Optimal Siting and Sizing of Wireless EV Charging Infrastructures Considering Traffic Network and Power Distribution System

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ABSTRACT The main challenges in the widespread deployment of electric vehicles (EVs) are limited driving range, long charging downtime, lack of charging stations in some areas, and high battery cost. Dynamic wireless charging (DWC) technology can overcome some of these obstacles by recharging EV batteries remotely while vehicles move over the charging infrastructures. However, most studies have limited this technology to public EVs working in specific routes like electric buses and taxis routes. This paper presents a long-term stochastic scenario-based mathematical model for allocating and sizing DWC infrastructures considering EV’s location-routing, power distribution system (PDS) losses, and transportation network traffic. The proposed long-term model allows all types of EVs to take advantage of the installed DWC infrastructures and facilitate EVs’ widespread use by overcoming conventional charging technologies problems. The optimization problem is structured in the form of a Mixed Integer Non-Linear Programming (MINLP) model. Simulation results with detailed analyzes are furnished to illustrate the characteristics and performance of the model in a coupled network combining transportation and power networks. The numerical analysis provides meaningful insight into the transportation system design based on DWC technology and the effect of EV routing on the charging infrastructure allocation. Simulation results show that using Location-Routing Problem (LRP) can save up to 45% of the total cost of the DWC system. In addition, the proposed model, along with the simulations performed, demonstrates the advantage of DWC technology in reducing the size of vehicle batteries.

INDEX TERMS Electrical vehicles (EVs), wireless power transfer (WPT), dynamic wireless charging (DWC), location-routing problem (LRP), energy management.

 NOMENCLATURE
The main symbols and notations used in this paper for quick reference are defined as follows:

A. Sets

| Symbol  | Description                                                                 |
|---------|-----------------------------------------------------------------------------|
| C       | Set of wireless charging EV fleets collection.                              |
| Dc      | Set of travel destination of EVs in fleets collection c.                    |
| F       | Set of wireless charging EV fleets.                                         |
| I       | Set of nodes of the transportation system.                                 |
| N       | Set of buses belonging the PDS.                                            |
| Oc      | Set of travel origin of EVs in fleets collection c.                         |
| R       | Set of lines in the PDS.                                                   |
| S       | Set of all scenarios.                                                      |
| Smax    | Upper limit of battery level of EV in fleet f and fleets collection c.      |

B. Parameters

| Symbol  | Description                                                                 |
|---------|-----------------------------------------------------------------------------|
| cpi     | Consumer price index.                                                       |
| dPq     | Distance between node p and node q of transportation system [km].           |
| ecf     | Upper limit of battery level of EV in fleet f and fleets collection c.      |
| EVcf    | EV in fleet f and fleets collection c.                                       |

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\( \tau \) Energy consumed of EV travel [kWh/km].

\( l_{\text{max}} \) Maximum level of current at PDS lines [A].

\( f_{\text{max}} / f_{\text{min}} \) Maximum/minimum length of power track for line \( pq \) [km].

\( m_f \) Maintenance cost of each unit of DWC infrastructure [$].

\( \sigma \) Cost of EVs routing at transportation network [$].

\( n_f \) Number of EVs in fleet \( f \).

\( \rho \) Travel cost of EV in fleet \( f \) and fleets collection \( c \) [$/km].

\( \rho \) Fixed installation cost of each DWC unit infrastructure [$].

\( P_{\text{gmax}} \) Maximum active power generated at PDS lines [kW].

\( \rho \) Charging energy/unit length of power track [kWh/km].

\( \rho \) Travel cost of EV in fleet \( f \) and fleets collection \( c \) [$/km].

\( \rho \) variable installation cost of one meter of DWC infrastructure [$].

\( r_{gh} \) Resistance of line \( g-h \) in PDS [\( \Omega \)].

\( \gamma \) Cost of EVs routing at transportation network [$].

\( \rho \) EV travel time on DWC infrastructure installed in the \( pq \) path [h].

\( v_{\text{max}} / v_{\text{min}} \) Maximum/minimum voltage at PDS nodes [V].

