Uncertainty-based strategic planning of charging network expansion in large urban areas

Aleksandra Colovic*[1], Mario Marinelli[1], Michele Ottomanelli[1]

[1] DICATECH, Polytechnic University of Bari, Via Edoardo Orabona 4, Bari, Italy

SHORT SUMMARY

The technological advancement of electric vehicles and charging stations emphasizes the requirements for more effective deployment strategies. To this end, a two-stage stochastic programming model is proposed to determine the location and capacity of charging stations, aiming to minimize the cost investment while maximizing expected revenues under uncertainty. The proposed methodology integrates spatial clustering techniques to identify candidate sites and incorporate demand patterns across the urban network. The outcomes of the model, applied to a case study of the city of Milan, supports a more balanced deployment by highlighting the importance of underserved areas to improve charging network efficiency, and encourage EV adoption. These findings support allocation decisions as preventing excessive concentration of charging stations in specific areas, reducing the number of chargers with inefficient utilization, and lowering operational costs for service providers in large-scale urban environment.

Keywords: electric vehicles; charging deployment; sustainable mobility; location model.

1. INTRODUCTION

The advancements in electric vehicles (EVs), battery technology and support by government initiatives have been accelerating the transition towards electric mobility. In addition, the integration of renewable energy sources enhances their environmental benefits, contributing to a more resilient and low-carbon energy ecosystem. The recent regulations set strategic priorities for promoting local incentives for EVs purchase and subsidies for private home chargers. Pan et al. (2020) demonstrated that 70% ownership rate of home chargers could support about 90% EVs drivers in realizing five weekdays' trips without revaluating routes. Furthermore, subside regulations and more careful placement of the charging infrastructure can attract more users and impact their market demand share, as well (Javazi et al., 2025). In Italy, recent targets prioritize the integration of the existing fuel distribution network with approximately 110,000 additional charging points, aiming to support the projected fleet of around 6 million electric vehicles (RRP, 2021).
The recent studies on charging facilities deployment have been dealing with estimation of charging utilization, fairness in resources, external costs, inclusivity, affordability, and social justice (Colovic et al., 2026; Nazari-Heris et al., 2022; Guo & Kontou, 2021). Sadeghi et al. (2022) developed region-based model by considering social, economic, and disruption aspects; the findings showed that 16.6% of the budget allocation can decrease users' dissatisfaction by 98%. However, limited data availability might enforce unplanned localization of charging facilities and their excessive concentration in one place leading to poor charging utilization. A common assumption is that urban areas characterized by dense residential communities or high economic activity are more attractive for charging demand. For instance, Li et al. (2021) developed a two-stage stochastic mixed-integer model by showing that valet charging services are most effective in areas with sparse demand. MirHassani et al. (2020) proposed a stochastic model under demand uncertainty

which highlighted the importance of slow and fast chargers in meeting charging requirements. Kadri et al. (2020) proposed a stochastic integer programming approach considering multi-period decision horizon and EVs recharging demand uncertainties when determining chargers' locations. Similarly, Faridimehr et al. (2019) modeled uncertainties related to EV flows and user charging preferences, showing that increasing the number of charging stations improves accessibility for EV owners.

Nevertheless, prioritizing high-density areas might result in an uneven spatial distribution of charging infrastructure and disparities in utilization, and consequently increase operational costs for service providers. To address these challenges, this study proposes a modeling framework that integrates uncertainty aspects and spatial clustering to guide the expansion of charging networks. Given a dataset of charging stations managed by one of the largest charging operators in Milano city, a K-means clustering analysis is initially applied to examine the spatial distribution of the current charging network and obtain clearer interpretation of current utilization patterns and potential charging demand generation as well; this also allows the identification of charging zones and individuation of candidate sites. Following this step, a two-stage stochastic programming model is proposed for determining the siting of charging stations based on minimal cost investments, highest profit revenues, by embedding the presence of stochasticity under random scenarios.

The extended abstract is summarized as follows. Section 2 presents the methodology, while Section 3 describes the application and results of the model for the Milano case study. Finally, Section 4 outlines the conclusions and directions for future research.

