

**A RELIABLE DEPLOYMENT STRATEGY FOR PUBLIC ELECTRIC VEHICLE
CHARGING STATIONS: A DISCRETE EVENT SIMULATION MODEL
FOR POWER GRID AND TRAFFIC NETWORKS**

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ABSTRACT

Today, with the help of low-cost and clean electricity, electric vehicles (EVs) show great potential for future urban transportation with little greenhouse gas emissions and air pollution. However, the use of EVs is still in its infancy with limited numbers of users worldwide. Public charging infrastructures can be one of the drivers to enhance the prevalence of EVs. In this paper, we aim to develop a framework to establish a reliable urban public charging infrastructure. We first determine the optimal locations and size of those stations by a robust optimization model incorporating uncertain traffic flows and existing power grid networks; and then we use a discrete event simulation approach to model more realistic charging demands. We further improve these optimal solutions and verify the EV charging infrastructure considering both power and transportation networks. We validate our models with real traffic and power grid data from a Southeast Chinese municipality.

1 INTRODUCTION

For the past few centuries, urbanization and industrialization have been the hallmarks of civilization; but they have raised several serious problems, such as environmental pollution and fossil fuel shortages. Private vehicles are the perfect example (World Health Organization 2019; Saad Alam 2018; Environment Protection Authority Victoria 2018). People enjoy the convenience of cars, but these vehicles suffer from greenhouse gas emissions and air pollution which have led to environmental and health issues worldwide (Carrington 2017; Green 2018). Electric vehicles (EVs), which take inexpensive electricity and generate almost zero air pollution, show promising potential to dominate future transportation industries (Hall and Lutsey 2017). Nevertheless, the existing EV market is still at an early stage with a limited number of users.

Public charging infrastructure has been identified as one of the pivotal bottlenecks of promoting private EVs in urban areas (Carolyn 2016; Tesla 2019). In fact, a reliable public charging infrastructure can raise travelers' awareness of EVs and encourage more private EV users (Hall and Lutsey 2017; Saad Alam 2018). That said, it is challenging to design a proper public EV charging infrastructure layout subject to inherent

economic, operational and social constraints. From the demand side, the location of charging stations should be adjusted to the transportation network in order to properly serve travelers by minimizing their travel time to public charging stations with a sufficient charging capacity. From the power supply perspective, public EV charging stations may affect the existing power networks. Newly installed charging infrastructures may increase the complexity of managing power network operations. Actually, the fast charging piles, which are the most efficient but expensive public chargers for EVs, require a power transformer with a sufficiently large capacity and transmission lines of a large cross section to accommodate a heavy power load and highly volatile voltages (Saad Alam 2018).

In order to address this challenge, we aim to design an optimal configuration of charging infrastructure in a metropolitan area, which is interactive with the existing power grid network in the same region. We focus on the tradeoff between upfront investments of setting up charging stations and users' time cost for traveling to the nearest stations; in other words, we aim to minimize the overall dollar value throughout the planning horizon by deploying the optimal number of fast charging piles at the optimal locations. The remainder of this paper is organized as follows. Section 2 reviews relevant existing literature, followed by an introduction of the project context presented in Section 3. In Section 4, we first use a robust optimization approach to address the uncertainty of traffic flows in our designated metropolitan area, providing a general guideline for locating and deciding capacity sizes of charging stations to be installed with fast charging piles among a set of candidate locations. In Section 5, we build a discrete event simulation model that represents the actual traffic on these roads. Our simulation approach can allow for further adjustment of the optimal configuration of the public charging stations by considering the utilization and service rates of these proposed charging stations. In Section 6, we finally discuss the results of our framework and future work on the same real traffic and power grid data at a medium-size town in Southeast China. Figure 1 gives an overview of the adopted methodology for this research work.