\( x_{gh} \) Reactance of line \( g-h \) in PDS [\( \Omega \)].

\( \delta_{pq} \) Traffic restrictions on the \( pq \) route [EV/min].

\( e_{u} / e_{l} \) Maximum/minimum allowable battery charge level.

\( \eta \) Number of years to convert to future value.

\( \xi_1 \) Weighting factor for total battery cost.

\( \xi_2 \) Weighting factor for DWC installation cost.

\( \xi_3 \) Weighting factor for EV routing cost.

\( \xi_4 \) Weighting factor for electrical energy losses cost.

\( \rho^{s} \) Probability of occurrence of \( s^{th} \) scenario.

\( \sigma^{cf} \) Percentage of EV battery level in fleet \( f \) and fleets collection \( c \) at the destination.

\( \tau_{cf}^{e} \) Percentage of EV battery level in fleet \( f \) and fleets collection \( c \) at the origin in the \( s^{th} \) scenario.

\( \beta \) Cost of batteries used in EVs [$].

\( \gamma \) Cost of wireless infrastructure installation [$].

\( \alpha \) Cost of EVs routing at transportation network [$].

\( \lambda \) Cost of electrical energy losses at PDS [$].

\( l_{pq} \) Length of the power track installed in the path starting from node \( p \) and ending in node \( q \) [km].

\( P_{gh} \) Active power in line \( gh \) of PDS [kW].

\( P_{gh} \) Active power generated at node \( h \) of PDS [kW].

\( Q_{gh} \) Reactive power in line \( gh \) of PDS [kVar].

\( Q_{gh} \) Reactive power generated at node \( h \) of PDS [kVar].

\( s_{c}^{cf} \) Maximum energy that EV in fleet \( f \) and fleets collection \( c \) can receive while moving over DWC between nodes \( q \) and \( p \) in \( s^{th} \) scenario [kWh].

\( v_{h} \) Voltage at node \( h \) of PDS [V].

\( y_{pq} \) Binary decision variable (1 if DWC is installed in the path from node \( p \) to node \( q \); otherwise, 0).

\( \alpha \) Cost of batteries used in EVs [$].

\( \beta \) Cost of wireless infrastructure installation [$].

\( \gamma \) Cost of EVs routing at transportation network [$].

\( \lambda \) Cost of electrical energy losses at PDS [$].

I. INTRODUCTION

Electrical vehicles (EVs) are promising solutions to resolve environmental problems and improve economic efficiency. Conventional EVs are charged by plugging their onboard energy storage systems like batteries into the grid. However, plug-in EVs have significant drawbacks such as limited travel ranges, high battery cost, large and heavy batteries, long recharging time, and limited charging station availability. These problems have limited the widespread usage of EVs in private and public transportation [1]. A potential solution is to perform EV charging while the vehicle is moving using the Wireless Power Transfer (WPT) technology [2].

By wirelessly charging a prototype of aircraft, William Brown demonstrated the feasibility of microwave power transfer in 1964 [3]. Also, Peter Glaser suggested a solar-powered satellite as a new idea for microwave power transfer in 1968 [4]. Researchers at MIT could wirelessly transfer 60W of power over a 2-m distance in 1964 [5]. In 2009, the feasibility of dynamic wireless power transfer in a practical system was validated by researchers at the Advanced Institute of Science and Technology in South Korea. The U-type power supply rails and I-type pickup coils have been employed, and the maximum output power of 60 kW with an efficiency of 72% has been recorded. This system was successfully established in Gumi, South Korea, to supply electric buses in the 48-km route with 83% efficiency and a 20cm transferring air gap [6]. In 2013, using a pickup coil attached to the EV chassis and a series of power tracks with circular coils buried underground, the Oak Ridge National Laboratory in the USA built a DWC system. In the USA, the Oak Ridge National Laboratory constructed a DWC system that achieved 2.2KW of transmission power.
with 74% efficiency [7]. Moreover, considerable investigation on DWC has recently proved the technical feasibility of this charging technology [8]. Researchers have also examined the development in the commercialization of DWC [9].

