Research Article

Optimal Deployment of Electric Vehicles’ Fast-Charging Stations

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1.Introduction

Climate change has been identified as a major concern nowadays, which is primarily produced by GHG emissions. The global warming is expected to rise by more than 2°C above preindustrial levels if no further steps are made to cut GHG emissions [1, 2]. In 2016, the transport sector contributed approximately 25% of worldwide emissions [3]. Although energy and fuel consumption significantly impact the global climate change, the usage and energy production themselves are fraught with difficulties [4, 5]. In 2012, the transport sector’s energy demand increased from 23% to 28% [6]. As a result, the notion of green transport is evolving, which refers to an easy, efficient, safe, low polluting, and diverse urban transport system [7–9]. With progressions in communication and technology, a green transport system provides one of the most effective solutions in combating air pollution, decreasing congestion, and easing the fuel crisis [10, 11].

Green transportation is essential to address climate change mitigation since they minimize CO2 and other pollutants that are frequently used in conventional vehicles [12, 13]. Amongst all green transportation choices, e-bikes, shared mobility, electric vehicles (EVs), and bus rapid transit are an intriguing option for addressing the aforementioned challenges [14, 15]. With the call for zero-emission vehicles and improved battery technologies, EVs are a solid contender to replace the gasoline-driven automobile. Aside
from contributing to energy security and sustainable environmental, EVs provide substantial benefits to users in terms of fuel economy and cost savings [16]. Because of these reasons, the EV market has seen commercial success recently. Several state and governmental entities have also established policies to encourage EV adoption, further accelerating the growth. Despite their benefits, EVs have not gained widespread acceptance among the public. Due to the inadequate and limited charging infrastructure and the shorter driving range, EVs drivers may have range anxiety or the concern that the energy storage may run out before they get to their destination [17, 18]. In order to alleviate the drivers' range anxiety and increase the usage of EVs, there is a need for adequate planning for charging stations to help drivers arrive safely at their destination.

Charging infrastructures are becoming crucial components for adopting EVs, connected to vehicle technology and efficiency and the accessibility of a reliable power supply to charging stations [12]. It is also tied with the increased electricity demand in other sectors [19]. In this context, infrastructure issues include charging station distribution planning, electrical grid resistance, dependability, and consumption patterns used to determine pricing and incentive policies. Performance and cost barriers are impeding the adoption of EVs [20]. Furthermore, travel through EVs may become unsustainable due to the limited availability of charging stations [21], nonoptimal location in urban surroundings [22], inconsistent power flow, and amount of energy taken from the primary electricity grid not initially catered for this use. Thus, it is critical to identify occupation patterns and, consequently, such issues may be resolved by employing charging profiles [23]. EVs recharge is a new type of electrical demand that is challenging to precisely estimate, particularly when the vehicle penetration is still low and a large data set is difficult to obtain. Another significant barrier to increasing EVs market share is the inconvenience faced due to the shortage of the public charging infrastructure and the limited range of batteries. Proper charging station planning could help the motorists in this aspect.

EVs need comparatively prolonged charging times than refueling internal compaction engine vehicles (ICEVs). Three types of charging stations are currently available, each having a different range of the charging power supply. Level-I and level-II chargers have a maximum charging power of about 1.5 kW and 10 kW, respectively; however, Level-III chargers have to charge powers up to 60–150 kW because they need high voltage [24]. Level-III chargers are more expensive to construct and can only be found in commercial places. A standard EV would still require more than 30 minutes even with a Level-III charger, which is significantly longer than refueling ICEVs [25]. Level-I and level-II chargers usually take several hours to charge an EV fully. As a result, an appealing alternative is placing charging stations at the EV driver's house, office, or other locations where they are expected to stay for a long time (recreational facilities, shopping malls).

Electric vehicle charging station (EVCS) planning issues have been extensively investigated over the last decade and continue to catch the attention of both researchers and practitioners. In the literature, the EVCS location issues are categorized into two groups, namely, intracity and intercity, depending on the type of travel the charging amenities intend to support. The intercity problem is primarily associated with the range anxiety issue, particularly for longer (intercity) trips, whereas intracity problems are more concerned with the limited accessibility of charging infrastructure within the boundary of metropolitan centers. In intercity problem, the charger can be installed anywhere on the highway, and this problem can solve the flow-capturing refueling problem and the charger location depending on the traffic volume of origin-destination pair and EVs range [26]. The authors proposed a conceptual model to examine EVs travel throughout a long route for intercity EVs trips [25]. The goal of their proposed model is to choose the battery size and charge capacity that will satisfy a particular level of service while minimizing the total social cost. Similarly, the authors employed a continuous facility location approach for optimizing EVs charging station placement for highway corridors [27]. Their model did not consider the cost of the battery. Considering demand uncertainty, their goal was to augment the private charging infrastructure with government-subsidized charging stations.