2. METHODOLOGY

The proposed methodology is founded, firstly, on the selection of the candidate sites, and secondly, on the problem formulation and the application of an adequate solution approach for determining chargers' places. The initiation of a clustering analysis of current charging points facilitates the interpretation of key parameters within charging zones, such as demand patterns and energy utilization. This analysis also enables the identification of potential candidate sites. The "hard" clustering techniques as the K-means clustering, is the appropriate one since it allows partitions of the dataset $X = \{x_1, x_2, \dots, x_n\}$ into k disjoint clusters S_k, by avoiding datapoints overlapping. In addition, the Elbow method is applied as a common technique for finding the "cutoff" point for finding k, i.e., the input related to the total number of clusters (Shi et al., 2021). The resulting charging points assignments have a higher similarity within one cluster and are dissimilar in other ones. The datapoints x_n are assigned to the clusters according to the minimization of the sum of the squared Euclidian distances between each data point and the centroid μ_i, calculated as $\underset{S}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2$. Afterwards, the candidate sites are identified in proximity to the cluster centroids (centers).

On one side, the site selection and capacity management are based on the operators' interest in reducing installation and operating costs and, on the other side, in obtaining highest profit from the charging utilization. The latter one is generally influenced by the satisfaction of charging demand, expressed as the level of service provided to users. However, the charging stations efficiency is the subject of the willingness-to-use, and the certain degree of charging and energy demand uncertainty that altogether are essential for real-time management. This implicates the adoption of certain modelling optimization techniques for obtaining adequate solutions. A two-stage stochastic programming (SP) is an appropriate mathematical framework in which data uncertainty can be represented as a vector of random variables ξ for each random event ω, $\xi = \xi(\omega)$, and handled through the set of two-stages decisions. In the first-stage decisions are taken before random events occur, while the second-stage decisions are corrective actions that consider

the occurrence of random events ω (Birge & Louveaux, 1997). Following those aspects, the problem is formulated in a way that first-stage decisions determinate the number and location of the charging stations to be installed by considering the presence of charging and demand uncertainty as given in the second-stage problem. The nomenclature is reported in Table 1.

Table 1: Nomenclature

Sets	Description
I	Set of candidate locations for placing charging stations, $i \in I$
R	Set of the charger's types $r \in R$
Parameters	
F_i	Fixed cost of locating charging station i, expressed in [€]
f_{ri}	Fixed costs of installing charger type r in station i, expressed in [€]
p	Number of charging stations to be located
u_{max}	Maximum number of chargers that can be located at station
u_{min}	Minimum number of chargers that can be located at station
h_i	Charging time utilization of station i [h]
E_i	Energy utilization of station i [kWh]
C_i	Target of active capacity of station i [kW]
D_i	Charging demand associated with charging station i
c_{ri}	The energy price of station i and charger type r
ξ	Random vector that represents the quantity of charging demand of stochastic scenario $\omega, \xi(\omega)$
ω	A stochastic scenario of set Ω, $\omega \in \Omega$
Decision variables	
x_i	Binary decision variable that takes the value 1 if the candidate charging station is located in i, and 0 otherwise
y_{ri}	Variable related to the number of chargers of type r installed in charging station i
z_{ri}	Share of demand served by a charger of type r installed at station i

The objective function in the first stage i.e., master problem (Eq. 1), aims at finding the number of charging points to be located considering the minimization of the total fixed costs for locating and installing chargers and the maximization of revenues under charging demand uncertainty in the sub problem. Then, the first-stage problem is formulated as follows:

$$Z = \sum_{i \in I} F_i \cdot x_i + \sum_{i \in I} \sum_{r \in R} f_{ri} \cdot y_{ir} - E_{\xi}[Q(x, \xi)] \quad (1)$$

$$s.t.$$

$$\sum_{i \in I} x_i = p \quad (2)$$

$$\sum_{r \in R} y_{ri} \leq u_{max} \cdot x_i \quad \forall i \in I \quad (3)$$

$$\sum_{r \in R} y_{ri} \geq u_{min} \cdot x_i \quad \forall i \in I \quad (4)$$

$$x_i \in \{0,1\} \quad \forall i \in I \quad (5)$$

$$y_{ri} \in \mathbb{Z}^+ \quad \forall r \in R, \forall i \in I \quad (6)$$

Constraint (2) indicates the number of charging points p to be located according to the available budget resources. Constraints (3) determinates the maximum number of chargers that can be installed in selected location of charging stations, while constraints (4) refer to the minimum number

of chargers. Constraints (5) – (6) indicate the binary and integer nature of variables x_i and y_{ri}. The decisions of the second-stage problem are modelled as an outcome of the random events $\omega, \xi(\omega)$ of the first stage. Thus $E_\xi Q(x, \boldsymbol{\xi})$ is the optimal value of the second stage problem that aims at satisfying charging demand at selected charging stations, and thus, obtaining the highest revenues, as reported in Eq. (7). The second stage problem is then formulated as follows:

$$Q(x, \boldsymbol{\xi}) = max \sum_{i \in I} \sum_{r \in R} \xi_i(\omega) \cdot c_i(\omega) \frac{E_i}{h_i} \cdot d_i(\omega) \cdot z_{ri} \quad (7)$$

s.t.