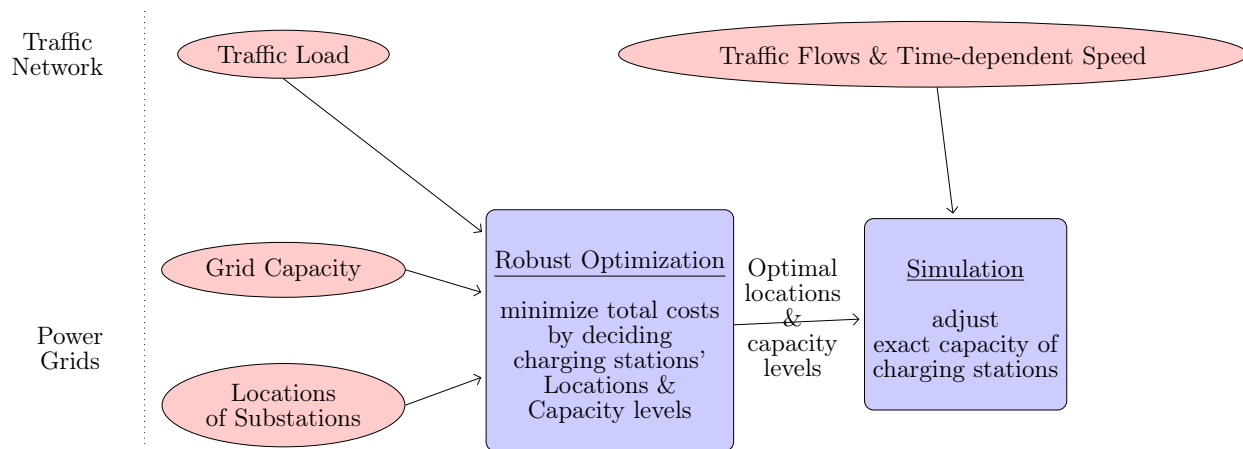


Figure 1: Overview of the adopted methodology.

2 RELATED LITERATURE

This study relates to the following fields from the Operations Research and Management Science (OR&MS) literature: optimizing EV charging infrastructures and simulating traffic flows.

One of the common modelling approaches for EV charging station allocation is the set covering integer programming method, which in general decides a minimal number of sets— each set represents the coverage of a charging station—to cover a certain region (Wang and Lin 2013; Cavadas et al. 2015). Interested readers can refer to more-recent applications of set covering and several derived approaches in He et al. (2016), Asamer et al. (2016), Xylia et al. (2017), Kunith et al. (2014) and Davidov and Pantoš (2017). In

addition, researchers have used other model approaches to address the allocation problem for EV charging stations, such as flow-capturing modelling (Chung and Kwon 2015; Shahraki et al. 2015; Fei and Sioshansi 2017; Wu et al. 2017; Zhang et al. 2017) and P-center location and allocation modelling (Jia et al. 2014). Different optimization models are also used, including mixed integer programming (Liu and Wang 2017), bi-level programming (Jung et al. 2014; Li et al. 2018) and nonlinear programming (Chen et al. 2018). In order to capture the uncertain EV charging demands, Pan et al. (2010) and Yıldız et al. (2019) proposed stochastic programming with emphasis on a vehicle-to-grid system and urban recharging infrastructure, respectively. With the help of robust optimization, Xie et al. (2018) focused on deciding the optimal number of EV charging piles along the highways by first using Monte Carlo simulation to find the proper locations of the charging stations. Our robust optimization model differs from existing literature, as it aims to determine both the allocation and capacity levels of public charging stations based on uncertain charging demands along the main roads in an urban area, in order to minimize total infrastructure and travel costs.