There are three types of WPT-based wireless charging: stationary, quasi-dynamic, and dynamic [10]. Stationary wireless charging is carried out while the EV is parked for a long time in a fixed point such as a garage or a parking lot. Quasi-dynamic wireless charging is done when EV is in motion at a low speed. It is usually used when the EV exits or returns to the starting point (such as parking). The more advanced version of WPT is Dynamic Wireless Charging (DWC, also referred to as road-way-charging or in-motion charging EV) that can perform charging while EVs are in full motion. In the DWC system, electrical energy from a primary power supply unit called a power track embedded below the road is remotely transferred to a secondary pickup unit installed under the EV. Since DWC process does not require physical contact and can charge EVs on the move, the charging downtime can be significantly reduced. In addition, the driving range of the EV is increased by the proper design of charging facilities, and the size and price of the battery are reduced. DWC can also improve the performance and increase the life cycle of some EV batteries such as lithium batteries by designing frequent and shallow charging instead of the usual deep charging [11]. To investigate the economic viability of the dynamic charging system, authors in [12] examine the cost of utilizing a dynamic charging system on the bus lane in Zuidtangent, Netherlands, where the dynamic charging power level is 200 kW, and the average speed of each bus is 38 km/h. Researchers in [13] and [14], based on dynamic vehicle models and the real-world GPS-stamped operating information, have examined the economic feasibility of DWC technology in the United States. The payback period as the time needed for the overall savings of a dynamic charging EV system compared to the conventional internal combustion engine vehicles is presented to cover the initial investment cost in [13] and [14]. The outcomes indicate that with a 25% penetration grade of DWC infrastructures, the payback time is 11.3 years. The comparison analysis between the stationary and dynamic charging systems is developed in [15]. This paper demonstrates if the stationary power transfer system is installed in an actual road map in Gumi City, each electric bus will require a battery of 100 kWh or larger, which is twice the amount of battery capacity required in a dynamic WPT system. This study also shows that the total cost of the stationary WPT system is $11.84 million, which is 26.2% larger than that of the dynamic WPT system. Therefore, DWC technologies are an economically viable alternative to other EV charging strategies. A cost analysis is proposed in [16] that demonstrates the economic viability of DWC of EVs in South Korea in comparison with the three other existing vehicles, including plug-in hybrid EVs, pure EVs, and internal combustion engine vehicles. The results of [16] indicate the cost comparison of these systems working for ten years. If the number of vehicles is 0.5 million, the overall costs of plug-in hybrid EVs, pure EVs, and internal combustion engine vehicles are $27.4 billion, $46.8 billion, and $23.5 billion, respectively. By employing DWC EVs, this cost will be $15.0 billion, which shows the economic viability of DWC.

Many universities and research institutes are currently developing and commercializing EV wireless charging systems. The works done can be divided into two categories: experimental and operational projects and research papers. The Partners for Advanced Transit and Highways project was the first prototype of the wireless charging EV. This prototype with wireless power transmission capacity of 60 kW and operating induction power transmission frequencies of 400 and 8500 Hz achieved an efficiency of 60% at distance of 2-3 inches [11]. The first commercialized DWC- EV is the On-Line Electric Vehicle (OLEV) built by KAIST [17]. Utah State University is home to the Sustainable Electricified Transportation Center, a research consortium of five partner universities and five associated institutions in the United States working on a prototype DWC [18]. In addition, PRIMOVE, Bombardier Transport’s electronic research unit, has tested and deployed DWC for buses in many European cities, including Mannheim and Berlin in Germany and Bruges in Belgium [19]. DWC-based bus systems have also been examined in Utrecht, the Netherlands, and Torino, Italy [20]. The use of wireless charging technology to expand the driving range of electric vehicles has been investigated in [21]. In this paper, assuming that the charging infrastructure’s location is optimally selected, a standard general driving cycle is applied to estimate the cost of the charging infrastructure. In [22] the extension of EVs driving range under a standard highway driving cycle (with different DWC infrastructure coverage from 10% to 100% of the highway and with the charging rate between 10 and 60 kW) have been studied. In [23], a passenger EV with DWC capability and equipped with a 24 kWh battery on different traffic flow (intensity and speed) and varying traffic road scenarios (motorway, highway, and urban stretch) has been evaluated. The supporting systems models in operations of DWC EVs are also described in [2].

