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Research article

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LOCATION MODELS OF ELECTRIC CHARGING STATIONS IN THE CITY OF ROME

Abstract

The issue of the location of charging stations for electric vehicles is becoming very important due to governmental decisions on electric mobility. Many authors have addressed this problem with the support of graph theory and graph optimization. In dealing with this problem, typical operational research models and approaches used for facility location, such as p-median, coverage problem and queuing theory, have been resorted to. In this paper we apply these models to the location of charging stations in the city of Rome. In particular, we analyze the suitability of existing charging sites and suggest where to implement new chargers using a p-median-like model. Finally, we study the waiting time distribution when the nearest charging stations are occupied, and we use queuing theory to show how much demand for the service would improve with the implementation of the new charging points.

Keywords: p-median, coverage problems, queuing theory, charging stations.

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1 Introduction

The deployment of electric vehicles (EVs) is instrumental to reduce CO_2 emissions and tackle climate change. According to the BCG report *Electric Cars Are Finding Their Next Gear* (Boston Consulting Group, 2022), it is estimated that electric vehicles will represent 20% of global car sales in 2025 and 59% in 2035, but with different rates of increase depending on geographical localization. The EU's strict environmental regulations will boost sales of electric cars in Europe by more than 90% by 2035. Regarding Italy, Forbes Italy (Forbes, 2022) estimates that in 2035 the expected market share of sales of new zero-emission vehicles will be over 85% of the total. Furthermore, zero-emission vehicles are estimated to grow from 1% in 2021 to over 27% in 2035.

Achieving these goals will require a major effort to create networks of charging stations capable of sustaining the above-mentioned growth rates, as highlighted by Beckers et al. (2015) and by The National Academies (2023).

Clearly location of charging stations is very important in order to meet future customers demand. For this reason, extensive literature has been devoted to this problem in recent years and various models, algorithms, and approaches, both in theory and in practice, have been proposed and studied. Here, we report some recent works where approaches are presented that share some similarities with ours. Frade et al. (2011) propose a location model to maximize the coverage of electric charging demand in a neighbourhood in Lisbon, distinguishing between night-time and day-time demand. In Xi et al. (2013), the authors propose a simulation-optimization model to determine location and size of electric charging infrastructures by estimating the expected number of electric vehicles charging at a location as a function of the stations at that location and apply the model to the central-Ohio region. Zhu et al. (2017) rely on a model which combines p-median and maximum-coverage approaches to determine the location of charging stations so to maximize traffic satisfaction and to optimize charging capacity using queuing theory. In Baouche et al. (2014), an optimization model is presented with the aim of locating charging stations so that fixed costs related to the stations and cost of travelling for electric vehicles are minimized. The model incorporates an estimate of energy consumption of electric vehicles in urban centres. In Zhu et al. (2016), the authors propose a mathematical model to determine where to locate charging stations and the number of chargers to be placed: construction and access costs, distance between destinations and charging points, and drivers preferences are taken into account. Andrenacci et al. (2016) present a demand-side approach to find the suitable locations for charging stations, assuming a complete switch to electric vehicles. The authors use a large dataset of vehicle usage in the city of Rome and, applying cluster analysis, estimate the energy demand. He et al. (2016) compare three classical facility location models, i.e. set covering, maximal covering location and p-median, by applying them to the real scenario of the city of Beijing; locations obtained from the p-median approach are shown to be more convenient and affordable. Likewise, in Bouguerra and Layeb (2019), a real case study is presented related to the city of Tunis, and five linear integer programming formulations are considered based on weighted set covering models, with real constraints.

Many other studies have been conducted on location strategies for charging stations: the interested reader is referred to the thorough reviews in Kchaou (2021); Pagany et al. (2019);

Shareef et al. (2016) and also to Farahani et al. (2012).

Following this line of research, we focus on the difficult context of the city of Rome, Italy. According to the fourth edition of MOTUS E reports (MotusE, 2023), Rome is the Italian city with the largest number of charging points. However, Rome is the most populous city in Italy, and the urban area has the largest surface in the country. So, when relating the number of charging points to these aspects, the pictures change.

Our aim is to improve the quality of charging services by identifying, among already existing charging sites, those where to place additional charging points. Under the assumption of demand and supply occurring at the existing sites, we propose to find the optimal ones where to install new charging points by minimizing a measure of their distance from all the other sites. In a nutshell, we rely on a p-median-like model, which result in a linear integer programming problem. This is a typical approach for the location of facilities where some service is available to customers. Then, we validate our approach via numerical testing and a posteriori analysis. We analyze the time needed to reach the nearest sites in the presence of congestion and, taking a hint from Marianov and ReVelle (1996), we resort to queuing theory to study the advantages of the approach in terms of service demand.

We believe that one of the strengths of our approach lies in its simplicity: it can be easily interpreted and replicated; also, solution procedures are available to practically implement it. Yet, the model we propose, while simple, seems to be sufficiently accurate and to retain descriptive power, as witnessed by the numerical evidence we have obtained. We remark that we have tested our approach on real-world data, focusing on the problem of improving charging services in the difficult context of the city of Rome.