Our work also falls into the simulation research area of traffic flows in transportation networks. Earlier on, Sheu (2006) proposed a hybrid traffic simulation-based approach to address the route choice problem on congested roads. In that paper, specific incident-induced link models were designed for traffic flows on lane-blocking links. A simulation method was then developed to determine the instantaneous shortest paths for each vehicle to reach any given intersection. López-Neri et al. (2010) presented a multi-level Petri net-based formalism, named n-LNS, to model the structure of the urban traffic systems and the components' behavior. Specifically, the vehicles are considered as mobile agents with decision making capabilities that interact with the environment and other entities within the traffic network, performing diverse activities according to numerous situations arising during the simulation. Basile et al. (2012) built a simulation-based control model requiring limited computational effort for urban traffic systems. They used Colored Timed Petri Nets to model intersections and on/off ramps, a stochastic discrete time model for road links and a Particle Filter algorithm for estimation of the system state. Considering the directional behavior of wireless communication in urban transportation systems, Thomin et al. (2013) developed a simulation platform with a low computational cost and further compared traffic congestion detection and traffic alarm transmission versus the ratio of vehicles allowing jam detection. Kamrani et al. (2014) used ARENA software to simulate the traffic conditions of two adjacent T-shape intersections during peak hours in Malaysia. Recently, Shanmukhappa et al. (2018) developed a super node graph structure, a novel bus transmission network modelling method, and a static demand estimation method based on node weight distributions. They use simulation with real-life data in Hong Kong, London and Bangalore to validate the impact of geographic center nodes on local traffic behaviors. Among many articles relevant with the simulation of energy systems in the engineering literature (e.g., Kremers 2013, Leobner 2016, and García-Villalobos et al. 2016), the number of simulation studies related to EVs is relatively limited. Under different scenarios of EV market penetrations, Mallig et al. (2016) simulated the EV charging demands in Greater Stuttgart to investigate the strategy of hybrid EVs with traditional combustion engines. Using Beijing taxi trajectory data, Shen et al. (2016) set up a time series simulation model to determine the locations and types of charging stations. The work of Marmaras et al. (2017) introduced a comprehensive simulation and analyzed the behaviors of EV drivers in transportation and power networks. In contrast to existing simulation works of EVs, our simulation approach considers time-dependent traffic flows of an urban network and the users' impatience, which leads to demand loss at a fully occupied charging station. Taking the optimal allocation and capacity sizes of charging stations resulted from a robust optimization model, the simulation model verifies the optimal decisions and further improves the solutions in terms of performance measures, such as utilization of charging piles and service rates for EVs needing charges.

3 THE PROJECT CONTEXT

This research project studies the traffic and power grid networks in the district of Liuhe (or Luhe), one metropolitan county of the City of Nanjing. Nanjing is the capital of Jiangsu Province in Southeast China. The population of the studied area includes over 900 thousand inhabitants (Baidu Baike 2019).

We consider the first two level of major roads, including Ningluo Expressway (G36), Nanjing Ring Expressway (G2501), Jiangbei Avenue Expressway, Shanghai-Shaanxi Expressway (G40), Changshen Expressway (G25), Ninglian Expressway (G205), Jinjiang Road, Changshen Bridge (S353), Yanyang Road (S353), G235 National Highway, Eastern Main Line (S4210), Liuhe Bridge (G328), Ninghai Line, Qinglu Line (S356) and Emei Road (S247). There are in total 46 road segments and 39 road intersections shown by stars in Figure 2. We use Baidu map picking coordinate system (<http://api.map.baidu.com/lbsapi/getpoint/index.html>) to determine the latitude and longitude of these points. We then use the Baidu map open platform (<http://lbsyun.baidu.com>) to collect the real-time traffic flow data on these road segments in both directions. We write JavaScript codes to design a webpage on localhost, which send out traffic data requests to Baidu every 15 minutes from December 2018 to March 2019.



Figure 2: The traffic network.



Figure 3: The optimal allocation of charging stations. Green: a large station; blue: a medium station; red: a small station; grey: no stations.

4 ROBUST OPTIMIZATION MODELLING

Between existing two types of public charging devices, namely level 2 and 3, level 3 chargers, which are also called direct-current (DC) fast chargers, are significantly efficient with respect to charging speed yet more than ten times expensive (Habib et al. 2017; Saad Alam, M. 2018). Hence, it is crucial to determine the investment and allocation of DC fast charging piles in cities. To this end, we determine the allocation of level 3 charging stations by the integration of 1) charging infrastructures into the existing power grid infrastructures and 2) the charging demands based on EV traffic flows. We first consider the locations of existing power substations with over 110kV, such that sufficient voltages are allowed for fast charging facilities. We then select the optimal locations to set up charging stations with fast charging piles so that the charging demands in the traffic network can be fulfilled with minimal dollar values of infrastructure investment and travel times. Recently, robust optimization, a typical method for modelling uncertainties, has been widely used in different fields such as natural sciences, engineering technology, and economic management. Interested readers can refer to Ben-Tal and Nemirovski (2002) and Sözüer and Thiele (2016) for a review on the theoretical methods and recent applications of robust optimization.