Charging facilities allocation is one of the most critical topics in studying systems and applications of conventional EV charging, such as plug-in or swap charging technology [24]. However, this topic is more important in wireless EV charging strategies because choosing power tracks length and location can highly affect the efficiency and performance of the system. Since the length of the charging infrastructure can also affect the size of the battery which has significant impacts on the overall price of EV, the allocation of charging infrastructure is critical in commercializing wireless-based transportation. The authors in [25] have proposed a model for allocating stationary wireless charging infrastructure to capture the maximum traffic flow on a multi-rout traffic network. This study has used the stochastic user equilibrium principle to describe electric vehicle drivers’ behavior. In [26], an optimization-based method is suggested for allocating charging infrastructure and determining the battery size for...
public transit buses moving in a single route and closed environment.

In addition, the authors of [27] have presented a multi-objective optimization to minimize the total cost of the public transportation batteries, the number of inverters, and the cable length of the wireless charging infrastructure in a multi-route traffic network. To solve this problem and approximate the Pareto front, the authors incorporate the integer and binary interpretations of the Particle Swarm Optimization (PSO) algorithm with a multi-objective arrangement. The OLEV EV bus developed at the KAIST campus is an example of this closed-environment system. Using the assumptions and modeling conditions presented in [26], Jang et al. has divided the route into several small segments and turned the proposed optimization approach into a discrete problem [28].

The relationship between allocating charging infrastructures and EVs routing significantly affects the optimal use of charging facilities. Moreover, using DWC technology, EV charging operation is accomplished while the EV is moving over the charging infrastructure. So it is essential to pay attention to both the location and routing problems in systems based on wireless charging [29]. The location-routing problem (LRP) is a branch of locational analysis research that is distinguished by paying close attention to the underlying issues with vehicle routing. It is well known that routing costs often influence the positioning of supply points, and sub-optimizing the facilities’ location and vehicle routing separately would increase the total investment risks/costs. In DWC technology, location and routing are even more interrelated because, in addition to the planning of charger equipment, their size and capacity will also be affected by their location and distance to other charging infrastructures. Therefore, the strategic decision on the location of the charging facilities should be combined with the tactical vehicle routing plan in an integrated decision-making problem.

One of the earliest formulations of LRP was introduced in [30]. The various types of LRP have been studied for locating plug-in charging stations, including single or multiple depots [29], [31], uncertainty of some parameters [32], and capacities on the vehicle or depots [33], [34]. Nevertheless, the application of this method in wireless charging systems has not received much attention. Most studies based on WPT technology have examined a location problem by considering specific routes for EVs instead of defining a location-routing problem [25], [28], [35]. Researchers have often developed wireless charging technology for the public transport fleet. A fundamental assumption in these studies is that the initial EV SOC is considered to be 100% [13], [36], [37]. Therefore, in these investigations, the uncertainty of the initial EV battery SOC has not been evaluated. Note that the correct choice of the initial EV battery SOC as a starting point in solving the optimization problem is decisive in achieving the optimal solution. In addition, multi-objective optimization is essential in EV charging systems based on WPT technologies due to the trade-off between the vehicle battery capacity and the length of the charging infrastructure [2], [15], [26].