The rest of the paper is organized as follows. In Section 2 we introduce the p- median-like model. In Section 3 we analyze the distribution of charging points in the city of Rome. In Section 4 we focus on the results obtained from the application of the model to the context of the city of Rome, focusing on several different scenarios. In Section 5 we investigate waiting times in case of congestion, and in Section 6 queuing theory is used to analyze improvements in terms of meeting the demand. In Section 7 we give some final remarks.

2 P-median-like model

Given a set of n already available charging sites, and assuming demand and supply to occur at such locations, we wish to find the best ones to be upgraded by installing additional charging points. We rely on the distance of these sites from the other ones as a selection criterion to be minimized.

We consider a graph $G(N; A)$ where N denotes the set of nodes corresponding to the charging sites and A the set of arcs connecting the nodes, and the distance matrix D where d_{ij} indicates the distance between node i and node j. We want to identify p nodes in the graph where new chargers are to be installed by solving the following linear integer programming problem (similar to Christofides (1975)):

$$
\begin{array}{lll}
\underset{x}{\text{minimize}} & \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ij} & \\
\text{s.t.} & \sum_{i=1}^{n} x_{ij} = 1 \qquad j = 1, ..., n & \\
 & \sum_{i=1}^{n} x_{ii} = p & \\
 & x_{ij} \leq x_{ii} \qquad \forall i, j & \\
 & x_{ij} \in \{0, 1\} &
\end{array} \tag{1}
$$

Binary decision variable x_{ij} is equal to 1 if upgraded service (consisting in the presence of additional charging points) is available for site j at location i, 0 otherwise. In particular, $x_{ii} = 1$ if site i is upgraded by placing there new charging points.

Constraints ensure that:

- upgraded service for site j is provided by one site where new charging points are to be installed, for every j;
- the number of charging sites where to install new charging points is equal to p;
- upgraded service for site j is not available at site i if no additional charging points are to be installed there.

The linear integer optimization problem (1) belongs to the class of p-median-like models. The p-median is a min-sum problem where the average distance between points where demand appears and locations where services are provided is to be minimized (see e.g., Hakimi (1964); Hakimi (1965);ReVelle and Swain (1970)). This model has been widely used and developed in the literature to determine the location of facilities (see e.g.,Drezner and Hamacher (2004); Daskin and Maass (2015); Serra and Marianov (1998); Karatas and Yakıcı (2019); Blanco (2019)).

Due to our initial assumptions and choices, model (1) turns out to be easily interpretable. Also, efficient algorithmic procedures are available to compute solutions. Thus, the core aspects of our approach are readily implementable and replicable. Yet, the simple model we rely on retains descriptive power, as confirmed by the numerical evidence we describe in the next sections.

3 Data analysis

To perform our analysis, we consider the charging points activated and operating at the date of 24th of October 2022 in the city of Rome in all the fifteen municipalities. The locations where the stations are located have been retrieved and collected from the *Roma Capitale* institutional website (Roma Capitale (a)). It turns out that the total number of functioning chargers is 656 as of the given date. [1]

We report the data per municipality in tab. 1 with a color scale ranging from deep green to deep red, where deep green represents the largest number of chargers installed and deep red the smallest one.

1 At https://www.comune.roma.it/web/it/informazione-di-servizio.page?contentId=IDS1090137. it is possible to find, for each municipality, the updated list of locations where the charging points are active

Table 1. Charging points for each municipality activated at the date 24 October 2022.

Municipality	**Activated Stations**	**%**
I	92	14.0%
II	99	15.1%
III	24	3.7%
IV	23	3.5%
V	24	3.7%
VI	12	1.8%
VII	84	12.8%
VIII	57	8.7%
IX	87	13.3%
X	65	9.9%
XI	23	3.5%
XII	19	2.9%
XIII	16	2.4%
XIV	15	2.3%
XV	16	2.4%
Total	**656**	**1**

Source: Authors' elaboration on data from Roma Capitale (a) website.

We also relate the number of charging points to population density of each municipality. Data are obtained from the *Roma Capitale* Institutional website (Roma Capitale (b)) and are updated to 31st of December 2022. For some areas, as reported in table 2, the number of chargers seems proportional to population density (see e.g., the I and II), but for other ones (which we highlight in bold) this relation does not seem to apply.

We consider as nodes in $G(N;A)$ the locations where charging stations are already present and active, and derive the coordinates of each point using Google Maps. We aggregate some locations that are a few meters apart to simplify the collection of coordinates and representation of data. We report, in figure 1, the resulting 358 nodes in a map of Rome, generated using MATLAB.

We consider the upgrade of existing charging sites and not the construction of new ones. We make this choice for simplicity, because to identify sites where charging stations are to be located, supply and demand factors must be considered. Demand factors may be proximity to attractive places and the purpose of parking, while supply factors are the availability of grid connection and parking areas (for more details see MotusE (2022)). Existing sites are, thus, the locations where demand is assumed to appear. Focusing on existing sites is also crucial to streamline construction procedures and to keep construction costs at bay. However, demand-related aspects are considered in the subsequent analysis of charging station congestion, in section 5, and of the arrival rate λ, in section 6.