4.1 Model Setup

Based on the Principal of Voronoi Diagram, we consider each road segment, the part between two adjacent intersections, as a power demand point, that is, a concentrated point of all traffic load in that road segment; and we use the weight of each point to represent the traffic density, the number of vehicles passing one point per time unit, of the road segments. For the simplified purpose, we regard the intersections of roads as the candidate set of charging stations. So the charging stations can only be built on those points in the candidate set. As long as a charging station is decided to be established, it will be integrated to the existing power grid network of the same region by setting up straight power transmission lines between the charging station and the closest power substation. EV users are assumed to choose the nearest public charging stations to fulfill their charging requirement. We also assume that the infrastructure cost of power transmission lines is a linear function with respect to the length of lines; and that the installation cost of a charging station is proportional to the number of chargers in the station.

Suppose \mathbf{W} is the set of candidate charging stations and f_i ($f_i \in \{0, 1, 2, 3\}$) represents the size, i.e., the capacity level at candidate charging station i , $\forall i \in \mathbf{W}$. That is, given a scaled factor λ_1 for the number of chargers, the number of DC chargers at station i is $\lambda_1 f_i$. Hence, we would like to minimize the total costs of the EV charging network by determining the allocation and size of charging stations, represented by the vector of decision variables $\mathbf{Y} = (f_1, f_2, \dots, f_{39})$. Let \mathbf{V} be the set of power substations that transmit power to EV charging stations, d_{ij} be the distance between candidate charging station i and substation j , d_i be the distance between candidate charging station i and its nearest substation, such that $\forall i \in \mathbf{W}$, $d_i = \min_{j \in \mathbf{V}} d_{ij}$.

We denote the uncertainty set $\Omega = (\omega_1, \omega_2, \dots, \omega_{46})$ representing the charging demand at power demand points with a mean vector μ and covariance matrix Ψ , t as the dollar value of unit time and d_{ki} as the distance from charging demand point k to candidate charging station i . Then the total traveling time given

\mathbf{Y} becomes $\mathcal{Q}(\mathbf{Y}, \Omega) \triangleq t \sum_{k=1}^{46} \omega_k \min_{i \in \mathbf{W}, f_i \neq 0} d_{ki}$. Let \mathbf{E}_Ω be the expectation with respect to the uncertainty set Ω , we can formulate the objective function as

$$Z_0^*(\mathbf{Y}) = \lambda_1 c_1 \sum_{i \in \mathbf{W}} f_i + c_2 \sum_{i \in \mathbf{W}} d_i + \lambda_2 \mathbf{E}_\Omega[\mathcal{Q}(\mathbf{Y}, \Omega)],$$

where c_1 is the dollar amount of installing a charger, c_2 is the unit infrastructure costs of setting up power transmission lines and λ_2 is the duration of the planning horizon. That is, the objective function representing the total dollar value consists of three parts: the installation costs of chargers, the expenses of building power transmission lines and the expected time costs of travelling to the nearest charging stations throughout the planning horizon. Furthermore, we consider service rate constraints which requires certain proportion of demands β ($0 \leq \beta \leq 1$) to be satisfied at charging stations. Let $\theta(i)$ be the set of charging demand points which are served at candidate charging station i . When $f_i = 0$, $\theta(i) = \emptyset$. We can now formulate the robust optimization problem as

$$\min_{\mathbf{Y}} Z_0^*(\mathbf{Y}) \tag{1}$$

$$\text{s.t. } \mathbf{P}\left(\sum_{k \in \theta(i)} \omega_k \leq \lambda_1 f_i\right) \geq \beta, \forall i \in \mathbf{W}. \tag{2}$$

4.2 Model Analysis

We solve the robust optimization problem by first simplifying the constraint with the random demands Ω . Typically, we address this chance-constrained problem by introducing conditional value-at-risk (CVaR) (Goh and Sim 2011), which is defined as

$$\text{CVaR}_\beta(\Omega) = \min_{\varepsilon_i} \left\{ \varepsilon_i + \frac{1}{1-\beta} \left(\mathbf{E}\left(\sum_{k \in \theta(i)} \omega_k - \lambda_1 f_i - \varepsilon_i\right)^+ \right) \right\},$$

where ε_i are randomly drawn real numbers. So we can rewrite the Inequation (2) as

$$\begin{aligned} \varepsilon_i + \frac{1}{1-\beta} \mathbf{E}_\Omega \delta_\omega^{(i)} &\leq 0, \\ \delta_\omega^{(i)} &\geq \varepsilon - \lambda_1 f_i - \varepsilon_i, \quad \delta_\omega^{(i)} \geq 0, \quad \forall i \in \mathbf{W}. \end{aligned} \tag{3}$$