In the intracity problem, the charger can be installed anywhere in the city. To locate EVCS in the city, the discrete network model was chosen, since stations can only be located at discrete locations, such as existing service stations or parking lots [26]. There are two different methods for determining where charging stations should be placed. The first involves the use of classical facility location methods such as set-covering problems, with the overall goal of reducing the number of chargers required so that all consumer can reach the charging station within a specific time and driving distance. The second method is the multicriteria decision making (MCDM) approach based on geospatial analysis [28]. In MCDM, individual potential location is assessed based on various criteria, including the cost of land, parking lots availability, and the location's slope. Each subcategory is scored, and location decision is based on each candidate's cumulative score. Frade et al. (2011) attempted to solve the intracity EVs' charging location problem by employing the covering model to maximize the number of customers served by each stations and maintaining a certain level of coverage provided by the charging station [29]. Dashora et al. (2010) suggested an early intracity EV location model intending to reduce the overall cost by converting parking lots to EVCS [30]. The cost of converting a parking lot includes installing charging devices, solar shading, and connecting these parking lots to the nearby grid stations. Chen et al. (2013) used a similar model to minimize the walking distance [31]. He et al. (2013) consider the interactions between the placement of EVCS, the operation of power networks, and the selection of route and destination choices [32]. Ahmad et al. (2017) developed an optimal framework for hybrid EVs based on the switching process from one trading place to another depending on the maximum selling (i.e., discharging of EVs) and minimum purchasing (i.e., charging of EVs) energy cost [33]. Based on
these results, the aggregator paid 4.22% lesser energy cost than day-ahead while 4.65% and 9.68% lesser than DISCOM and the bilateral based trading platform.

So far, existing research studies have examined the performance of several optimization strategies for solving the optimal location of the EVCS problem. Various researchers have already investigated the most efficient placement of EVCS in distribution lines using various computational techniques such as evolutionary algorithms [34], Jaya algorithm [35], particle swarm optimization (PSO) [36], and genetic algorithm (GA) [37]. Mostly, the problem is the same, and it is based mainly on the availability of traffic flow data and the total number of EVs in the observed area. Xiong et al. (2017) proposed the optimal location of EVCS considering distribution network and city traffic [38]. The objective is minimizing energy not supplied while also considering charging station costs. Zeb et al. (2020) employed a method for the optimal deployment of the solar power-based charging station considering different charging levels with minimal losses and installation costs [39].

Nevertheless, the constraints incorporated within the optimization problem vary, such as the type of EVCS, courage routes, land cost, maintenance cost, fixed cost, electric grid impact, and traffic flow [40]. Shahraei et al. (2015) proposed the application of mixed-integer linear programming (MILP) for the optimal placing of EVCS based on real-world data of vehicle travel patterns [41]. The findings indicate that an appropriate charging station placement can result in significant improvements. Ge et al. (2011) employed a GA for sizing and locating EVs’ charging stations using grid partitioning [42]. The main constraints considered are charging station capacity and traffic density. An equilibrium modeling framework was proposed by He et al. (2013) to capture the interactions between the availability of charging opportunities, destination, electricity prices, and EVs’ route choices at regional power transmission and transportation networks [32]. The paper’s objective was to consider the constraints of power and transportation network. Dong et al. (2014) employed GA for EVCS, an activity-based technique using multitravel data [43]. The finding suggested that the placement of public chargers at popular sites with some adequate infrastructure investment could considerably increase electric miles and trips.