Table 2. Population density for each municipality

Municipality	Surface (sq.km)	Population	Density (pop/sq.km)
I	20.1	164520	8185.1
II	19.7	165496	8400.8
III	98	204342	2085.1
IV	48.9	171890	3515.1
V	26.9	237648	**8834.5**
VI	112.3	242082	**2155.7**
VII	47.6	311500	6544.1
VIII	47.2	128417	2720.7
IX	183.2	183282	**1000.4**
X	150.7	228042	**1513.2**
XI	71.5	152569	2133.8
XII	73.1	140337	1919.8
XIII	66.9	130379	1948.9
XIV	133.5	190283	1425.3
XV	187.2	160630	858.1
Not classified		2127	
Rome	1286.8	2813544	2186.47

Source: Roma Capitale (b) website; Authors' representation with a color scale for Density.

Relying on the coordinates of the 358 nodes, we compute, via an API[2] implemented in MATLAB R2021b, the distance matrix in meters/km and minutes of journey (in the absence of traffic).

4 Computational results

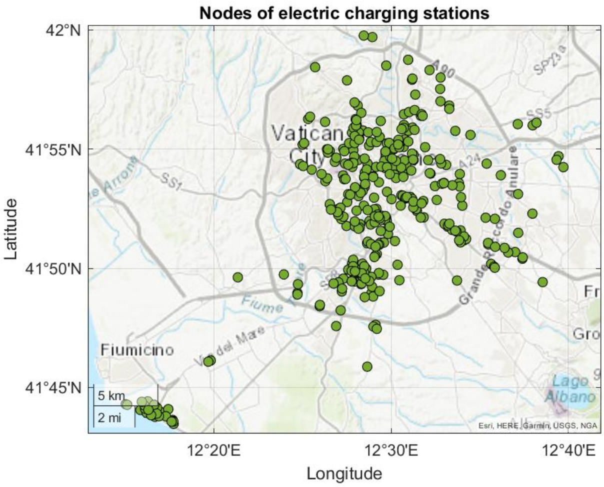
To address the integer linear problem, we use the Gurobi 10.0.0 optimizer. We test our approach considering four different scenarios, depending on the value of the parameter p: we set p equal to 72,107,143 and 179, that is a fraction of 20%, 30%, 40% and 50% of the total number of the sites, respectively. So, we take into account considerable increases in the number of charging points. We also apply the model to two matrices of distances, one in terms of travel minutes, one in terms of km.

The output of the approach is given by the matrix containing all the Boolean variables x_{ij}, where the diagonal represents the p-median. We remark that for all the tests we have conducted the procedures give the output in the order of seconds.

After identifying the sites to be upgraded, we estimate the number of chargers to be added to each of them. We make assumptions to satisfy as many requests from other nodes as possible, and at the same time, consider a plausible scenario. In order to do so, according to the output matrix from Problem (1), for each site a where additional charging points have to be installed, we compute the number of sites ($nodes_a$) for which the upgraded service

2 OSRM API Documentation: https://project-osrm.org/docs/v5.5.1/api/#general-options

Figure 1. Map of existing nodes of electric charging stations in the city of Rome



Source: Authors' elaboration on existing positions generated via MATLAB.

is given at location a. Given maximum (denoted by max), minimum (denoted by min) and median [3] of $nodes_a$ over sites a, we estimate the number of charging points to install ($newpoints_a$) as follows:

$$\begin{array}{lll} newpoints_a = 1 & if & nodes_a = min \\ newpoints_a = 2 & if & min < nodes_a \leq median \\ newpoints_a = 3 & if & median < nodes_a < max \\ newpoints_a = 4 & if & nodes_a = max \end{array} \tag{2}$$

Fig. 2, 3 show the nodes where one has to increase the number of charging points in a map of Rome generated by MATLAB. We represent nodes in a color scale ranging from yellow (where to add 1 charger) to dark red (where to add 4 chargers), both for the distance matrix in minutes and in km.

In the summarizing tables, tab. 3 - 6, we report, for each municipality, the number of charging points to be installed. We note no differences in our analysis if distances are evaluated in terms of space or time. Furthermore, as for the sensitivity analysis we perform with respect to the value of parameter p, the number of charging points to be installed increases significantly from $p = 72$ to $p = 107$, while, for larger values of p, the growth of the number of new chargers is smaller.

3 We considered the median and not the mean to get integer numbers

Table 3. Summary table of the new chargers to install, matrix in minutes, p=72 and p=107

Municipality	Nodes to upgrade p=72	Chargers to add p=72	Nodes to upgrade p=107	Chargers to add p=107
I	6	14	12	27
II	7	18	11	27
III	4	8	6	11
IV	5	9	7	11
V	3	6	5	9
VI	3	6	5	7
VII	9	20	14	27
VIII	6	14	9	20
IX	9	20	13	27
X	6	15	5	14
XI	3	5	5	8
XII	2	5	3	7
XIII	2	4	4	7
XIV	3	6	3	7
XV	4	7	5	8
Total	**72**	**157**	**107**	**217**

Table 4. Summary table of the new chargers to install , matrix in km, p=72 and p=107

Municipality	Nodes to upgrade p=72	Chargers to add p=72	Nodes to upgrade p=107	Chargers to add p=107
I	7	16	11	25
II	6	16	12	27
III	4	8	6	11
IV	4	8	7	11
V	3	6	5	9
VI	3	6	6	8
VII	8	18	13	27
VIII	6	15	8	19
IX	9	20	14	28
X	6	14	6	15
XI	3	5	4	6
XII	2	5	3	7
XIII	3	6	3	6
XIV	3	6	3	7
XV	5	7	6	9
Total	**72**	**156**	**107**	**215**