The main contributions of this paper can be summarized as follows:

(i) A location-routing problem is formulated to provide a long-term mathematical model that optimally determines DWC power tracks’ economic sizing and siting, the vehicle’s routing and battery size. (ii) The proposed model accomplished under a stochastic programming framework to properly account for system uncertainties; and (iii) It provides a realistic system modeling approach for developing charging systems based on DWC technology for private and public EVs by considering the bidirectional multi-route traffic network coupled with a power distribution system. The main advantages of the proposed model are:

- The DWC infrastructure has been allocated according to selecting the best routes and analyzing the impact of these facilities on the power distribution system (PDS). The importance of this role becomes more apparent as the number of EVs that use DWC increases.
- It reduces the battery size/weight of the EV and facilitates green transportation by solving an optimization problem and considering the EV routing by reducing battery size/weight. In addition, the use of DWC technology leads to increasing driving range and reducing charging downtime.
- It is a practical system modeling approach for EV DWC by considering multi-route traffic networks with bidirectional routes between the nodes, coupled with a PDS. Also, it is designed not only for public EVs but also for personal EVs with different battery sizes.

The rest of the paper is organized as follows. Section II describes the components of EV DWC system. Section III presents problem description and the proposed stochastic scenario-based framework to allocate the DWC infrastructures. Section IV evaluates the performance of proposed model in a coupled network combining transportation and power networks with small and large dimensions followed by detailed discussion of simulation results. Section V summarizes the outcomes and conclusions.

II. DWC SYSTEM COMPONENT

DWC system components for EVs can be divided into two parts (Fig. 1): power transmission system and power pickup system. The power transmission system is a part of the charging infrastructure that transmits power from the grid to the EV by creating an electromagnetic field. This system consists of a transmission unit that includes cables (power tracks) and a power supply. The power tracks are installed under the road. Using the rectifier, inverter and controllers, the power supply unit transmits power from the grid to the power tracks and from there to the power pickup system. The power pickup system includes the pickup unit and auxiliary units such as regulators and rectifiers. The pickup unit, which is connected to the bottom surface of the EV, receives electrical energy from the power transmission system and transmits it to the battery and motor using auxiliary units.
on plug-in EVs. We use this model to consider the worst case conditions for SOC in our design. The reason is that plug-in EVs lose their battery energy while driving, but EVs equipped with DWC technology have got charged when they are driving over charging tracks and thus, their SOC values would be higher than plug-in EVs. It is notable that the proposed stochastic scenario-based optimization problem is designed to solve from the perspective of a private investor which intend to install cost efficient DWC infrastructures as well as to reduce the size and cost of public EVs battery to convince them to install the wireless charging equipment. The above optimization problem is a multi-objective problem which converts to a single-objective optimization utilizing the weighted-sum approach.

### B. MATHEMATICAL MODEL

A long-term stochastic location-routing optimization framework based on scenarios for the allocation of the wireless charging facilities in a smart city is proposed and formulated in equations (1) - (29). The objective function in (1) seeks to minimize the total cost, including four terms with weighting factors $\xi_1, \xi_2, \xi_3$ and $\xi_4$.

The first term of the objective function, described in (2), is the total battery cost of EVs. It should be noted that the capacity of the EV battery for public buses and taxis is determined by the optimization problem, but a certain value is predetermined for other EVs. The second term of the objective function, defined in (3), is the fixed and variable costs for the construction of DWC infrastructures and their maintenance costs. Fixed costs include costs related to equipping and installing components of the power supply unit such as inverters and rectifiers. In addition, the variable cost is relevant to the power transmission unit, especially the transmission lines buried in the road. The third term of the objective function comprises the expected cost of routing and maintenance costs incurred by the movement of EVs in each scenario in the traffic network.

Minimize: $\xi_1 \cdot \alpha + \xi_2 \cdot \beta + \xi_3 \cdot \gamma + \xi_4 \cdot \lambda$

\begin{equation}
\alpha = \sum_{c \in C} \sum_{f \in F} n_f \cdot P_b \cdot E_{0,c,f} \cdot (1 + cpi)^{y}\n\end{equation}

\begin{equation}
\beta = \sum_{p \in I} \sum_{q \in I} \left[ (p \cdot v \cdot \ell_{p,q}) + (p \cdot f \cdot m) \cdot y_{p,q} \right] \cdot (1 + cpi)^y
\end{equation}

\begin{equation}
\gamma = 8760 \cdot \sum_{s \in S} \sum_{p \in I} \sum_{q \in I} \sum_{c \in C} \sum_{f \in F} (n_f \cdot p_t_{c,f} \cdot d_{q,p} \cdot b_{q,p}) \cdot (1 + m_t_{c,f}) \cdot (1 + cpi)^y
\end{equation}

\begin{equation}
\lambda = 8760 \cdot \sum_{g \in R} n_f \cdot p_e \cdot (r_{g,h})^2 \cdot (1 + cpi)^y
\end{equation}