Liu et al. (2012) used a modified primal-dual interior-point algorithm to select an appropriate location for EVCS placement, taking environmental factors and EVs’ service radius to solve the problem [44]. They considered cost as an objective function. Wang et al. (2013) employed data envelope analysis for the EVCS problem considering the multiobjective function, power loss, EVs’ flow, and voltage deviation [45]. Zhang et al. (2015) employed PSO for optimal location planning of EVCS [36]. The placement problem for fast-charging stations and public parking lots was developed while the cost as the objective functions. Yao et al. (2014) developed a multiobjective evolutionary algorithm to locate fast-charging stations considering the multiobjective function, EV flow, cost, and energy losses [46]. Ahmad et al. (2021) presented a modified chicken swarm optimization (MCSO) approach for optimal deployment of solar power charging station considering distribution network. The outcomes are compared to the teaching-learning-based optimization and the Jaya algorithm; the comparison demonstrates the superiority of the MCSO [47].

According to the Liao et al. (2016), range anxiety, EVCS availability, and charging duration time are the three major drawbacks for faster EV adoption [48]. Furthermore, easy access to EVCS directly influences on EVs’ penetration levels. This is due to the fact that ICEVs is viewed as a convenience purchase and the user do not prefer to plan ahead to find refueling stations. Consequently, fast-charging stations serve as “emergency service” amenities, and it is essential to consider consumers’ behavior while locating charging stations. Meanwhile, the fuel/gas retail industry is well-established and optimized to serve vehicles, and these locations are natural candidates for installing fast chargers. To address the abovementioned issues, the following contributions have been made.

The current study aims to develop a mathematical model for minimizing the total cost by optimizing the location planning of charging stations, their sizing, and the number of total chargers within each charging station. The charging station opening capital cost and the user’s convenience cost (defined by station access cost) are the two essential considerations while planning for an optimal charging location. This study proposes five different integer linear programming (ILP) models to address the problem of EVCS location and sizing. The proposed models may be grouped under two main categories. First, ILP models are solely used for chargers location decisions; second, ILP models consider both location and sizing decisions. Both categories are distinguished by definite decision variables, relevant real-world constraints, and a corresponding objective function.

The remainder of the paper is as follows. Section 2 details the proposed mathematical models. Section 3 reports the main results of the conducted computational experimentation. Section 4 concludes and provides future research avenues.

2. Model Formulation

Different covering models (optimization models) are proposed. The objective is to minimize various formulations of objective costs while satisfying all demands. The suggested models deal with the planning of EVs charging network for a metropolitan region based solely on an existing gas station.

2.1. Assumption. The study was based on the following main assumptions for simplicity:

(i) For EV users, only daytime charging is considered. This appears to be convenient for a workplace in an urban region.

(ii) Only fast charging stations are considered, and each charger may provide service to multiple EVs, as fast charging is usually considered the best solution for gas stations.
(iii) Access to installed chargers within a reasonable travel distance is necessary for EV drivers.

(iv) Each EV can be charged to a single charging station.

2.2. Network Planning. Identifying potential locations for future charging stations is an essential component of this research. Based on the previous research studies [49, 50], the existing gas stations in the neighborhood could be suitable places for the charging station. Google Maps is used to acquire geographic information. Table 1 contains a list of possible locations. In Figure 1, we found 18 possible charging stations. After the 18 candidates for potential locations had been identified, an adjacency graph is created in Figure 2. Based on the graph theory, a linked undirected graph \( G = (V, E) \) has been created, with \( V = (1, \ldots, n) \) indicating a set of nodes representing the feasible charging, and \( E = (1, \ldots, m) \) is the set of edges which represents the possible connections between charging stations \( (n = 18) \). The distance between the locations is used to weight each edge \( (m = 54) \). The Cartesian distance in each station’s neighborhood was determined and noted as \( d_{i,j} (i, j \in V) \) denoted the distance between locations \( i \) and \( j \). Table 2 provides the distance matrix.

2.3. Linear Programming Models. Different models might be used to optimize the installed resources. This section contains a description of these proposed models. The location of installed stations, their size, and where to charge are all considerations made at the scope level. Users of not-yet-placed stations should charge within a reasonable radius \( R \) of an installed station. Apart from assuring a service coverage distance, these models minimize various costs while adhering to appropriate constraints. In this section, we look at two decision-based (location only and location and sizing) ILP models. The first two models focused on only location and last three models focused on both location and sizing.