We also conservatively approximate

$$\min_{i \in \mathbf{W}, f_i \neq 0} d_{ki} \approx \min_{j \in \mathbf{W}} d_{kj} + \min_{\tau \in \mathbf{W}, f_\tau \neq 0} d_{j\tau}.$$

To this end, we can rewrite the optimization problem (1) as

$$\min_{\mathbf{Y}} \left\{ \lambda_1 c_1 \sum_{i \in \mathbf{W}} f_i + c_2 \sum_{i \in \mathbf{W}} d_i + \lambda_2 t \sum_{i \in \mathbf{W}, \Omega} f_i \delta_\omega^{(i)} \right\}. \tag{4}$$

We can solve the optimization problem (4) subject to constraints (3) with ROME (Goh and Sim 2011).

5 SIMULATION MODELLING OF TRAFFIC NETWORKS

Simulation has been proven to be a powerful computational tool to study large-scale complex systems, such as transportation and power transmission network (Thomin, Gibaud, and Koutcherawy 2013; Kremers 2013; Leobner 2016). In the same vein, this study uses a simulation model of real traffic flows and power grids to analyze the performances of the optimal solutions provided in Section 4. We further improve our recommendations on deploying fast chargers and setting up charging stations in Luhe District. We implement our simulation modelling using ARENA software version 16.0 (Rockwell). This software has been used to simulate a wide range of systems and their related problems. More specifically, it allows a suitable and effective representation of traffic problems as shown in Kamrani et al. (2014).

5.1 Modelling Framework

We first build a discrete event simulation model considering uncertain traffic intensity (numbers of vehicles at a unit length of roads per unit of time) and speed at all the road segments in the transportation network. We start the simulation by generating traffics at each end nodes, which are at the boundary of the region, using time dependent density distributions derived from the historical traffic flow data and their fitted distributions using MATLAB. At each intersection, the aggregated traffic inflows travel to any of other adjacent routes with appropriate speed following probabilities calibrated from the actual data. We assume that 5% of vehicles need on-route charging service, which is reasonably projected considering the significant growth of EV ownership in China. Although dated in 2018, EVs accounted for 0.5% of all vehicles in China, EV sales in China were more than doubled than in North America (Wikipedia 2019). EV adoption rate is around 5% in California in 2017 (Bellan 2018) and the EV sales are over 10% of all passenger cars in Canada by the end of 2018 (Schmidt 2019). As suggested by the optimization model, we model each proposed charging station with an independent queueing system and each charging pile is modeled as a server. Because few data are available regarding charging stations, we further assume that the charging time follows a triangle distribution of 20, 30 and 40 minutes as lower limit, mode and upper limit, respectively. As the traffic network is non-terminating horizon, we run 30 replications of the simulation model in order to provide output statistics, which are then analyzed through ARENA output analyzer. This analysis shows a reachable steady state after less than 5 days. Consequently, we identify a warm-up period of 5 days followed by 15 days of run length as a study period.

5.2 Model Validation

The quality of our simulation models is verified through model validation. In Figure 4, we show a screenshot of the model animation. Indeed, the animation of the model allows us to verify that the simulated network