Figure 2. Map of additional charging points for the distance matrix in minutes, created with MATLAB

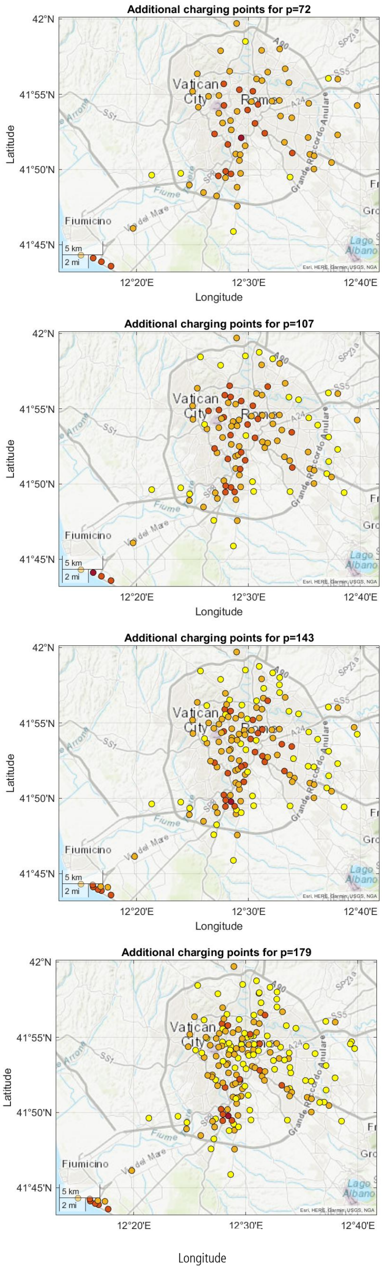


Figure 3. Map of additional charging points for the distance matrix in km, created with MATLAB

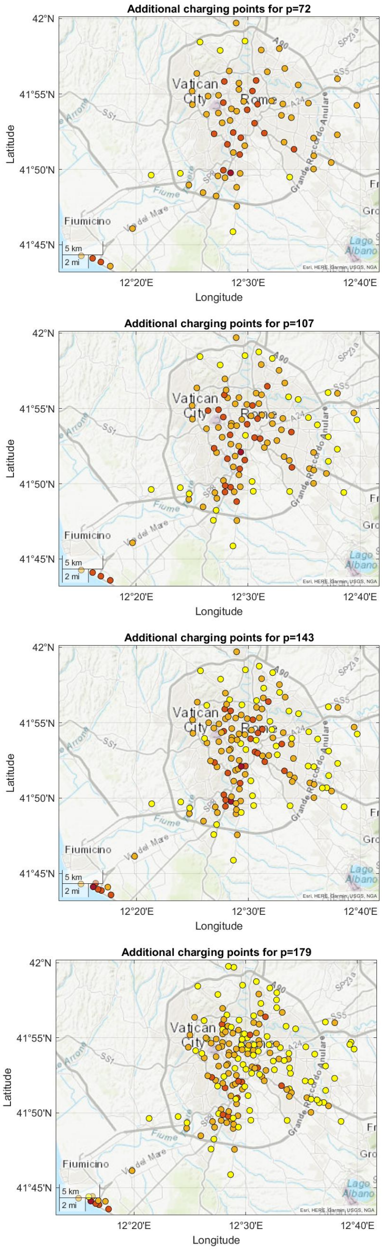


Table 5. Summary table of the new chargers to install, matrix in minutes, p=143 and p=179

Municipality	Nodes to upgrade p=143	Chargers to add p=143	Nodes to upgrade p=179	Chargers to add p=179
I	19	38	25	39
II	17	34	23	40
III	10	15	11	15
IV	7	11	9	12
V	6	11	10	12
VI	7	8	8	8
VII	15	31	20	36
VIII	12	25	16	28
IX	17	34	19	36
X	9	23	9	23
XI	5	8	7	12
XII	4	9	5	9
XIII	4	7	5	8
XIV	4	7	5	8
XV	7	10	7	10
Tot	**143**	**271**	**179**	**296**

Table 6. Summary table of the new chargers to install, matrix in km, p=143 and p=179

Municipality	Nodes to upgrade p=143	Chargers to add p=143	Nodes to upgrade p=179	Chargers to add p=179
I	18	36	22	39
II	16	34	24	39
III	9	15	10	15
IV	8	11	9	12
V	8	12	10	12
VI	7	8	8	8
VII	17	34	23	38
VIII	11	24	13	25
IX	17	34	20	35
X	9	24	11	26
XI	4	6	6	9
XII	4	9	5	10
XIII	4	7	5	8
XIV	4	7	5	8
XV	7	10	8	10
Tot	**143**	**271**	**179**	**294**

5 Charging station congestion and waiting times

Focusing on demand, we also study charging station congestion with the aim of deriving waiting times estimates. More precisely, we deal with time and travel distance to reach the nearest node if the stations at the considered location and in the surrounding area are occupied.