2.3.1. ILP Models Considering an Only Location. The first class of ILP models used an NP-hard set covering problem [51]. For that purpose, we define a binary variable \( x_i \) for each location \( i \in V \), which takes the value 1 for an EVCS installation at location \( i \); otherwise, 0. \( R \) represents a constant coverage radius that denotes the EVs user’s tolerable distance while looking for a charging station. Then, the intermediate constant is utilized. Let \( a_{i,j} (i, j \in V) \) be a binary constant which takes the value 1 if \( d_{i,j} \leq V \); otherwise, 0, and \( d_{i,j} \) is the same as described in the preceding section. As a result, the model \( M_1 \) can be obtained as follows:

\[
M_1: \text{Minimize } \sum_{i\in V} x_i, \quad (1)
\]

Subject to:

\[
\sum_{i\in V} a_{i,j} x_i \geq 1; \forall j \in V, \quad (2)
\]

\[
x_i \in \{0, 1\} \forall i \in V. \quad (3)
\]

The objective function shown in equation (1) [19], which represents the number of stations installed, is minimized in this model. Constraint (2) establishes the coverage radius for the accessibility of EVs’ users. The constraints conditions shown in equation (3) indicate the binary restraints on \( x \) variables. The \( M_1 \) model minimizes the total number of installed stations. It refers to minimize the total numbers of charging station in the proposed area. Based on set covering combinatorial optimization models [36], the \( M_1 \) model is useful when the cost of installation is fixed from one station to the next. For example, under normal service operation of the station network, the charger cost is somehow low relative to the opening cost. We add \( f_i (i \in V) \) a size-independent cost of opening a charging station at each possible location \( i \) to account for the infrastructure opening cost. It is the cost of converting a gas station into EV compatible lot, specifically
Table 1: Attributes of a potential location for EVCS (Google Map) [19].

<table>
<thead>
<tr>
<th>Indices (i)</th>
<th>Type</th>
<th>Names</th>
<th>Coordinates</th>
<th>Capacity ($c_i$)</th>
<th>Opening cost ($f_i$) $</th>
<th>$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gas station</td>
<td>Oguchitoyota</td>
<td>35.322687, 136.888781</td>
<td>16</td>
<td>2210</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Gas station</td>
<td>Toho</td>
<td>35.292428, 136.909384</td>
<td>14</td>
<td>2170</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Gas station</td>
<td>Jeieesuesu</td>
<td>35.284581, 136.806338</td>
<td>12</td>
<td>1990</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Gas station</td>
<td>Consulate</td>
<td>35.189240, 136.892905</td>
<td>17</td>
<td>2150</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Gas station</td>
<td>Meihokogyo</td>
<td>35.189240, 136.886038</td>
<td>12</td>
<td>2205</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Gas station</td>
<td>Daiko</td>
<td>35.133104, 136.916251</td>
<td>17</td>
<td>1912</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Gas station</td>
<td>Yuni</td>
<td>35.0842, 137.008261</td>
<td>13</td>
<td>1890</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Gas station</td>
<td>Kondosh</td>
<td>35.112885, 137.131858</td>
<td>11</td>
<td>2150</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Gas station</td>
<td>Idemitsu</td>
<td>35.062318, 137.148337</td>
<td>16</td>
<td>2090</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Gas station</td>
<td>Uny 1</td>
<td>34.992595, 136.850333</td>
<td>15</td>
<td>2170</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Gas station</td>
<td>Uny 2</td>
<td>34.909300, 136.829734</td>
<td>12</td>
<td>1930</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Gas station</td>
<td>Centrair</td>
<td>34.885647, 136.811881</td>
<td>14</td>
<td>2010</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Gas station</td>
<td>Uny 3</td>
<td>34.893532, 136.909384</td>
<td>11</td>
<td>2075</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Gas station</td>
<td>Utsumi</td>
<td>34.762766, 136.866812</td>
<td>14</td>
<td>2113</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Gas station</td>
<td>Eneos</td>
<td>34.875618, 137.048192</td>
<td>19</td>
<td>2203</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Gas station</td>
<td>Casyal</td>
<td>34.865367, 137.321372</td>
<td>18</td>
<td>2119</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>Gas station</td>
<td>Solato</td>
<td>34.865367, 137.321372</td>
<td>11</td>
<td>1999</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>Gas station</td>
<td>Shitara</td>
<td>35.121872, 137.572684</td>
<td>12</td>
<td>1901</td>
<td></td>
</tr>
</tbody>
</table>
the accommodation capacity for all the possible locations is fixed, the size-dependent costs are constant, and then the model is focused on minimizing only the opening costs. As a result, the model $M_2$ is formulated as follows:

$$M_2 : \text{Minimize } \sum_{i \in V} f_i x_i,$$  \hspace{1cm} (4)

Subject to:

$$\sum_{i \in V} a_{i,j} x_i \geq 1; \forall j \in V,$$  \hspace{1cm} (5)

$$x_i \in \{0, 1\} \forall i \in V.$$  \hspace{1cm} (6)

The objective function (4) reduces and minimizes the overall cost of all installed stations to the lowest possible value as investigated in [52]. Constraint (5) states that a minimum of 1 station on a radius R is installed for every location $j$ (location $j$ included), and constraint (6) expresses the variable nature.

