electric vehicles. Against about 2 million vehicles sold in 2016, the penetration

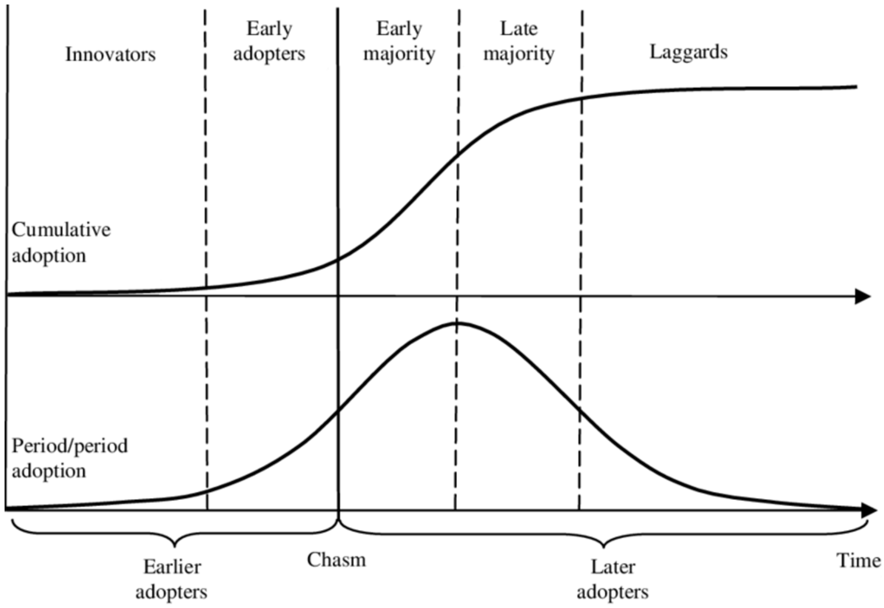

Fig. 1 Representation of the Sigmoid function.

of electric vehicles settles at less than 0.1%. Annual sales in Italy settle at 1400 units/year, with a fleet of 5,657 cars. In order to estimate the number of electric vehicles in the district of Biella, we assume that the propensity to use electrical technology in the district of Biella is the same as that of the rest of Italy. By crossing this data with the vehicles sold in Piedmont and the absorption by the district of Biella, we obtain an estimate of approximately 35 vehicles sold per year and 270 vehicles in the park circulating at the current date, on a total of approximately 152,000 vehicles. In order to determine the future number of electric vehicles, it is important to estimate the diffusion of the technology. The most used model in the literature is the sigmoidal function in Figure 1, obtained from the integration of a normal curve.

The curve can be divided into three different phases:

– a first phase, in which the curve grows slowly, in which users are the so-called *innovators*;
– a phase of rapid adoption, in which users are the so-called early adopters and early majority, that is users who require mature technology, but are willing to pay more than others for its access;
– a last phase of reduction of market penetration (due to the saturation of the same), in which users want a service with maximum efficiency and minimum cost (the so called late majority and laggards).

The estimate of the parameters of the diffusion curve starting from historical data therefore makes it possible to estimate the effective size of the market and the adoption factors. A universally recognized approach is that of the so-called Bass diffusion model (see [18]). To this end, we have set up a model for estimating parameters using the R statistical software and the Diffusion package, starting from the sales data of electric vehicles in Italy 2009-2016 [20]. The electric car fleet in the district of Biella in 2030 can therefore be estimated at 56,000 cars, equal to about 30% of the car fleet in circulation at that time and an electricity market share of 13%. The impact of freight transport (no more than 100 expected electric vehicles) is considered limited and then disregarded.

Since the key factor for the adoption of electric mobility is the availability of fast charging stations (and some ultra-fast charging ones), making the hypothesis of an average charge of 2 hours and a use for about 16 hours a day of the recharging and that only 70% of the circulating car fleet use public stations, an estimate of around 4,900 fast recharging stations is reached. By dividing all these stations proportionally to the population in each municipality, we obtain the number of charging stations to locate in each city (from a minimum of 72 in the smallest municipality to a maximum of 41,139 in Biella). From an economical analysis of the company's economic flow, the optimal way to proceed is to install charging stations in just one municipality by the end of 2019, in 10 municipalities by the end of 2022, in 37 by the end of 2025, and in all remaining municipalities by the end of 2030.