$$\sum_{r \in R} z_{ri} \cdot d_i(\omega) \leq d_i(\omega) \cdot x_i \quad \forall i \in I \quad (8)$$

$$z_{ri} \cdot d_i(\omega) \frac{E_i}{h_i} \leq C_i \quad \forall r \in R, \forall i \in I \quad (9)$$

$$x_i \in \{0,1\} \quad \forall i \in I \quad (10)$$

$$y_{ri} \in \mathbb{Z}^+ \quad \forall r \in R, \forall i \in I \quad (11)$$

$$0 \leq z_{ri} \leq 1 \quad \forall r \in R, \forall i \in I \quad (12)$$

Constraints (8) indicate that the percentage of demand served by charger type r should be lower than the stochastic demand under scenario ω assigned to station i. Constraints (9) states that the stochastic energy charging demand of charger type r in scenario ω in station i should be lower than the active capacity threshold of station i. Constraints (10) – (11) indicate the binary nature of variables x_i and y_{ri}. Constraints (12) indicate the continuous nature of variable z_{ri}.

3. RESULTS AND DISCUSSION

The case study

In Italy, most of charging infrastructure is concentrated in the northern regions (57%), with Lombardy leading the way with 14,242 charging points as of 2025 (Motus-E, 2025). Most of the charging points, i.e., 4.970, are concentrated in the city of Milan with charging density exceeding 183 points per 100 km^2. In the context of this study, the proposed model is applied to a study area comprising a dataset of 160 charging points distributed across both central and peripheral zones of Milan (see Fig. 1). Overall, 139 charging points are equipped with quick, and 21 with fast chargers; the power capacity of fast ones is ranging from 72 to 150 kWh. The total population of Milan's municipality is 1,349,930 inhabitants, distributed across 6,085 census tracks. The largest of these tracks contains approximately 2,573 residents (ISTAT, 2026). The charging units are distributed among 147 census tracts, resulting in the density of 1 to 5 units per census tract. Notably, both the number and density of charging units have upper values in the central zone, characterized with a larger presence of touristic, residential, and commercial activities, while census tracts with larger surface area remain underserved.

The parameter values of the two-stage stochastic programming model are reported as follows. Two types of chargers have been considered as quick and ultra-fast; the maximum and minimum number of quick and ultra-fast chargers to be installed are $u_{max} = 2$ and $u_{min} = 1$. The costs of installing chargers are $f_{quick} = 2000€$, and $f_{\text{ultra_}fast} = 26.000€$. Fixed cost F of locating charging station are equal to 1600 €. The probabilities of the stochastic scenarios are generated using a Dirichlet distribution with a uniform concentration parameter. Specifically, a probability vector prob is sampled from a Dirichlet distribution with parameters $\alpha = 1$ as $\text{prob} \sim \text{Dir}(\alpha)$, by ensuring that all scenarios are treated with equal priority and there is no prior knowledge of

favoring one component over another. In addition, the number of stochastic users across scenarios is modeled using a multinomial distribution. For the total number of residents N associated with candidate location i for each cluster, the number of EVs users D_i are generated among the different scenarios according to a probability vector as $\mathrm{D}\sim\mathrm{Mult}(N, \mathrm{prob})$. The total population N is calculated using population data at the census tract level, obtained from open-source datasets (ISTAT, 2026). Furthermore, the charging energy targets E_i at candidate sites are derived from the maximum average utilization levels observed among existing charging units within each cluster. Also, the values of the energy prices for different random scenarios are considered in the range from 0.5 to 0.8 €/kWh for ultra-fast chargers and from 0.2 to 0.25 €/kWh for quick chargers.