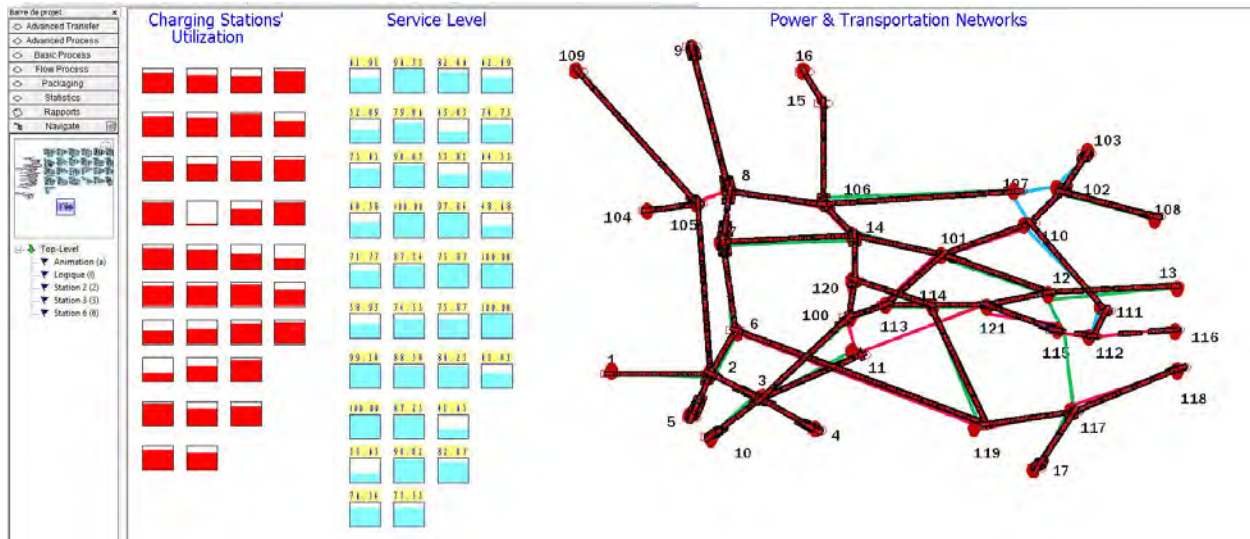


Figure 4: A screen shot of the model animation.

is reasonably similar to the actual network. Additionally, in order to validate the model, we compare two arbitrarily chosen sections of the simulated network (one highway section and one local road section) with the corresponding real ones. The comparison showed in Table 1 demonstrates insignificant difference between the simulated traffic and real traffic. The model is consequently valid given 95% level of confidence.

Table 1: Compare simulated and real traffic flows.

| Road Sections | Traffic flow (vehicles per day) | | Percentage Error |
|---------------|---------------------------------|-----------|------------------|
| | Real data | Simulated | |
| Local | 15,965 | 15,390 | 3.60% |
| Highway | 12,661 | 12,254 | 3.22% |

5.3 Scenarios

We run three scenarios to evaluate and adjust the deployment strategy of EV infrastructures under normal traffic conditions due to page limit. More scenarios under extreme circumstances of transportation and power distribution will be presented in future works.

Scenario 1: A charging infrastructure network consists of the recommended charging stations with capacities determined by the optimization model. EV users are served on First-Come-First-Serve (FCFS) policy at each charging station. Moreover, EVs will leave the station immediately without charging the vehicles if all the chargers are busy.

Scenario 2: Capacities are adjusted in proposed charging stations compared to the results of the optimization problem. All other factors and the operational rules remain the same as in Scenario 1.

Scenario 3: We use the adjusted charging infrastructure configuration of Scenario 2. EV users wait in queues at charging stations as long as the queueing length is no more than the number of chargers in that station; otherwise the EVs leave the station without being served immediately upon arrival. EVs are served on FCFS basis at each charging station.

Because there is no such charging infrastructure in the studied area, Scenario 1 serves as our baseline scenario. The focus of Scenario 2 lays on the performance improvement using simulation approach to adjust slightly capacities from optimization models. Indeed, performance indicators, namely service level and charging station utilization allow us to evaluate if the suggested capacity by the optimization model is appropriate to meet the actual demand. If the service level is low and stations' utilization rate is very high, we need to increase the capacity. Otherwise, if the service level is high and stations' utilization rate is low, we should decrease the capacity. Scenario 3 is an enhancement of Scenario 2, where we try to simulate EV user behaviors more realistically. Indeed, some EV users may be willing to wait several minutes at those public stations when their vehicles are in demand of charging.

5.4 Simulation Results

We analyze three performance measures, namely service rates, rates of being immediately served and utilization rate, for all proposed charging stations under the above mentioned scenarios.

Service rates present the proportion of EVs being charged at the charging station out of all EVs attempt to charge at the same station.

Rate of being immediately served indicates the percentage of EVs that get charged immediately upon arrival at the charging station.

Utilization rates are the average portion of times when a charging pile is occupied over all chargers at the charging stations.