2.3.2. ILP Models Considering Both Locations and Sizing.

The focus of the second ILP model is to develop suitable station sizes, in addition to identifying charging station locations. To begin, we assign the following numbers to individual feasible location $i \in V$, (i) a capacity $c_i$, which represents the maximum chargers numbers that may be installed concerning the location station capacity, (ii) price per unit for installing a charger, represented by $u_i$, and (iii) finally, a demand $m_i$ that represents the number of EVs that can use the location $i$. The maximum number of EVs served by a charger is introduced $\emptyset$, and its formulation is shown in equation (7) [19].

$$\emptyset = \lambda \ast s'.$$  \hspace{1cm} (7)

In the abovementioned relation, where $\lambda$ implies the service rate or the number of EVs that could be charged in one hour, and $s'$ represents the entire charger service time. The service rate is firstly introduced in the review study [53]. Every location $i \in V$ might be considered a possible construction place for charging stations as well as the centroid of territory for EVs’ drivers. Here, two new decision variables are also introduced. Defining every location $(i \in V)$ as a non-negative integer variable $n_i$ that denotes the number of total chargers installed in each location $i$. Defining a binary variable $y_{i,j}$, which is set to 1 if the EV from $ith$ location $i$ are charged at $jth$ location. As a result, the third ILP model $M_3$ is as follows:

$$M_3 : \text{minimize } \sum_{i \in V} f_i x_i + u_i n_i,$$  \hspace{1cm} (8)

Subject to:

$$\sum_{i \in V} y_{i,j} = 1; \forall j \in V,$$  \hspace{1cm} (9)

$$x_i \geq y_{i,j}; \forall i, j \in V,$$  \hspace{1cm} (10)

$$x_i \leq n_i \leq c_i x_i; \forall i \in V,$$  \hspace{1cm} (11)

$$\sum_{i \in V} m_i y_{i,j} \leq n_j \emptyset; \forall j \in V,$$  \hspace{1cm} (12)

$$d_{i,j} Y_{i,j} \leq R; \forall i, j \in V,$$  \hspace{1cm} (13)

$$x_i \in \{0, 1\}; \forall i \in V,$$  \hspace{1cm} (14)

$$n_i \in \mathbb{N}; \forall i \in V,$$  \hspace{1cm} (15)

$$Y_{i,j} \in \{0, 1\}; \forall i, j \in V.$$  \hspace{1cm} (16)

The objective function is shown in (8) for the $M_3$ model that aims to optimize (minimize) charger installation and capital costs. Constraint (9) requires that all EVs be assigned
to a specific EVCS. Constraint (10) defines that EVs can only be charged in location \( j \in V \) if this site is chosen for accommodating a charging station. Constraint (11) stipulates that for the chosen station, a minimum one charger must be installed, with the total number of chargers not exceeding the station’s capacity. If a station is not specified within it, no chargers are deployed. Constraint (12) requires that all EV owners who prefer charging their vehicles at a selected location should be less than the number of available service chargers. Constraint (13) denotes that the EV task from a selected position \( (i \in V) \) to location \( (j \in V) \) is feasible if only the provided distance between stations is less than the tolerance radius. Lastly, (14) and (15) show the integrality constraints and constraint (16) are the non-negative integer variables \( n \).