We remark that each station may have different size, number of plugs, and capacity in terms of charging. However, we just focus on selecting the municipalities of the Biella district where to locate at least one charging station, while the real characteristics of the stations will be derived in a successive phase. For example, the number of plugs for each municipality can be calculated as a proportion to the demand rate of that particular municipality (and its surroundings).

4 Mathematical models for optimal location

In this section, we describe the classical p-median, p-center, and p-centdian models to find the optimal location for the charging stations since, despite of their simplicity, they well describe the main goal of the company. Furthermore, since these models are easy to solve in practice, it is possible to compute several solutions with different inputs in a short amount of time.

In the rest of this section and throughout the whole paper we use the following notation:

- $G = (N, E)$: complete undirected graph with a set of nodes N representing possible locations for the charging stations and a set of edges $E = \{(i, j) | i, j \in N, i \leq j\}$;
- d_{ij}: distance between node i and node $j \in N$ (note that distance d_{ii} may be non-null since it represents the internal distance to travel within municipality $i \in N$);
- Q_i: service demand in node $i \in N$;
- $h_i = Q_i / \sum_{j \in N} Q_j$: demand rate of node $i \in N$;

- p: predefined number of stations to locate, with $p \leq |N|$;
- $\bar{d}$: coverage radius, i.e. the threshold distance to discriminate the covering. It represents, e.g., the maximum distance that an EV can travel (due to the battery capacity) or that a user is willing to drive to reach a charging station;
- $\mathcal{C}_i = \{j \in N, d_{ij} \leq \bar{d}\}$: covering set of $i \in N$, i.e. the set of all stations nearer than $\bar{d}$ from node i.

4.0.1 p-median

The *p-median* problem is to find p nodes of the network in which to locate a charging station so to minimize the weighted average distance between the located stations and the demand nodes. It can be stated as

$$\min \sum_{i \in N} h_i \sum_{j \in N|(i,j) \in E} d_{ij} x_{ij} \tag{1}$$

subject to

$$\sum_{j \in N|(i,j) \in E} x_{ij} = 1 \quad \forall i \in N \tag{2}$$

$$\sum_{j \in N} y_j = p \tag{3}$$

$$\sum_{i \in N|(i,j) \in E} x_{ij} \leq |N| y_j \quad \forall j \in N \tag{4}$$

$$y_j \in \{0,1\}, \quad \forall j \in N \tag{5}$$

$$x_{ij} \in \{0,1\}, \quad \forall (i,j) \in E \tag{6}$$

where $x_{ij}$is a binary variable for each edge $(i,j) \in E$ that takes value 1 iff the demand of node $i \in N$ is served by a charging station located in $j \in N$. The objective function (1) consists of minimizing the average distance traveled by the total demand flow towards charging stations. Constraints (2) ensure that each demand node is served by exactly one station. Constraint (3) ensures to locate exactly p stations. Logical constraints (4) ensure to locate a station in j (i.e., $y_j = 1$) if it is assigned to serve at least one demand node (i.e., $\sum_{i \in N|(i,j) \in E} x_{ij} > 0$). Finally, (5) and (6) state binary conditions on the variables.

4.0.2 p-center

The *p-center* problem is to find p nodes where to locate charging stations so to minimize the maximum distance between a demand node and its closest station. In the proposed version of the problem, sometimes called *vertex restricted p-center* problem, the stations can be located only in the nodes of the graph. Obviously, the problem is focused on the worst case in terms of distance and can be stated as

$$\min M \tag{7}$$

subject to

$$M \geq \sum_{j \in N | (i,j) \in E} h_i d_{ij} x_{ij} \quad \forall i \in N \tag{8}$$

and the already presented constraints (2)–(6). The objective function (7) aims at minimizing an auxiliary variable M that, according to constraints (8), will take the maximum value of the expression $\sum_{j \in N} h_i d_{ij} x_{ij}$ over all the nodes $i \in N$.

