Designing an Optimized Electric Vehicle Charging Station Infrastructure for Urban Area: A Case study from Indonesia

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Abstract—The rapid development of electric vehicle (EV) technologies promises cleaner air and more efficient transportation systems, especially for polluted and congested urban areas. To capitalize on this potential, the Indonesian government has appointed PLN, its largest state-owned electricity provider, to accelerate the preparation of Indonesia’s EV infrastructure. With a mission of providing reliable, accessible, and cost-effective EV charging station infrastructure throughout the country, the company is prototyping a location-optimized model to simulate how well its infrastructure design reaches customers, fulfills demands, and generates revenue. In this work, we study how PLN could maximize profit by optimally placing EV charging stations in urban areas by adopting maximal covering location model. We use data from the city of Surabaya, Indonesia, in our experiments and take into account the two main transportation modes for the locals to charge: electric motorcycles and electric cars. Numerical experiments with 11 candidate EV charging station locations and the projected number of electric vehicles in the early penetration phase across 98 sub-districts throughout the city show that only four charging stations are needed to cover the whole city, given the charging technology that PLN has acquired, but consumers’ time-to-travel is exceptionally high (about 35 minutes), which could lead to poor consumer service and hinderance toward EV technologies. Sensitivity analysis reveals that building more charging stations could reduce the time, but comes with higher costs due to extra facility installations. Adding layers of redundancy to buffer against outages or other disruptions also incurs larger costs but could be an appealing option to design a more reliable and thriving EV infrastructure. The model can provide insights to decision-makers to devise the most reliable and cost-effective infrastructure designs to support the deployment of electric vehicles and much more advanced intelligent transportation systems in the near future.

I. INTRODUCTION

The ever-increasing use of fossil fuels in Indonesia, the largest economy in Southeast Asia, is one of the main contributing factors to the poor air quality problems faced by numerous cities. Energy consumption for the transportation sector is estimated to double in the coming years, which is alarmingly high despite government efforts in promoting green energy and energy conservation [1]. The recent increase in gasoline prices globally exacerbates the problem [2], requiring the government to provide more than 110 trillion Rupiahs in energy subsidy in the coming years [3].

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The contribution of this work can be summarized as follows. First, we present a study case on EV facilities design for an urban area from a developing country perspective, a potentially colossal EV market shortly. More concretely, we consider reliability issues such as uncertain outage or blackouts in cities in developing countries and add layers of redundancy to buffer against them. In the experiment, we contrast the solutions obtained by not requiring extra coverage from other facilities (Fig. 2) with one that requires such redundancy (Fig. 5 and Fig. 6). Second, we propose a quantitative model based on the maximal covering location model to obtain the optimal facility locations for EV charging stations for the urban area. Finally, we analyze the sensitivity of the optimal locations for an EV charging station concerning customer distance-to-travel and highlight the tradeoff between cost or revenue objective and level of service. These contributions add to the literature optimization model and insights to design effective EV infrastructure for urban areas and thriving EV ecosystems at a larger scale.

The rest of this paper is organized as follows. In Section II, we present the problem formulation and provide a short overview of related work. We explain our framework and model in Section III and describe our experiment in Section IV. Finally, we discuss our findings in Section V and conclude in Section VI.

II. RELATED WORK

This study deals with facility locations for EV fast-charging infrastructure for urban areas from a developing country perspective. Below we highlight a few selected related works that inspire our formulation.

Much work on EV facility location problem considers the new facilities to be integrated into a smart-grid design [7]–[9] or other renewable energy sources, such as solar cell [10]. While this view provides an integrated solution to the renewable energy issues to amplify the positive impact of EVs on environment, this setting is too ideal for urban areas in developing countries.

Case studies on developed and developing countries can be found in EV facility design literature. Research in [11], set in Lisbon, addresses similar problem to ours, but focuses on slow-charging technology, motivated by the fact that vehicles around the city are often parked overnight. Model proposed in [12] considers both fast- and slow-charging technologies and uses data from Toronto, focusing on robustly covering all demands, avoiding leaving some demands to be fulfilled only partially. A study case in Ankara uses GIS-based model and adopt fuzzy approach [13]. A city-scale simulation is developed in [14] using data from Singapore, focusing on the tradeoff between cost minimization and customer accessibility maximization objective.

Research related to optimizing the location of EV charging station that considers characteristics of urban areas and incorporate the uncertainty and outage of the electricity, a common phenomenon in developing countries, is still limited. Earlier study develops a min-max facility location problem to optimize the number of public gas stations in West Surabaya area that considers the population and traffic densities and number of public facilities (such as hospitals and schools) [15]. A mixed-integer linear model is utilized to minimize the installation cost to build charging stations, considering the number of vehicles in the area [16]. Agent-based simulation model is developed in [17] that considers the number of EVs visiting to charge every hour at each installed charging station, allowing more dynamic analysis but requires extensive effort to build and validate the model.