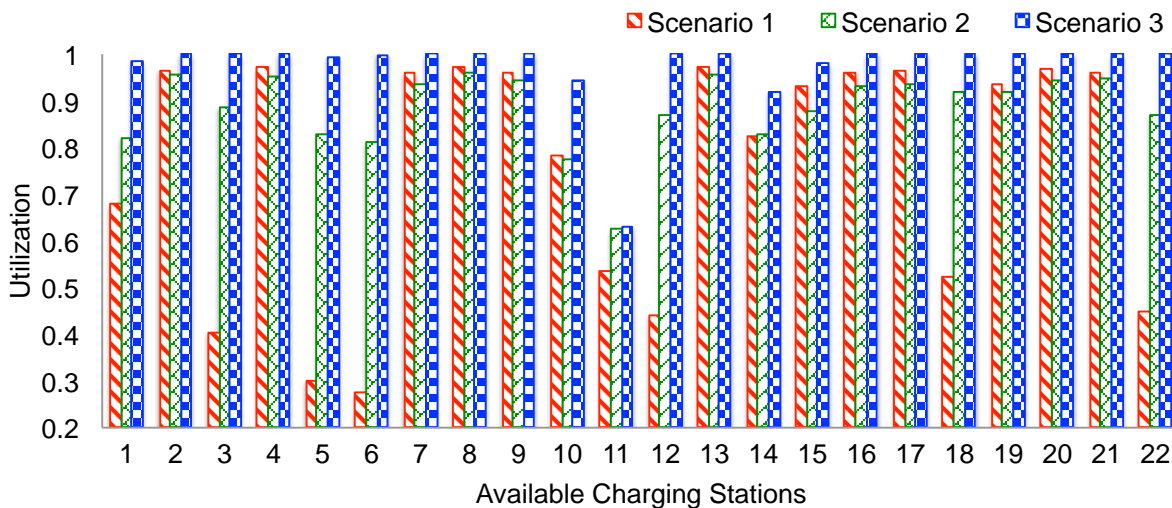


Figure 5: Charging station utilization.

The first two performance measures are the indicators of accessibility for the charging infrastructure. Indeed, they both show EV users' ability to access charging stations immediately or after a certain waiting time. One can note that the *rate of being immediately served* also highlights the efficiency of charging stations, which is a crucial factor of user satisfaction. Please note that these two measures are the same in Scenario 1 and 2, because no EVs wait in those two settings by assuming immediate loss of these users who arrive at a full station. On the other hand, utilization rates indicate how well these expensive charging resources are being used. In other words, a low utilization rate of a charging station implies an insufficient use of those charging piles. Hence, they are critical to provide practical insights on the investment decisions of a charging infrastructure network.

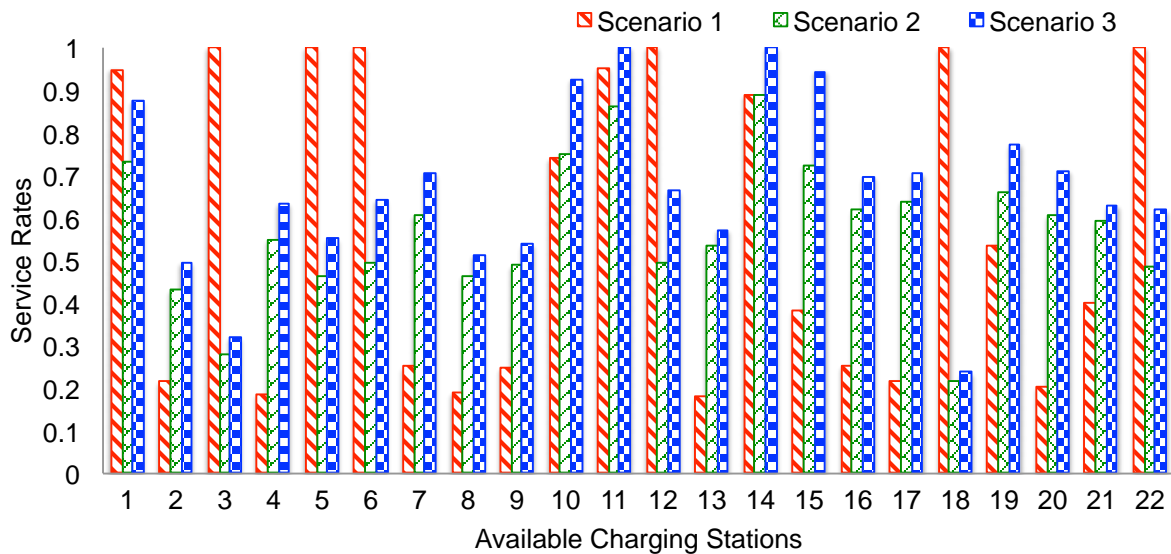


Figure 6: Service rates of proposed charging stations.