Therefore, the main focus is to minimize the charging infrastructure installation costs. Following that, it is also essential to consider the access cost. More specifically, the travel cost was also included since EVs owners can drive from one location to another to find a suitable charging facility for their vehicles. Zhu et al. (2016) first suggested this aspect in their analysis of a 60-km² Beijing metropolitan region because the charging station is far from the user’s workplace [49]. They believe that EV drivers may walk and take a cab or bus to get from one location to other. In our study, we consider only walking to get into the possible charging station. Indeed, EV users are unlikely to take a cab or bus from their destinations to the charging station. The estimated cost of each walked kilometer is denoted by \( \phi \), the walking cost, which is determined in equation (17) as investigated in [52]

\[
\phi = \frac{W^h}{W^s},
\] (17)

where \( W^s \) is the average walking speed and \( W^h \) is the average hourly wage of an EV owner. As a result, model \( M_4 \) is as follows:

\[
M_4 \text{ minimize } \omega_1 \sum_{i \in V} u_i n_i + \omega_2 \phi \sum_{i \in V} m_i \sum_{j \in V} d_{i,j} Y_{i,j},
\] (18)

Subject to:

\[
\sum_{i \in V} Y_{i,j} = 1; \forall j \in V,
\]

\[
x_j \geq Y_{i,j}; \forall i, j \in V,
\]

\[
x_i \leq n_i \leq c_i x_i; \forall i \in V,
\]

\[
\sum_{i \in V} m_i y_{i,j} \leq n_j \phi; \forall j \in V,
\]

\[
d_{i,j} Y_{i,j} \leq R; \forall i, j \in V,
\]

\[
x_i \in [0, 1]; \forall i \in V,
\]

\[
n_i \in \mathbb{N}; \forall i \in V,
\]

\[
Y_{i,j} \in [0, 1]; \forall i, j \in V,
\]

where \( \omega_1 \) and \( \omega_2 \) are non-negative weights. The objective (18) is to minimize the total weighted costs. The remaining equations are the same as the previous model (\( M_3 \)). Each user’s preferences for station installation and access cost are reflected in the weights assigned to each station. Therefore, we suggest that the preceding model can be improved by including the total construction costs of a station. Finally, the model \( M_5 \) is introduced.

\[
M_5 \text{ minimize } \omega_1 \sum_{i \in V} (f_j x_j + u_i n_i) \omega_2 \sum_{i \in V} m_i \sum_{j \in V} d_{i,j} Y_{i,j},
\]

Subject to:

\[
\sum_{i \in V} Y_{i,j} = 1; \forall j \in V,
\]

\[
x_j \geq Y_{i,j}; \forall i, j \in V,
\]

\[
x_i \leq n_i \leq c_i x_i; \forall i \in V,
\]

\[
\sum_{i \in V} m_i y_{i,j} \leq n_j \phi; \forall j \in V,
\]

\[
d_{i,j} Y_{i,j} \leq R; \forall i, j \in V,
\]

\[
x_i \in [0, 1]; \forall i \in V,
\]

\[
n_i \in \mathbb{N}; \forall i \in V,
\]

\[
Y_{i,j} \in [0, 1]; \forall i, j \in V,
\]

As in [54], model \( M_5 \) corresponds to model \( M_4 \) as a particular case under the condition where \( \omega_1 = 1 \) and \( \omega_2 = 0 \).

3. Numerical Experiments

After presenting the case study, the results for the base and recommended models are discussed and compared. After that, an experimental and comprehensive sensitivity analysis of the proposed ILP models was carried out to determine the sensitivity of the model to various cost components and also to other variables. This experiment was conducted on Intel Core i5-8400 CPU@2.80 GHz (6CPUs) desktop with 12 GB RAM. The optimization programming language (OPL) was used to code the five ILP models, and the general MIP solver (IBM Cplex, version 12.6) was used to solve them. It is worth noting that all of the models found an optimal location in less than 30 seconds of the CPU time.

3.1. Parameters Setting. Using the following experiment, the cost of the deployed charger is assumed to be constant and not dependent on the installation location. As per the previous studies, \( u_i (i \in V) \) is used as 56,000 [52, 55]. The charging demand is expected to be uniformly distributed between each charging station. Therefore, \( m_i (i \in V) \) is considered fixed at 13 based on [49]. Equation (7) specifies a charger service rate of 3 EVs for a unit hour and a charger’s service duration of 12 hours during a day. The average hourly wage \( W^h \) is $17/hour. It is calculated by dividing the mean monthly wage ($3000) of an EV owner by accumulated worked hours in a month. An average walking speed is assumed to be 5 km/h [52, 56]. For \( M_4 \) and \( M_5 \), models equal emphasis is placed for the station and user access costs by setting out the \( \omega_1 = \omega_2 = 0.5 \).
3.2. Sensitivity Analysis