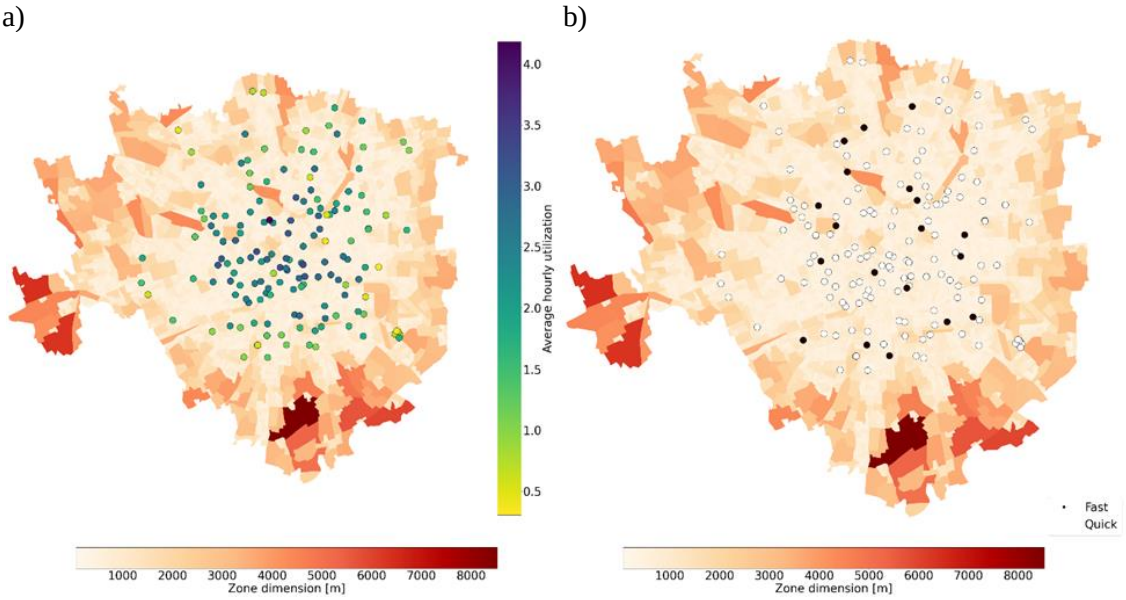


Fig. 1. The dataset of charging units in Milan city represented by: (a) the average hourly utilization; (b) the distribution of fast and quick chargers.

Results

With respect to the existing charging network, a K-means clustering analysis is initially applied to group charging points and identify candidate sites for the installation of new chargers. Based on the Elbow method, the optimal number of clusters is determined as $k = 22$, and the proximities to the resulting clusters' centers have been selected as candidate sites. The results of the two-stage stochastic programming model, applied to the Milano case study, are obtained using the L-shaped method by following Benders decomposition. The method split the extensive form into master problem Eq. (1-6) and subproblem Eq. (7-12). The first-stage decisions are made prior to the realization of uncertain parameters, while second-stage decisions correspond to recourse actions taken after the uncertainty is revealed. Finanly, the objective aims at minimizing the sum of the first-stage cost (master problem) and the expected value of the second-stage cost (sub-problem) over finite number of scenario realizations ω. The subproblem is solved by using the optimal solution of the master problem (selected locations x_i) to determine the optimality cut over five scenarios, which are iteratively added to the master problem as additional constraint (Birge & Louveaux, 1997). The outcomes of the model for different budget resources defining number of stations to be located as $p = 5$ and $p = 10$ are depicted in Fig. 2. Mainly, highly populated clusters (ranging from 1329 to 4042 residents) with higher average energy utilization targets (ranging from 77 to 190 kWh) have been selected as those for locating chargers, when $p = 5$ in Fig. 2a; those have been substantially expended starting from central to peripheral zones, when $p = 10$ in

Fig. 2b. In this manner, the inputs of clusters and the outcomes of sensitivity analysis, when varying p value, support a more efficient and balanced charging infrastructure while reducing the excessive concentration of chargers in central areas.

a) b)



Fig. 2. The selected locations for placing new chargers in the city of Milan for: (a) $p = 5$; (b) $p = 10$.

4. CONCLUSIONS

Coordinated charging deployment strategies, developed through collaboration between transportation planners and urban service providers, are essential to ensure adequate charging service availability for diverse user groups. In this work, we propose a two-stage stochastic programming model for the placement of charging stations based on the minimization of costs investments and maximization of potential revenues under stochastic demand. The model is applied to the case study of the city of Milan. The results highlight the impact of demand concentration and targeted utilization rates on the expansion of current charging infrastructure. Moreover, these outcomes may provide useful guidance for the reallocation of underutilized charging stations, particularly in high-density urban areas. As an outcome, this study develops a location model for charging infrastructure network expansion under demand uncertainty, while preventing excessive concentration in specific areas and emphasizing the importance of under-served zones to stimulate EV adoption. As further developments, we intend to incorporate a detailed spatial analysis, as well as to extend the model by considering the presence of other variables influencing the locations of charging stations.

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