Furthermore, work in [18] uses p-median facility location model for two different objective functions. The model aims to maximize the profit of charging station under fixed cost while maximizing consumer travel satisfaction, represented by a goal of minimizing the maximum distance between users and charging stations. Another work in [19] uses Multi-Source Weber Problem to minimize the total distance from users to their nearest charging stations. Work in [20] uses p covering formulation and discrete location theory to minimize the total cost, considering variable driving behavior (traffic flow), driving range, charging facility installation cost, and road network. Finally, [21] use quantum particle swarm optimization algorithm to minimize the cost of using electric vehicles, considering two cost components comprising user costs (including cost of charging electric vehicles, and costs due to travel and waiting for charging) and the charging station costs (including infrastructure construction costs, (land acquisition costs, equipment and electrical component cost, and charging station management costs). A good review for EV charging station facility location is available in [22].

In this study, we adopt a location set covering problem, which aims at identifying the minimum number and location of facilities to best meet customers’ demands [23]. This model is suitable for problems aiming to determine the number and assignment of facilities to meet demand points. One key property of the model is the pre-set coverage radius parameter (often expressed as distance or time threshold), which determines the feasibility of assigning a certain demand node to facilities. This particular threshold value is used to evaluate how large the population or demands can be covered and reached by each facility, which is often helpful to pre-set the facility level of service (the farther the customers are, the more likely the service to be lower since the customers have to wait or travel longer to be serviced by the facility).

III. FORMULATION AND PROPOSED MODEL

We consider a set of demand points I and supply stations J, representing sub-district regions and charging station candidate locations in an urban area, respectively. We also consider K vehicle types, incorporating types of vehicle modalities that urban cities accommodate (here, we include electric motorcycles and cars). The average time to travel from demand i ∈ I to charging station j ∈ J is denoted by d_{ij}. A threshold parameter d_{max} is used to limit this time in the following analysis to see the robustness of the solution w.r.t. consumer time-to-travel for charging. The decision
variables associated with these points are binary variables

\[ x_j = \begin{cases} 
1, & \text{if station } j \text{ is selected} \\
0, & \text{otherwise} 
\end{cases} \quad (1) \]

and

\[ y_{ij} = \begin{cases} 
1, & \text{if EVs from } i \text{ are served by station } j \\
0, & \text{otherwise}, 
\end{cases} \quad (2) \]

indicating whether a charging station candidate location \( j \) is selected or not and whether demand point \( i \) is to be fulfilled by charging station \( j \), respectively. In addition, we also use integer decision variables \( u_{ij} \) and \( u_j \), denoting the number of electric vehicles of type \( k \) from point \( i \) charged at station \( j \) and the number of units of charging connectors installed at charging station \( j \), respectively.

Each opened station \( j \) incurs a daily cost \( h_j \) and can only accommodate \( q_j \) charging connectors due to limited space. Each charging connector incurs \( g \) daily cost and has a limited daily charging throughput of \( c_j \) kWh. For a vehicle type \( k \), it takes \( e_k \) kWh energy and \( t_k \) time to fully charge using fast-charging technology that PLN adopts. To convert the energy used to monetary value, we use Indonesian electricity price denoted by \( r \) Rupiah/kWh (Rupiah or Rp. is Indonesian currency).

With this setting, the objective is to maximize daily profit

\[
\text{maximize } \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \left( r e_k v_{ij}^k \right) - \left( \sum_{j \in J} u_j + \sum_{j \in J} h_j x_j \right),
\]

which takes into account daily revenue as well as operational and investment costs that have been broken down to daily nominal costs (assuming five years depreciation schedule). This objective is maximized subject to the following set of constraints:

\[
\sum_{k \in K} u_{ij}^k \leq y_{ij} M, \quad \forall i \in I, j \in J, \quad (4)
\]

\[
d_{ij} y_{ij} \leq d_{max}, \quad \forall i \in I, j \in J, \quad (5)
\]

\[
\sum_{j \in J} u_{ij}^k = w_i^k, \quad \forall i \in I, k \in K, \quad (6)
\]

\[
\sum_{i \in I} \sum_{k \in K} t_k u_{ij}^k \leq c_j u_j, \quad \forall j \in J, \quad (7)
\]

\[
u_j \leq x_j q_j, \quad \forall j \in J, \quad (8)
\]

\[
\sum_{i \in I} y_{ij} \leq x_j M, \quad \forall j \in J, \quad (9)
\]

\[
\sum_{j \in J} y_{ij} \geq 1, \quad \forall i \in I, \quad (10)
\]

\[
\sum_{j \in J} x_j \leq N, \quad (11)
\]

\[
x_1 = 1. \quad (12)
\]