3.2.1. Coverage Radius Impact. We focused on the coverage radius (R) to investigate its impact and variation on the deployment of the optimal infrastructure for each ILP model’s output. The tolerable distance R range is computed and ranged between 0 and 16 km. Table 3 represents the models $M_1$ and $M_2$ which simply outputs only location decisions. The tables show the numbers of charging stations and corresponding opening costs. The number of charging stations and numbers of the charger are 5 and 16, respectively. However, based on model $M_4$, which does not include the station opening costs, 10 stations should be chosen for nearly half the cost of those shown by model $M_1$. The number of chargers are same for models $M_3$, $M_4$, and $M_5$ because the charging demand is uniformly distributed. Moreover, in model $M_5$, the high price is attributable to the user’s access cost. The evolution of models $M_3$, $M_4$, and $M_5$ outputs is shown in Figures 4–6.

Table 3: The impact of the coverage radius on the results of models $M_1$ and $M_2$.

<table>
<thead>
<tr>
<th>R (km)</th>
<th>Number of stations</th>
<th>Cost ($)</th>
<th>Number of stations</th>
<th>Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>18</td>
<td>37,287</td>
<td>18</td>
<td>37,287</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>37,287</td>
<td>18</td>
<td>37,287</td>
</tr>
<tr>
<td>4</td>
<td>17</td>
<td>35,277</td>
<td>17</td>
<td>35,277</td>
</tr>
<tr>
<td>6</td>
<td>17</td>
<td>35,277</td>
<td>17</td>
<td>35,277</td>
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<tr>
<td>8</td>
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<td>20,836</td>
<td>10</td>
<td>20,436</td>
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<tr>
<td>10</td>
<td>9</td>
<td>18,666</td>
<td>9</td>
<td>18,028</td>
</tr>
<tr>
<td>12</td>
<td>7</td>
<td>14,440</td>
<td>7</td>
<td>14,025</td>
</tr>
<tr>
<td>14</td>
<td>7</td>
<td>14,180</td>
<td>7</td>
<td>13,825</td>
</tr>
<tr>
<td>16</td>
<td>6</td>
<td>11,887</td>
<td>6</td>
<td>11,767</td>
</tr>
</tbody>
</table>

Figure 3: Models $M_1$ and $M_2$ output variation.

3.2.2. Impact of Charging Time. EVs fast charging technology is transforming speedily, and the current study aims to investigate the impact of charging time change on the deployed EVCS. Table 5 shows the model results for the charging time evolution and the service rate $\lambda$ of the charger. It is worth mentioning that the prolonged charging time increases the number of chargers; as a result, increasing installation costs, which is also dependable on the number of total chargers. The 5 EVCS can be installed for $M_1$ and $M_4$, which demonstrates that the suggested models continue to use a similar EVCS placement. Even as technology progresses and decreases charging times, the established EV charging scheme remain effective.
3.2.3. Effect of the EV Charger Cost. To begin, let us look at how the model’s outputs fluctuate as the unit cost of the EV’s charger is increased in the range ($42000 to $70000) with an increase of 5%. Table 6 shows the numerical results. Increasing the unit cost of EV chargers, unsurprisingly, increases the proposed models’ objective costs. Following Tables 3 and 4 demonstrate that each model’s outputs, both in terms of the total number of stations and chargers to be installed, are unaffected by the model.

3.2.4. The Proposed EV Charging Networks. Now, we have come up with a solution for a suitable EV charging infrastructure deployment. The proposed installation
techniques for each ILP model are shown in Figures 7–11. Figure 7 shows the first network only considered minimizing the EVCS numbers. Figure 8 is constructed to consider the only opening cost of EVCS. Furthermore, when solely the investor’s convenience is regarded, the framework shown in Figure 9 should be constructed. The network depicted in Figure 10 should thus be established when the convenience of users and investors is equally important, but the station opening costs are not taken into account, like in the case of [49]. Figure 11 depicts the most appropriate EVCS deployment, considering actual station installation costs and EV users’ access costs. As a result, the convenience of both investors and EV owners is considered equally. We strongly endorse these proposed locations for EVCS placement in the proposed prefecture to avoid squandering private and public resources while maintaining a suitable service level for EV users. Several previous studies have been focused on EVCS in existing parking lots, fuel stations with different aspects, such as minimizing the total cost [49, 57], minimizing access cost [50], EV charging demand [26], minimizing trips [58], and minimizing the total system cost [52]. So far, the overall