This term is defined in (4) and shows that moving the EVs on long routes increases the routing and maintenance costs of them, so the existence of this term in the cost function helps to select shorter routes by EVs. Note that the sum of probabilities of all scenarios is equal to 1 ($\sum \rho^s = 1$). The last term of
the objective function, illustrated in (5), determines the cost of increased power losses in the PDS by installing DWC infrastructure. This term prevents the allocation of DWC infrastructure in places that increase the PDS losses. Note that all terms of the objective function are defined along an epoch of one hour and are aggregated by coefficient 8760 for one year. Also, these terms are shifted to a future value by specifying parameter \( \eta \) and the consumer price index \( CPI \).

The optimization constraints associated with EV battery energy, EV movement within the traffic network, PDS operation, and traffic restriction are formulated in equations (6)-(14), (15)-(20), (21)-(28), and (29), respectively.

\[
e^{c,f}_{p,s} = \sum_{q \in \ell} (se^{c,f}_{q,p,s} - h_q d_{q,p} b^{c,f}_{p,q,s}), \quad \forall c \in C, f \in F, p \in I \setminus \{O_c\}, s \in S \quad (6)
\]

\[
se^{c,f}_{q,p,s} = \min \{ (se^{c,f}_{q,p,s} + ps \cdot \eta_{q,p}, (e^{c,f}_{p,s})_\max \}, \quad \forall c \in C, f \in F, p \in I \setminus \{O_c\}, q \in I, s \in S \quad (7)
\]

\[
e^{c,f}_{p,s} + \sum_{q \in \ell} p_f \cdot \eta_{p,q} \cdot b^{c,f}_{p,q,s} \geq \sum_{s' \in S} h_{d,p,q,s'} \cdot b^{c,f}_{p,q,s'}, \quad \forall c \in C, f \in F, p \in I, q \in I, s \in S \quad (8)
\]

\[
\sum_{q \in \ell} E^{c,f}_{p,s} \leq \sum_{q \in \ell} E^{c,f}_{p,s}_{\max}, \quad \forall c \in C, f \in F, p \in I, s \in S \quad (9)
\]

\[
e^{c,f}_{p,s} = \xi^{c,f}_{p,s}, \quad \forall c \in C, f \in F, p \in O_c, s \in S \quad (10)
\]

\[
e^{c,f}_{p,s} \geq \sigma^{c,f}_{p,s} \cdot E^{c,f}_{p,s}, \quad \forall c \in C, f \in F, p \in D_c, s \in S \quad (11)
\]

\[
e^{c,f}_{p,s} \geq 0, \quad \forall c \in C, f \in F, p \in I, q \in I, s \in S \quad (12)
\]

\[
se^{c,f}_{q,p,s} \geq 0, \quad \forall c \in C, f \in F, p \in I, q \in I, s \in S \quad (13)
\]

\[
\sum_{q \in \ell} b^{c,f}_{p,q,s} \leq 1, \quad \forall c \in C, f \in F, p \in I, q \in I, s \in S \quad (14)
\]

\[
\sum_{q \in \ell} b^{c,f}_{p,q,s} \leq 1, \quad \forall c \in C, f \in F, p \in I, q \in I, s \in S \quad (15)
\]

\[
\sum_{q \in \ell} b^{c,f}_{o,p,s} = 1, \quad \forall c \in C, f \in F, o \in O_c, s \in S \quad (16)
\]

\[
\sum_{q \in \ell} b^{c,f}_{d,p,s} = 1, \quad \forall c \in C, f \in F, d \in D_c, s \in S \quad (17)
\]