4.0.3 p-centdian

The *p-centdian* problem is to find p nodes where to locate charging stations so to minimize a linear combination of the objective functions of the *p-median* and *p-center* problems. Thus, the p-centdian has characteristics in between the the p-center and p-median. The formulation is as follows

$$\min \lambda M + (1 - \lambda) \sum_{i \in N} h_i \sum_{j \in N | (i,j) \in E} d_{ij} x_{ij} \tag{9}$$

subject to

$$M \geq \sum_{j \in N | (i,j) \in E} h_i d_{ij} x_{ij} \quad \forall i \in N \tag{10}$$

and the already presented constraints (2)–(6). Through the parameter λ, with $0 \leq \lambda \leq 1$, it is possible to define the relative importance of one objective with respect to the other one. In this work, we set the parameter λ dynamically by using the optima of the p-center and p-median subproblems and calibrating their combination in order to have the two terms with the same magnitude.

5 Key Performance Indicators

In this section, we define the set of KPIs that were used in the project in order to measure the performance of the solution provided by the model. For simplicity, we define $\mathcal{L}_i = \{j \in \mathcal{C}_i \mid y_j = 1\}$ as the set of nodes where a charging station has been located that covers demand node i, and $\mathcal{C} = \{i \in N \mid \exists j \in \mathcal{C}_i \text{ such that } y_j = 1\}$ as the set of demand nodes covered by at least one charging station.

The proposed KPIs consider topological, coverage, and accessibility measures. They are summarized in Table 1 and detailed explained in the following:

Table 1 KPIs definition.

Description	**Name**	**Formula**
Worst-case distance	D_{max}	$\max_{i \in N} \min_{j \in \mathcal{L}} d_{ij}$ (11)
Weight of the worst-case distance	D^h_{max}	h_i such that $\arg\max_{i \in N} \min_{j \in \mathcal{L}} d_{ij}$ (12)
Best-case distance	D_{min}	$min_{i \in N} \min_{j \in \mathcal{L}} d_{ij}$ (13)
Weight of the best-case distance	D^h_{min}	h_i such that $\arg\min_{i \in N} \min_{j \in \mathcal{L}} d_{ij}$ (14)
Average distance	D_{avg}	$\frac{1}{\lvert N \rvert} \sum_{i \in N} \min_{j \in \mathcal{L}} d_{ij}$ (15)
Weighted average distance	D^h_{avg}	$\frac{1}{\lvert N \rvert} \sum_{i \in N} \min_{j \in \mathcal{L}} h_i d_{ij}$ (16)
Dispersion	$Disp$	$\sum_{i \in \mathcal{L}} \sum_{j \in \mathcal{L}} d_{ij}$ (17)
Accessibility	Acc	$\sum_{i \in N} h_i A_i,$ with $A_i := \sum_{j \in \mathcal{L}} e^{-\beta d_{ij}}$ (18)
Coverage	C	$\lvert \mathcal{C} \rvert / \lvert N \rvert$ (19)
Weighted coverage	C^h	$\sum_{i \in \mathcal{C}} h_i$ (20)
Weight of redundant coverage	RC^h	$\sum_{i \in N} \sum_{j \in \mathcal{L}_i} h_i$ (21)
Worst-case coverage	C_{min}	$\min_{i \in N} \lvert \mathcal{L}_i \rvert$ (22)
Weight of the worst-case coverage	C^h_{min}	h_i such that $\arg\min_{i \in N} \lvert \mathcal{L}_i \rvert$ (23)
Best-case coverage	C_{max}	$\max_{i \in N} \lvert \mathcal{L}_i \rvert$ (24)
Weight of the best-case coverage	C^h_{max}	h_i such that $\arg\min_{i \in N} \lvert \mathcal{L}_i \rvert$ (25)
Average coverage	C_{avg}	$\frac{1}{N} \sum_{i \in N} \lvert \mathcal{L}_i \rvert$ (26)
Weighted average coverage	C^h_{avg}	$\frac{1}{N} \sum_{i \in N} h_i \lvert \mathcal{L}_i \rvert$ (27)

– Worst-case distance: Eq. (11) represents the maximum distance between a demand node and its closest charging station.
– Weight of the worst-case distance: Eq. (12) represents the demand rate that is affected by the worst-case scenario in terms of distance.
– Best-case distance: Eq. (13) represents the minimum distance between a demand node and its closest charging station.