In the above formulation, constraint (4) ensures that charging stations can only charge vehicles if assigned. Constraint (5) ensures the maximum time-to-charge for consumers does not exceed the set threshold \( d_{max} \). Constraint (6) ensures all charging demands are fulfilled, where \( w_i^k \) denotes the number of vehicles of type \( k \) to charge at demand point \( i \). Constraint (7) ensures the required charging capacity to fulfill each station’s assigned demand does not exceed the installed capacity. Constraint (8) restricts the number of charging connectors installed in each station. Constraint (9) ensures that demands are assigned only to opened stations. Constraint (10) guarantees that at least one station covers each demand. Constraint (11) limits the maximum number of stations to open. Finally, constraint (12) enforces that Station 1 (which is the main EV charging station in Surabaya operated by PLN) to open (as demanded by PLN).

In addition, we also have a few variable type constraints

\[
x_j \in \{0, 1\}, \quad \forall j \in J, \quad (13)
\]

\[
y_{ij} \in \{0, 1\}, \quad \forall i \in I, j \in J \quad (14)
\]

\[
v_{ij}^k \in \{0, 1, 2, \ldots \}, \quad \forall i \in I, j \in J, k \in K, \quad (15)
\]

\[
u_j \in \{0, 1, 2, \ldots \}, \quad \forall j \in J, \quad (16)
\]

This formulation uses linear objective function and linearized constraints, which yields a mixed-integer programming (MIP) model, allowing us to solve it efficiently using standard MIP solvers.

**IV. NUMERICAL EXPERIMENTS**

We run the model presented in Section III using data collected from the city of Surabaya, along with interviews with PLN and EV stakeholders in the city. We combined vehicle registration data with the projection of the number of electric motorcycles \((k = 1)\) and electric cars \((k = 2)\) for the early penetration phase in Surabaya, distributed on each of its 98 sub-districts as our demand points \( u_{ij}^k \)’s. We accumulate the number of EVs on a sub-district level and use sub-district coordinates on Google Maps as our demand points.
to remove personally-identifiable information and maintain confidentiality. Furthermore, we prepopulate 11 candidate locations of EV charging stations and enforce Station 1 to open, based on PLN inputs, reflecting the current conditions in the field.

We also obtain the following information. The estimated daily cost to open a charging station $h_j = \text{Rp. 403,288}$ $\forall j \in J$, and the estimated daily cost to install a charging connector $g = \text{Rp. 110,244}$. PLN fast-charging technology takes 20 minutes to fully charge an electric motorcycle and about 90 minutes for an electric car. At the time of writing, the current electricity rate for business uses is $r = \text{Rp. 2,644.78/kWh}$. We use information obtained from Google Maps to estimate the average travel time $d_{ij}$ from demand $i$ to station $j$. Finally, we set $N = 11$ for the maximum number of charging stations, $q_j = 10, \forall j \in J$ for the maximum charging connectors, and $M = 1000$ as a practical value for our big-$M$ constraints.

In the experiment, we test numerous values for time-to-travel threshold $d_{\text{max}} = \{25, 30, 35, 40, 45\}$ minutes to assess the sensitivity of the optimal solutions with respect to customer level of service. In this regard, $d_{\text{max}}$ parameter (i.e. the maximum distance a customer has to travel to reach an EV charging facilities) represent the level of service toward customers whereas lower values means higher service levels (customers can easily find an EV charging stations) while larger values means lower service levels (customers need to travel further to reach a charging stations). Fig. 2 shows that higher service level (lower $d_{\text{max}}$ values) requires higher costs, which highlight the tradeoff between service level and total costs. The optimal solution for the baseline problem (without adding layer of redundancy) is found using OpenSolver [24] with optimal cost, profit, and revenue reported in Fig. 2. We found that the number of optimal charging stations differ for different $d_{\text{max}}$ threshold values (either 4 stations or 5 stations for $d_{\text{max}} \in \{25, 30, 35, 40, 45\}$ minutes). Fig. 3 and Fig. 4 show the selected stations as red markers overlaid in Surabaya map for 5-station solution and 5-station solution, respectively.

Finally, we study how to increase the reliability of the overall systems by adding layers of redundancy to buffer against outage and improve customer level of service, incorporating some level of reliability uncertainties common in developing countries. To account for this, we modify the RHS of constraint (10). Instead of requiring each demand to be covered only by one stations, we require 2 or 3 stations to cover each demand. The new revenue, cost, and profit for such more reliable system is summarized in Fig. 5 and Fig. 6.