\[
\sum_{q \in \ell} b^{c,f}_{q,p,s} - \sum_{q \in \ell} b^{c,f}_{q,p,s} = 0, \quad \forall c \in C, f \in F, \quad p \in I \setminus \{D_c, O_c\}, s \in S \quad (18)
\]

\[
b^{c,f}_{p,q,s} + b^{c,f}_{p,q,s} \leq 1, \quad \forall c \in C, f \in F, p \in I, q \in I, s \in S \quad (19)
\]

\[
P_{g,h} - \sum_{h \in R} (P_{h,j} + \sqrt{Q_{h,j}^2 + r_{h,j}^2}) + P_{g,h} - P_{d,h} - \sum_{q \in \ell} (P_{q,p,q} - \sqrt{Q_{q,p,q}^2}) = 0, \quad \forall g \in N, h \in N, j \in N \quad (20)
\]

\[
Q_{g,h} - \sum_{h \in R} (Q_{h,j}^2 + \sqrt{Q_{h,j}^2}) + Q_{g,h} - Q_{d,h}^2 = 0, \quad \forall g \in N, h \in N, j \in N \quad (21)
\]

\[
\sum_{h \in R} (Q_{h,j}^2 + \sqrt{Q_{h,j}^2}) + Q_{h,g} - Q_{d,h}^2 = 2(r_{h,g} \cdot P_{h,g} + x_{h,g} \cdot Q_{h,g}) + \sqrt{Q_{h,g}^2 + r_{h,g}^2} \quad (22)
\]

The optimization constraints associated with EV battery energy and SOC are formulated based on [15], [17] in equations (6)-(14):

- Eq. (6) shows the battery energy of EV in fleet \( f \) and fleets collection \( c \) in the \( s^{th} \) scenario when this vehicle is located at node \( p \). This constraint indicates that the energy stored in EV battery at node \( p \) and in each scenario is equal to the difference between the EV’s energy received in the path from node \( q \) to node \( p \) and the energy consumption of EV to travel from node \( q \) to node \( p \).

- Eq. (7) ensures that the EV does not receive more energy than its maximum capacity when moving over DWC infrastructure in the path between nodes \( p \) and \( q \) during the \( s^{th} \) scenario.

- Eq. (8) guarantees that the EV battery’s energy does not run out while driving until it reaches the DWC facility. In other words, it ensures that the EV does not stop until it gets the DWC infrastructure.

- Eq. (9) specifies the length limit for transmission unit. It also emphasizes that DWC infrastructure can only be installed in the path where its associated decision variable \( y_{pq} \) is equal 1.

- Eq. (10) indicates that the battery energy of each EV during travel must be between the upper and lower limits.

- Eqs. (11) and (12) show the EV battery’s initial energy at the start of the travel and the amount of power remaining in the EV battery at the end of the trip in each scenario, respectively.

- Eqs. (13) and (14) emphasize that the EV energy at each node and the maximum EV energy received at each traffic network path in all scenarios must be a non-negative value.

Optimization constraints associated with the EV movement within the traffic network are formulated based on [31] and [33] in Eqs. (15)-(20):

- Eqs. (15) and (16) state that each EV in \( s^{th} \) scenario can arrive at each node from a maximum of one route and exit that node from only one path.

- The logical constraints that indicate the beginning and end of the journey for all EVs are given in (17) and (18).

- Eqs. (19) and (20) guarantee the continuity of movement of each EV during the travel from origin to destination.

Optimization constraints associated with the operation of PDS are formulated based on [2] and [40] in Eqs. (21)-(28):
Eqs. (21) and (22) impose the balance of active and reactive power in all nodes of the PDS systems, respectively.

Eqs. (23) and (24) determine the bus voltage and the line currents of the PDS, respectively.

Eqs. (25) to (27) ensure that the bus voltages, line currents, and the power generations remain within acceptable limits.

The binary decision variables are shown in (28).

Finally, the traffic restriction for each route of the traffic network is applied by Eq. (29) [2].