We deal with four different cases when considering a location: the two nearest nodes are occupied, the three nearest nodes are occupied, the four nearest nodes are occupied, the eight nearest nodes are occupied.

Then, we calculate the Probability Density Function (PDF) and the percentiles of the distance distribution in minutes and in km. Namely, we order the results (i.e., minutes/km to reach the nearest nodes) from the largest one to the smallest one and take the values corresponding to different percentiles to study the distribution. We use the results to represent the empirical PDF and identify the most frequent values, normalizing the number of events to have a frequency between 0 and 1. The results are reported in tables 7-9 below and in the plots 4-6 in the Appendix.

If we analyze congestion when distances in km are considered (see tab.7 and fig. 4), we notice that, on average, drivers do not have to travel long distances in case nearby stations are occupied. For instance, to reach the 5th nearest node, drivers have to travel less than 1.5 km in 50% of cases, and only 5% of cases require more than 5.5 km. To reach the 9th nearest node, 2 km and 6.5 km have to be covered in 50% and 5% of cases, respectively.

If we consider the distance matrix as expressed in time, without traffic, the picture does not change much (see tab.8 and fig. 5). For example, if the stations of the considered location and of the three nearest nodes are occupied, the time to reach the 4th nearest node is less than 2.35 minutes in 50% of cases and, only in 5% of cases it is greater than 8.5 minutes. But such a scenario is almost unrealistic for a busy city like Rome.

Table 7. Congestion with distance matrix in km

	5perc	25perc	50perc	75perc	95perc
to the 3th nearest node	0.36	0.72	1.06	1.65	4.52
to the 4th nearest node	0.44	0.87	1.24	1.87	5.24
to the 5th nearest node	0.56	0.99	1.38	2.02	5.38
to the 9th nearest node	0.75	1.39	1.87	2.59	6.46

So, it is worthwhile to study how these values change in presence of traffic, but we cannot obtain this information from the API we rely on. In absence of actual data, we attempt to estimate a distance matrix with traffic correction by adding, to the distance in minutes, an increasing multiplying factor ranging from 0.5 (in case of shorter distances in km) to 1 (in case of longer distances in km).

Indeed, the analysis conducted when traffic correction is adopted reveals longer travel times of about 5-10 minutes, depending on the circumstances (see tab. 9 and fig. 6). Hence, the time needed to reach the 4th nearest node is about 4 minutes in 50% of cases, and in 5%

Table 8. Congestion with distance matrix in minutes

	5perc	25perc	50perc	75perc	95perc
to the 3th nearest node	0.73	1.44	2.06	3.09	7.33
to the 4th nearest node	0.86	1.61	2.36	3.44	8.48
to the 5th nearest node	1.09	1.90	2.62	3.61	8.96
to the 9th nearest node	1.46	2.53	3.43	4.54	10.14

of cases it is above 13 minutes, while to reach the 9th nearest node, drivers need more than 5 minutes in 50% of cases and more than 15 minutes in 5% of cases.

Therefore, since, if traffic is accounted for, the time to reach the furthest stations can be long, one can expect queues to form at the stations closest to the demand point. For this reason, in order to quantify the improvements resulting from the installation of new chargers, it is useful to study the fractions of demand that can be satisfied in a certain area in an hour, both in the current situation and after applying our approach.

Table 9. Congestion with distance matrix in minutes with estimated traffic correction

	5perc	25perc	50perc	75perc	95perc
to the 3th nearest node	1.10	2.16	3.08	4.64	10.99
to the 4th nearest node	1.29	2.42	3.54	5.15	12.72
to the 5th nearest node	1.63	2.84	3.94	5.41	13.44
to the 9th nearest node	2.19	3.80	5.15	6.82	15.21

6 The arrival rate λ

We try to calculate the flow of charging demand that can be satisfied at each node and its surroundings.

Following the work of Marianov and ReVelle (1996) and referring to the queuing theory, we calculate the customers' arrival rate (λ_i) at each node and in a surrounding area, which indicates how many charging requests per hour each node and its neighborhood can meet. We calculate this metric in the initial conditions and after applying our approach, so as to capture the improvements in meeting the demand that would result from adding new chargers [4].

We rely on the formula proposed by Marianov and ReVelle (1996) to compute the prob-

4 We do this study only using the matrix in time because queuing theory is based on the study of waiting times.

ability α of at least one "server" being available within the radius considered:

$$1 - \left(\frac{\rho_i}{s_i}\right)^{s_i} \geq \alpha, \tag{3}$$

where $\rho_i = \frac{\lambda_i}{\mu_i}$ is the traffic intensity since $\frac{1}{\mu_i}$ is the single server's mean service time and s_i is the number of available servers in the considered area. We measure the arrival rate λ_i for each node i as follows:

$$\lambda_i = \mu_i s_i (1 - \alpha)^{(1/s_i)}. \tag{4}$$

For each node, we consider the total number of charging points within two minutes, including those at the node itself. This value is the number of chargers easily reachable from each node, that is the number of available servers s_i within the radius. We set a radius of two minutes, considering that, even with traffic, it is an easy distance to cover.

Then, we fix the single server's mean service time $\frac{1}{\mu_1} = 1.5$ i.e. we consider an average charging time of an hour and a half [5]. We focus on three different levels of reliability of the probability of at least one server being available within the range considered, i.e. $\alpha = 0.90, 0.95, 0.98$.