V. DISCUSSIONS

We first note that we tried to simulate a better level of service situations ($d_{\text{max}} < 25$ minutes) in the experiment, but our model could not find a feasible solution. This is mainly due to high time-to-travel ($d_{ij}$) values due to extensive traffic in Surabaya. Hence, regardless of how the infrastructure is designed, the travel time could not be lowered (unless other forms of traffic intervention are incorporated, such as smart city integration, etc.). Therefore, we only discuss the case for $d_{\text{max}} \geq 25$ minutes.

We immediately see from Fig. 2 the tradeoff between profit maximization objective with consumer time-to-travel. For example, with a 30-minute threshold for consumer travel time, our model prescribes 5 charging stations (see Fig. 3 for the locations) to fulfill all demands and a total of 33 units of charging connectors, yielding a revenue of Rp. 24,667,800, total cost of Rp. 5,654,497, and thus a profit of Rp. 19,013,303. On the other hand, with a more relaxed time-to-travel threshold, say, 35 minutes, our model prescribes only 4 charging stations (see Fig. 4 for the locations), with a total of 33 units of charging stations also, giving the same revenue, but a lower cost of Rp. 5,251,209, resulting in an increased profit Rp. 19,416,591 (2% higher). We realize that the current improvement in numerical value is marginal, mainly due to small projected demand of EVs in Surabaya.
We also observe highly imbalanced demand distribution from the provided data, with more EVs concentrated on the richer neighborhoods of the city. This encourages sparse solutions, resulting in optimal solutions maximizing the number of charging connectors installed only in one or two of the selected stations and leaving the rest to install only one or two connectors. In fact, the different solutions depicted in Fig. 4 and Fig. 3 highlight how relocating one facilities will shift a few other facilities, since they are serving a highly density-imbalanced region of the city. This highly imbalanced solution could provide insights for decision makers to make a more targeted policy to increase the penetration rate of EVs more equally throughout the city. This well-informed policy could potentially exponetiate the positive impacts of EVs for public, reducing concentrated traffic and pollution, as well as increasing consumer satisfaction overall.

Finally, we highlight the cost of adding layers of redundancy in demand coverage, as an effort to buffer for service uncertainty, which is particularly important in developing countries since electricity often breaks down, even before adding EVs electricity demand. Fig. 5 and Fig. 6 confirm our hypothesis, that such redundancy forces the optimizer to output a more reliable network design, hence often comes solutions with higher costs, if such solutions even exists. In our case, there is no such solution for $d_{\text{max}} = 25$ minutes, mainly due to the already constraining travel times $d_{ij}$’s. Thus, we only show the results for $d_{\text{max}} \in \{30, 35, 40, 45\}$ in Fig. 5 and Fig. 6. Meanwhile, solutions for $d_{\text{max}} > 25$ are at higher costs (7% increase on average compared to the optimal solution without demand coverage redundancy). With these results, we would advocate for using the solution with $d_{\text{max}} = 25$ minutes to achieve better service level and absorb the 5% lower profit at the earlier years. If higher profits are demanded, then we suggest to yield to solution with $d_{\text{max}} = 35$ minutes at later years. Our view is that the government and PLN intend shall create a thriving ecosystem for EVs and consider long term benefits and thus incorporating demand redundancy in the infrastructure design. We believe that the incurred extra costs will pay off as the public adopts EV technologies more widely.

VI. CONCLUSION AND FUTURE WORK

In this study, we present a study case concerning EV infrastructure designs for urban areas for developing countries, with data collected from Surabaya, Indonesia. We adopt a maximal covering location problem for our model and solve for the optimal location of EV charging station as well as the number of charging connectors installed at each station. Considering 11 alternative locations and 98 sub-districts throughout Surabaya as demand points as well as projected EV units in each district, our model obtains feasible solutions only when consumers are willing to travel for 25 minutes,
given the current traffic conditions in the city. Sensitivity analysis on consumers’ time-to-travel reveals that solutions with lower costs are available, but force consumers to travel longer. Adding redundancy to the EV infrastructure designs, as an effort to buffer against outage or disruptions, requires higher costs. However, such extra costs might be justifiable in the long term to create a thriving EV ecosystem so that public can enjoy more environmentally friendly transportation systems and cleaner air. We envision that our model can be applied to incorporate intelligent vehicles as well, optimizing not only the location of the charging, but also the microscopic driving behavior that an intelligent vehicle can learn. Such an approach will be one of the subjects of our future studies.

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