![Figure 6: Model M5 output variation.](image)

### Table 5: Effect of the charging time on M₃, M₄, and M₅ model outputs.

<table>
<thead>
<tr>
<th>Charging time ( u )</th>
<th>( \lambda )</th>
<th>Number of stations</th>
<th>Number of chargers</th>
<th>Model M₃ Cost $</th>
<th>Number of stations</th>
<th>Number of chargers</th>
<th>Model M₄ Cost $</th>
<th>Number of stations</th>
<th>Number of chargers</th>
<th>Model M₅ Cost $</th>
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<td>5</td>
<td>290,162</td>
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<td>5</td>
<td>146,483</td>
<td>5</td>
<td>5</td>
<td>2,728,154</td>
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<tr>
<td>10</td>
<td>6</td>
<td>5</td>
<td>8</td>
<td>458,162</td>
<td>6</td>
<td>8</td>
<td>229,597</td>
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<td>8</td>
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<td>13</td>
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<td>16</td>
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<td>23</td>
<td>650,483</td>
<td>5</td>
<td>23</td>
<td>11,800,154</td>
</tr>
</tbody>
</table>

### Table 6: Effect of the EVs’ charger costs on M₃, M₄, and M₅ model outputs.

<table>
<thead>
<tr>
<th>EVs’ charger costs</th>
<th>Number of stations</th>
<th>Model M₃ Number of chargers</th>
<th>Cost $</th>
<th>Number of stations</th>
<th>Model M₄ Number of chargers</th>
<th>Cost $</th>
<th>Number of stations</th>
<th>Model M₅ Number of chargers</th>
<th>Cost $</th>
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<tr>
<td>42,000</td>
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<td>16</td>
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<td>339,650</td>
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<td>5</td>
<td>16</td>
<td>726,961</td>
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<td>16</td>
<td>362,050</td>
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<td>16</td>
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<td>563,650</td>
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<td>16</td>
<td>10,288,154</td>
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</tbody>
</table>
Figure 7: EVCS locations (model $M_1$).

Figure 8: EVCS locations (model $M_2$).

Figure 9: EVCS locations (Model $M_3$).
The findings of this current study are extremely promising compared to previous studies. The proposed ILP method’s analysis was validated using several experimental designs. Finally, it is proved that the proposed ILP method produced more accurate and precise results within the scope of its intended use. Based on these findings, we conclude that the ILP model is an effective method for accurately solving problems of EVCS. It is beyond the scope of this study to determine how effectively the various approaches described will scale to issues that are very different from the ones analyzed. Nevertheless, the aim of this study is to determine appropriate locations for EV charging stations in Aichi Prefecture, Japan. More precisely, our concern is to ensure that the deployed infrastructure has a tolerable coverage radius. In fact, EV drivers are hesitant to accept a long walk distance from charging stations to their destination. This study provides an optimum infrastructure network that policymakers could adopt within the emerging environmental policy.

4. Conclusion

EVs are one of the potential alternatives to transportation’s environmental and energy concerns. Due to the limited range, insufficient charging station enabling drivers to make long-distance trips is a critical step in promoting their widespread adoption. The deployment of the optimal charging infrastructure is essential for promoting EVs. This study proposes an effective method for locating fast-charging stations. It is based on the optimization technique of integer linear programming. Particularly, we are more concerned with ensuring that the deployed infrastructure has a tolerable coverage radius for the EV owners. On the other hand, drivers are less willing to accept long walking distances from their destinations to charging stations. To achieve this goal, we employed five linear integer programming based on a weighted set covering models. In spite of their apparent ease, the numerical simulations can assist policymakers in determining the locations and sizing of suitable EVCS while lowering investment and consumers’ convenience costs. It is worth noting that this study has some limitations that can be addressed in future research. EV users’ preferences from their home location to other charging spots are treated as a fraction, considering that the decision variables in the current models are treated as a continuous variable. Instead of using the Cartesian distance, the distance matrix could be made more precise by estimating suitable paths between all pairs of possible locations, for example, average paths. Conducting an extensive study on the estimation of EV demand and incorporating consumer behavior, market anticipation, and energy consumption in the proposed study area further consider the impact of EVs’ charger deployment as well as the forecasted number of EVs on the city’s electrical grid.

Data Availability

The data used to support the findings of this study are available on request from the corresponding author.
Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors’ Contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

References