- Weight of the best-case distance: Eq. (14) represents the demand rate that is affected by the best-case scenario in terms of distance.
- Average distance: Eq. (15) represents the average distance between a demand node and its closest charging station.
- Weighted average distance: Eq. (16) represents the average distance in which each node is weighted by its demand rate.
- Dispersion: Eq. (17) represents the sum of the distances between all the located stations. It is a measure of homogeneity of the service from a purely topological point of view.
- Accessibility: Eq. (18) is the total accessibility of the charging service, where
$$A_i := \sum_{j \in \mathcal{L}} e^{-\beta d_{ij}} \tag{28}$$
is the accessibility of a facility in the sense of [14]. The parameter $\beta > 0$ must be calibrated and represents the dispersion of the alternatives in the choice process (the calibration has been performed according to [22] and [5]).
- Coverage: Eq. (19) represents, in percentage, the number of covered locations with respect to the total.
- Weighted coverage: Eq. (20) represents, in percentage, the demand rate of the covered locations with respect to the total demand (we remark that, by definition, $\sum_{i \in N} h_i = 1$).
- Weight of the redundant coverage: Eq. (21) represents, in percentage, the demand rate of the covered locations multiplied by the times that such locations are covered. This indicator measures the weighted redundancy of the coverage.
- Worst-case coverage: Eq. (22) represents the minimum number of charging stations covering a demand node.
- Weight of the worst-case coverage: Eq. (23) represents the demand rate that is affected by the worst-case scenario in terms of coverage.
- Best-case coverage: Eq. (24) represents the maximum number of charging stations covering a demand node.
- Weight of the best-case coverage: Eq. (25) represents the demand rate that is affected by the best-case scenario in terms of coverage.
- Average coverage: Eq. (26) represents the average number of charging stations covering a demand node.
- Weighted average coverage: Eq. (27) represents the average coverage in which each node is weighted by its demand rate.

6 Numerical Experiments

The instances of the Biella problem are generated according to real data. In particular, the matrix of distance d_{ij} considers the time, in minutes, to travel from i to j. The diagonal elements (i.e., $d_{ii}, \forall i \in N$) are estimated according to the geographical extension of the city. The estimations are considered from the Istat (Istituto Nazionale di Statistica) website[3]

Among the three proposed and described in Section 4, the model chosen by the company for the solution of the problem is the p-centdian. This choice is due to its flexibility with respect to the company goal and to its global performance in terms ok KPIs (which has appeared to be better than the one of the p-center and p-median models in some preliminary experiments). The p-centdian model, accurately instantiated with the data deriving from the Biella district case study, can be easily solved by exact algorithms as the branch-and-cut implemented in the available commercial and academic solvers. In our particular case, we used the GUROBI solver v.8.1.0. The resolution was performed on a common PC (Intel Core i7-5500U CPU@2.40 GHz with 8 GB RAM) and took on average 12 seconds. Notice how the resolution efficiency obtained allows to possibly perform a large number of experiments with different input data, thus refining the analysis.

The solutions for the different time thresholds studied, obtained using the p-centdian model, are the following (clearly, at each intervention, the locations chosen in the previous steps are forced to remain in the solution):

- one municipality ($p = 1$) by the end of 2019: the only municipality chosen is Biella, the chief town (see the first map of Figure 2). This was expected since Biella is the most important city in terms of demand.
- 10 municipalities ($p = 10$) by the end of 2022: some small municipalities close to and other big ones far from Biella are chosen (see the second map in Figure 2).
- 37 municipalities ($p = 37$) by the end of 2025: the solution tends to select municipalities close to the previously selected ones, creating clusters (see the third map in Figure 2)
- all municipalities ($p = 78$) by the end of 2030 (this corresponds to the trivial solution with $y_i = 1, \forall i \in N$).