We then calculate how many requests can be fulfilled in one hour at a node and its neighbors up to a two-minute radius. To make a comparison, keeping the other parameters unchanged, we calculate again the arrival rate λ after applying our approach and increasing the number of chargers accordingly, and thus updating the number s_i of available servers in the selected area.

The results show, as detailed next, that in sites where additional charging points are installed, an increase in the number of requests that can be met is experienced.

We report statistics related to the arrival rate for the three α reliability levels and for the four scenarios about the number p of sites to be upgraded. Referring to tab. 10, 11, 12 and plots concerning the empirical PDF (fig. 7, 8, 9) reported in the Appendix, increasing the confidence level of finding at least one unoccupied server leads to a reduction of λ. We also observe that the percentile values of the distribution of the new arrival rate do not change substantially from p=72 to p=179, except regarding 5th and 95th percentiles, which, however show minor variations.

So, one might infer that, if new charging points are well positioned to optimize the distance between the different sites, upgrading already existing nodes by 20%-30% may suffice to satisfy more requests. As a consequence, it would be possible to meet the new charging demand, while also keeping construction time and costs at bay.

Overall, the application of our approach leads to a significant increase of the value of λ. Indeed, with the activation of new charging points, each upgraded site is able to meet more charging demands. For example, to date, with a 90% probability of finding an unoccupied server within a 2-minute radius, in 75% of cases, the areas within 2-minute radius from each node's location are able to serve up to 6 cars per hour. Following the indications given by our approach, this number is 8 when $p = 72$, and almost 9 for other values of p.

5 We used an indicative charging value, considering that the stations are both quick and fast. For actual charging times, see MotusE (2022)

Table 10. Summary statistics for the arrival rate with $\alpha = 0.90$

P=72	5perc	25perc	50perc	75perc	95perc
Initial λ	0.07	0.93	2.73	5.95	17.86
New λ	0.21	1.50	4.00	7.92	21.85

P=107	5perc	25perc	50perc	75perc	95perc
Initial λ	0.07	0.93	2.73	5.95	17.86
New λ	0.42	1.50	4.00	8.58	21.85

P=143	5perc	25perc	50perc	75perc	95perc
Initial λ	0.07	0.93	2.73	5.95	17.86
New λ	0.42	2.10	4.00	8.58	23.84

P=179	5perc	25perc	50perc	75perc	95perc
Initial λ	0,07	0.93	2.73	5.95	17.86
New λ	0.42	2.10	4.65	8.58	23.84

Table 11. Summary statistics for the arrival rate with $\alpha = 0.95$

P=72	5perc	25perc	50perc	75perc	95perc
Initial λ	0.03	0.74	2.43	5.59	17.44
New λ	0.14	1.26	3.67	7.54	21.42

P=107	5perc	25perc	50perc	75perc	95perc
Initial λ	0.03	0.74	2.43	5.59	17.44
New λ	0.30	1.26	3.67	8.19	21.42

P=143	5perc	25perc	50perc	75perc	95perc
Initial λ	0.03	0.74	2.43	5.59	17.44
New λ	0.30	1.83	3.67	8.19	23.41

P=179	5perc	25perc	50perc	75perc	95perc
Initial λ	0.03	0.74	2.43	5.59	17.44
New λ	0.30	1.83	4.30	8.19	23.41

Table 12. Summary statistics for the arrival rate with $\alpha = 0.98$

P=72	5perc	25perc	50perc	75perc	95perc
Initial λ	0.01	0.54	2.08	5.14	16.89
New λ	0.08	1.00	3.27	7.06	20.87

P=107	5perc	25perc	50perc	75perc	95perc
Initial λ	0.01	0.54	2.08	5.14	16.89
New λ	0.19	1.00	3.27	7.70	20.87

P=143	5perc	25perc	50perc	75perc	95perc
Initial λ	0.01	0.54	2.08	5.14	16.89
New λ	0.19	1.52	3.27	7.70	22.86

P=179	5perc	25perc	50perc	75perc	95perc
Initial λ	0.01	0.54	2.08	5.14	16.89
New λ	0.19	1.52	3.88	7.70	22.86

7 Conclusion

The use of electric vehicles is spreading in all countries: this is one of the actions that can be taken to tackle climate change and to help decarbonization. Accordingly, a widespread network of charging stations needs to be implemented in all urban centers. We choose to address this issue in the city of Rome by relying on an optimization p-median-like technique. In summary, our goal is to devise a simple methodology that can be relied upon by the city administration to make decisions on where to place new charging points to improve charging service. With such aim in mind, a crucial feature of our approach is its simplicity: to streamline construction procedures and to keep construction costs at bay, we focus on already existing charging sites; we then resort to a p-median-like optimization model to identify charging sites where to install additional chargers. The best charging sites to be upgraded are selected by minimizing their distances from locations where demand is assumed to appear. The resulting model belongs to the class of linear integer programming problems; also, one can rely on available efficient algorithms to compute solutions. Hence, the overall approach turns out to be easily interpretable, implementable and replicable.