In Figure 5 and 6, we compare the performance measures under three scenarios. Figure 5 compares charging stations utilization, whereas Figure 6 compares service rates. Figure 5 explicitly shows that the utilization rates of several charging stations are very low in Scenario 1. Similarly, Figure 6 shows that service rates are very high for those stations having very low utilization rate in Figure 5 (namely, Stations 3, 5, 6, 11, 12, 18 and 22). This indicates that a downsizing adjustment of the optimization solution is required. Hence, for those stations with very low utilization in Scenario 1, we reduce their capacities in Scenario 2; while for those resulting in low service rates in Scenario 1, we adjust the capacity in Scenario 2 by adding more charging piles, in order to increase accessibility of the whole infrastructure network. Scenario 2 exhibits improved performance of the modified charging configuration, specifically Stations 3, 5, 6, 11, 12, 18 and 22, with relatively higher service rates, compared to Scenario 1. Using the same adjusted capacities as in Scenario 2, we explore a more realistic situation in Scenario 3 — EV users may wait for charging piles if only one or two vehicles are waiting in lines, rather than leave immediately a fully occupied station. Hence compared with Scenario 2, the resulting utilization and service rates of all available charging stations are relatively higher in Scenario 3, the more realistic setting.

Geographically, we find that the stations in central areas tend to have larger sizes with higher utilization and service rates. Typically, those downsized stations in simulation modelling, namely, Stations 3, 5, 6, 11, 12, 18 and 22, are all located in the outskirts of the studied municipality. This may be due to the fact that traffic flows tend to move towards the center of the town, which is captured in the simulation model; whereas the optimization model simply focuses on the magnitude of traffic flows without taking into account the travel direction of those flows.

These results demonstrate the advantage of combining simulation modelling to optimization methods in order to grasp more realistic factors, which are difficult to include in analytical models for the sake of feasibility and tractability. Moreover, simulation results show that including these factors can significantly impact the performance analysis of the system under study. Scenario 3 shows disparities of the rates of being immediately served from the service rates, implying a considerable part of EV users may wait for charging piles at charging stations. This drives our further investigations on the tradeoff of expanding the charging stations and the possible idleness of the costly charging piles in future research.

6 CONTRIBUTIONS, LIMITATIONS & FUTURE RESEARCH

In this study, we show a multi-disciplinary framework for configuring optimal public EV charging infrastructure by determining the locations and capacities of charging stations installed with DC fast chargers, given actual transportation and power grid networks in a Chinese urban area. From the investment perspective, our robust optimization approach provides a preliminary recommendation to allocate charging stations with a proper capacity level, with the objective to minimize the total infrastructure expense and users' travel time cost. The optimum acts as the baseline of the simulation modelling, which confines the quantity of testing scenarios and hence largely increase the efficiency of the simulation models. The simulation approach enables the verification of the optimal deployment strategies under varied uncertainties and realistic settings. Moreover, our simulation result demonstrates the superior power of the optimization recommendations and brings more valuable insights for the knowledge translation and implementation stages.

In future research, we will model more specifically power generation, transmission, and distribution in the grid network of the same region, in order to systemically capture the uncertain residential, commercial, and industrial power usages, as well as random urgency, such as usage spikes, breakdowns of generators or transformers in substations (e.g., Kremers 2013; Leobner 2016). This study considers a small number of scenarios and presents limited performance measures. In the future, we plan to investigate extensively a larger number of scenarios, such as power outage, extreme weather conditions and their impacts on transportation, power grids, and EV users. We will examine other critical performance measures, including waiting times and travel times to charging stations. Moreover, we may also improve the simulation modelling by considering the demand flows, that is, the EVs requiring charging can travel to other charging stations if the nearest ones are too busy. To this end, we can further explore the scenarios of closing some stations and opening new ones as recommended in the baseline model. Finally, we need to analyze the assumptions in both the optimization and simulation models with sensitivity analysis, such that the proposed framework is validated and robust.

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