The value of all the KPIs, in the various steps of intervention, is calculated and shown in Table 2. Note that the last column, corresponding to the case in which all the locations are chosen, contains the best possible value for each KPI. Several observations can be done:

- D_{max} decreases with the increase in the number of municipalities in which at least one charging station has been located and, as it can be seen, it reaches reasonable values from $p = 10$ onward.
- D^h_{max} increases with the increase in the number of municipalities in which at least one charging station has been located. This KPI is complementary to the D_{max} since it is the importance of the node most distant from a server. Hence, its monotonicity is not a standard feature of the model and it strongly depends on the instance considered.
- D_{min} decreases as the number of municipalities in which at least one charging station has been located increases, and it stabilizes at the best value already with $p = 10$.

[3] `http://www.istat.it/storage/cartografia/matrici_distanze/Piemonte.zip`

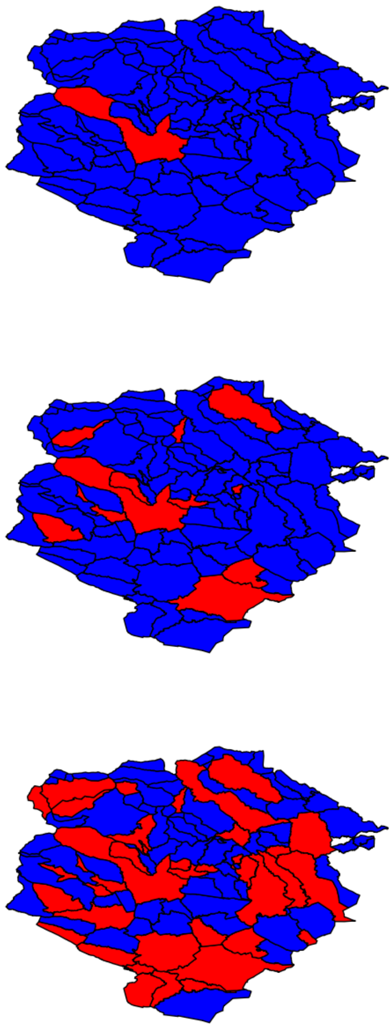

Fig. 2 Optimal location for $p = 1, 10$ and 37 (2019). Chosen locations in red.

– D^h_{min} decreases as the number of municipalities in which at least one charging station has been located increases. This KPI is complementary to the D_{min} since it is the importance of the node nearest to a server. Hence, its monotonicity is not a standard feature of the model and it strongly depends on the instance considered. Usually, the smallest distance is achieved by the internal distance of the node in which an electric station is located. In fact, if just 1 location is considered, the node nearest to a facility is the most important (Biella). Then, if more stations are located, the nearest node has a lower importance, this is reasonable since node with a smaller internal distance usually are less important (they have a smaller population, hence a smaller demand).

- D_{avg} decreases as the number of municipalities in which at least one charging station has been located increases. It is interesting to note that the percentage improvement in the indicator decreases as the number of selected municipalities increases.
- D^h_{avg} decreases as the number of municipalities in which at least one charging station has been located increases. It reaches its asymptotic value already when p=10 (faster than D_{avg}). This is reasonable since the model considers the weighted distances.
- $Disp$ increases as the number of municipalities in which at least one charging station has been located increases. Its growth is very marked due to the factorial growth of the number of pairs of selected municipalities. The starting value is set to zero since with a single municipality the summation in the definition cannot be calculated.
- Acc increases as the number of municipalities in which at least one charging station has been located increases. Also in this case the improvements are less marked as the number of selected municipalities increases.
- C increases as the number of municipalities in which at least one charging station has been located increases. It can be seen that with only 10 selected municipalities, the coverage reaches very high levels (96% of the municipalities are covered).
- C^h increases as the number of municipalities in which at least one charging station has been located increases. Its convergence is faster than the convergence of C because the nodes that are not covered until $p = 78$ have less importance.
- RC^h increases as the number of municipalities in which at least one charging station has been located increases. It is important to note that the largest part of this KPI is provided by the multiple coverage of the most important nodes. As the reader can notice, the increment of the value is very fast.
- C_{min} increases with the number of municipalities where at least one charging station has been located. Since this is the most pessimistic case, this indicator remains at zero when 1, 10, and 37 selected municipalities are considered. The data then verifies the non-total coverage shown by the KPI previously discussed.
- C^h_{min} decreases as the number of municipalities in which at least one charging station has been located increases. As the reader can notice, the least covered nodes have always a very low importance.
- C_{max} increases as the number of municipalities in which at least one charging station has been located increases. It can be seen that the increase in value grows with the number of selected municipalities. However, it can be noted that already with 10 municipalities the most covered municipality has the choice between 7 charging stations within a 25 kilometers radius.