Despite its simplicity, the model appears to be accurate, as witnessed by the results that we have obtained in our numerical analysis; in fact, empirical evidence supports our choices. We remark that the tests we have conducted are based on the real-world data related to the context of the city of Rome. In the a posteriori study, we focus on demand, whose dynamics has not been factored in explicitly in the model. More in detail, we rely on queuing theory to give estimates on the number of charging requests that can be met including the new charging points. Notably, we also incorporate the presence of traffic in our study.

Moreover, we consider several scenarios to perform a sensitivity analysis and to investigate the behavior of the output of our approach with respect to some problem parameters values.

The coverage of charging stations, in most cases, results to be correlated with the population density of municipalities. Indeed, applying our approach essentially requires new charging points to be installed where they are already numerous and, mainly, in most populated municipalities. Even so, the most peripheral areas are still not perfectly covered. However, we point out that to determine number and position of new chargers to be implemented, we use simplifying assumptions based on the possibility of being able to easily accommodate requests coming from other nodes.

In terms of charging demand that can be met, in almost all cases, the improvements resulting from the suitable increase in the number of charging points at existing nodes are significant. They do not seem to depend substantially on the number of nodes to be upgraded (i.e. whether p=72, p=107, p=143, or p=179): this indicates that, if new charging points are well located, even if fewer of them are built, charging sites can handle the overall demand.

Clearly, our study leaves room for further developments: as future research, we would like to enhance our analysis by using more elaborated models in the optimization phase. For instance, we intend to treat demand not only in an *a posteriori* analysis, but already in the optimization model. For this purposes, we wish to consider, e.g. Competitive Location models (see e.g., Drezner and Eiselt (2023)), set covering and maximal covering location models (see e.g., Farahani et al. (2012)) and Capacitated Facility location models (see e.g., Current and Storbeck (1988)). In addition, we would like to compare some of these facility location models to identify the ones that suit the most the context of complex and crowded cities like Rome.