- C^h_{max} is constant with respect to the number of municipalities in which at least one charging station has been located increases. This is due to the fact that at each iteration, the node that is covered the greatest number of times is the most important node, i.e, the city of Biella.
- C_{avg} increases with the increase in the number of municipalities in which at least one charging station has been located and, as it can be seen, has a much lower value than the C_{max}. This implies a heterogeneous situation in terms of coverage of the various locations. In fact, we have a large number of municipalities covered by a few charging stations and a small number of municipalities covered by many charging stations. Since the towns that are not covered are those with a lower demand (i.e., with less electric vehicles) this feature is in line with the technical specifications of the problem.
- C^h_{avg} increases with the increase of the number of municipalities in which at least one charging station has been located. The increase rate of this value is similar to the one of C_{avg}, except for the first step $p = 1 \rightarrow p = 10$.

Table 2 KPIs value in the four intervention p-centdian.

KPI	$p = 1$ **(2019)**	$p = 10$ **(2022)**	$p = 37$ **(2025)**	$p = 78$ **(2030)**
D_{max}	53	24	20	11
D^h_{max}	0.001	0.001	0.001	0.002
D_{min}	5.7	2	2	2
D^h_{min}	0.285	0.005	0.005	0.001
D_{avg}	20.3	8.9	5.8	4.4
D^h_{avg}	0.19	0.08	0.06	0.06
$Disp$	5.73	2158.2	34663.9	167201.3
Acc	0.024769	0.115986	0.329689	0.456748
C	55%	96%	98%	100%
C^h	0.781	0.993	1	1
RC^h	0.062	4.44	14.32	29.41
C_{min}	0	0	0	1
C^h_{min}	0.002	0.002	0.001	0.001
C_{max}	1	8	23	43
C^h_{max}	0.285	0.285	0.285	0.285
C_{avg}	0.089744	2.653846	8.833333	19.28205
C^h_{avg}	0.01	0.06	0.21	0.38

A common trend of almost all the KPIs is that the second intervention is the one providing the highest proportional change with respect to the previous one (e.g., C almost doubles its value for $p = 10$ while it gains only few units for $p = 37$ and $p = 78$). Interesting enough, D_{min} reaches its optimal value even for $p = 10$. This represents a very important insight for the company for two main reasons. First, it means that the users will perceive the biggest improvement in terms of service in relatively small amount of time (the first 3-5 years) and in response to a small effort in terms of installed stations. Second, it means that the last interventions, which are the ones affected by the most uncertainty (e.g., in terms of economical sustainability), are not very critical for the process overall quality.

7 Conclusions

In this paper, we have conducted an extensive comparative analysis of models and Key Performance Indicators concerning the optimal location of charging stations for electric vehicles. Motivated by a real case-study concerning the district of Biella in Italy, we highlighted the fact that a perfect location model does not exist but, instead, different models might be jointly considered to face a certain set of requirements and objectives. Therefore, a battery of topological and coverage Key Performance Indicators have been identified and calculated for the solutions given by the different models. The analyzed KPIs include measures about the covering capabilities, the robustness, the dispersion, and the accessibility of the resulting solutions.

Several future research lines can be defined. First, a similar analysis can be performed by explicitly including stochasticity into the decision process. Given the application at hand, the demand rate h_i of node i is the parameter that makes more sense to represent as a stochastic variable. This is due both to the difficulty of estimating the service demand Q_i for any node according to a static vision (e.g., number of EV users living around a demand node) and for the unpredictable dynamics of traffics flows and their issues. Second, as already mentioned in the Introduction, a comparative study can be performed for several other location models.

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