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A Additional results

Figure 4. PDF in case of congestion for matrix in km

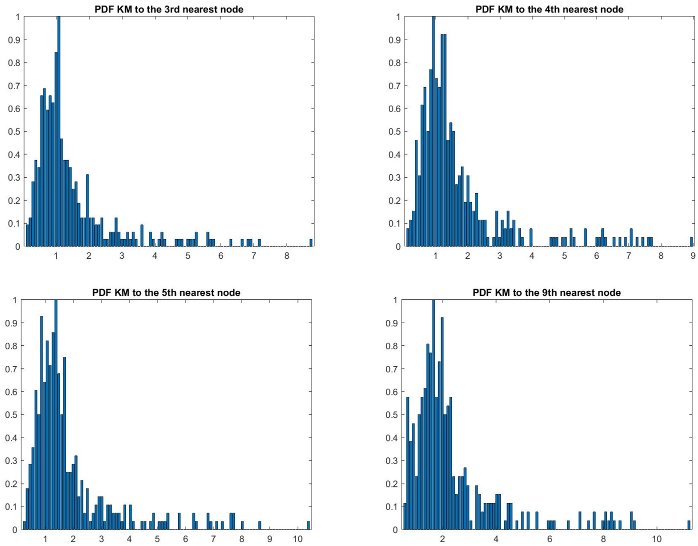

Figure 5. PDF in case of congestion for matrix in minutes

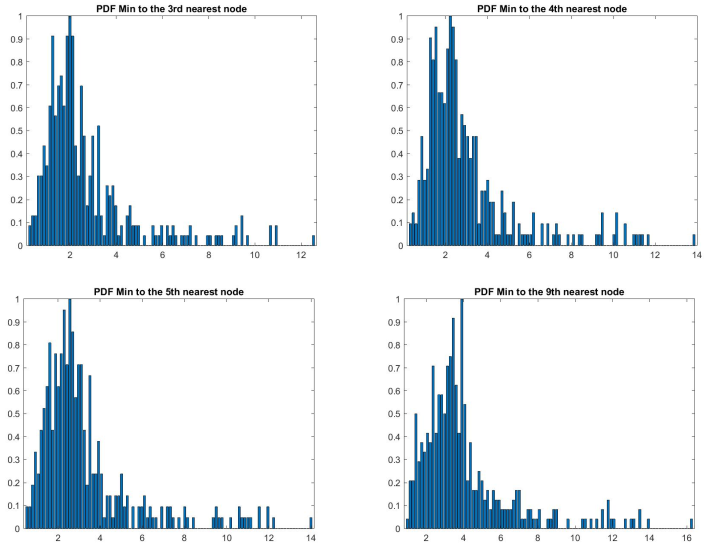

Figure 6. PDF in case of congestion for matrix in estimated minutes of traffic

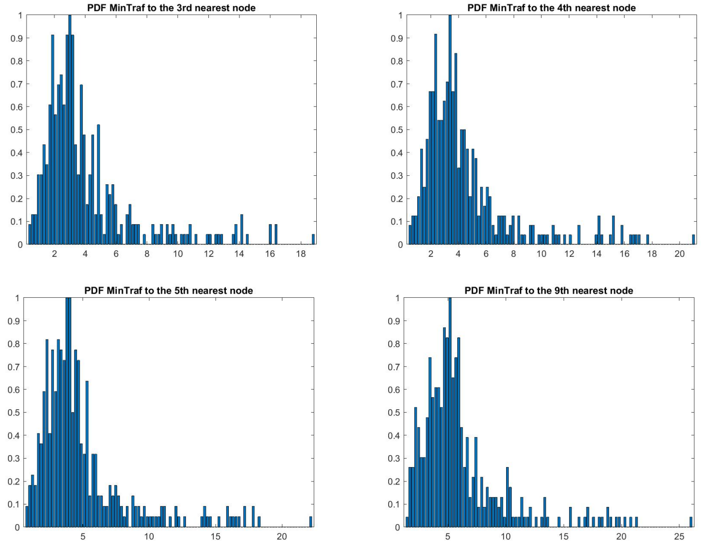

Figure 7. PDF of the arrival rate with $\alpha = 0.90$

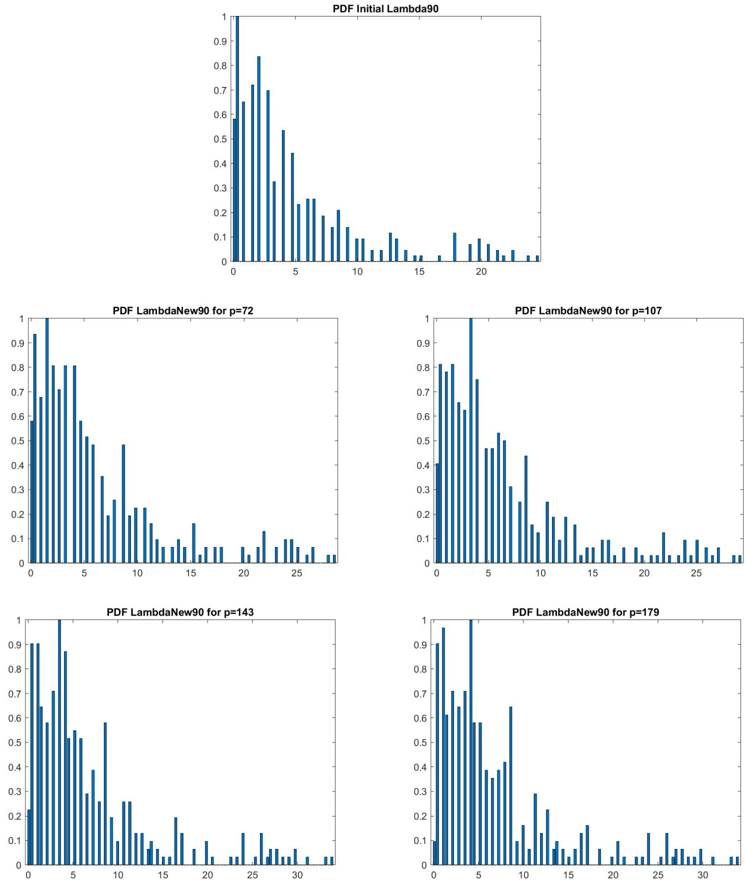

Figure 8. PDF of the arrival rate with $\alpha = 0.95$

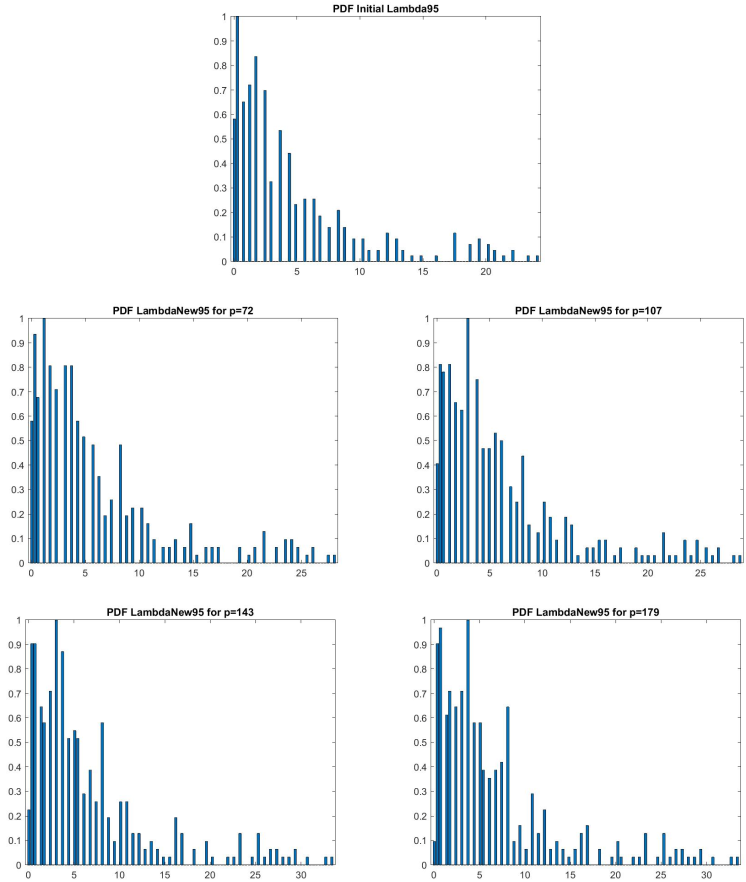

Figure 9. PDF of the arrival rate with $\alpha = 0.98$