C. SOLUTION METHODOLOGY

In this paper, the scenario-based optimization method has been developed to optimal siting and sizing of dynamic wireless EV charging infrastructures considering traffic network and power distribution system. The first stage in the scenario-based optimization strategy is the scenario generation. This generation procedure, founded on the roulette wheel mechanism and the Monte Carlo sampling [41], [42], is illustrated as follows:

Given the expected accuracy [40], the PDF of the initial battery SOC (shown in Fig. 2) is discretized into distinct sections with the center of zero (depicted in Fig. 3). In addition, the area relevant to each section illustrates the probability of such forecast error. Note that the discretized PDF of EV’s initial battery SOC forecast error is characterized in Fig. 3, and each section is described with a certain probability represented by $\lambda_k$. In the second step, the probabilities related to the PDF sections are normalized so that their summation becomes identical to unity. As shown in Fig. 4, each section is related to an accumulated normalized probability of EV’s initial battery SOC forecast error. Consequently, each scenario includes a vector of binary parameters identifying the initial battery SOC forecast error [41], [42]:

$$\left[\tau^1, \tau^2, \tau^3, \ldots, \tau^C \right]_{1 \times (|C| \cdot |F|)} \quad (30)$$

The scenario-reduction methods achieve practicability and tractability while preserving an accurate expression of uncertain EV’s initial battery SOC behavior. Therefore, the reduced scenario set is produced by removing those scenarios with a very low probability of happening or many similarities with other scenarios. In this paper, an efficient backward scenario reduction method using the GAMS/SCENRED library is utilized. The scenario reduction algorithm first selects the generated scenarios; then, a new probability is appointed to each maintained scenario. These latest probability should be chosen such that the reduced probability estimate ($\gamma'$) is the nearest to the original measure ($\gamma$) in terms of probability difference between $\gamma$ and $\gamma'$ [42], [43]. Detailed definitions of the GAMS/SCENRED library and backward scenario reduction techniques can be found in [42] and [44].

In addition, we implement our model using the General Algebraic Modeling System (GAMS) environment (GAMS Development Corporation 2018). All the cases are run on a desktop PC, 64-bit Windows operating system, with an Intel Core i7 @ 3.3 GHz processor and 8 GB of RAM. Due to nonlinearity and the existence of integer and continuous variables in the equations, the suggested mathematical model is a mixed-integer non-linear programming (MINLP), and to solve this long-term model, the Branch-And-Reduce Optimization Navigator (BARON) solver is employed in GAMS that is designed to find globally optimal solutions for non-convex optimization model types. While conventional NLP and MINLP algorithms are guaranteed to converge only under certain convexity assumptions, BARON executes deterministic global optimization algorithms of the branch-and-bound category that are secured to furnish global optima under fairly general assumptions [45].

IV. PERFORMANCE EVALUATION OF THE PROPOSED STOCHASTIC MODEL IN COUPLED TRAFFIC AND POWER NETWORK

The performance of the proposed stochastic scenario-based model is evaluated by implementing it in the following networks:

- Case A: The Nguyen-Dupuis 13 node traffic network [27] coupled with the IEEE 13 node test feeder [33] (Fig. 5).
- Case B: The Sioux-Falls 23 node traffic network [32] coupled with the IEEE 34 node test feeder [33] (Fig. 7).
In each case, based on statistical data from the past several years, the most used origins and destinations are selected. Also, several collections of various EV fleets travel between origins and destinations are predicted [46].

### A. NGUYEN-DUPUIS 13 NODE TRAFFIC NETWORK COUPLED WITH IEEE 13 NODE TEST FEEDER

The Nguyen-Dupuis traffic network consists of 38 directed paths and 13 nodes as shown in Fig. 5 [47]. The distance between the nodes (link length) is shown in Fig. 5. Other specifications of this traffic network can be found in [47]. The coupled power distribution system is the IEEE 13 node test feeder, with 13 nodes and 12 lines. The IEEE 13 Node Test Feeder distribution system’s information is presented in [33]. Also, the base values of the system are 1000 kVA and 4.16 kV. It is assumed that based on statistical data from the past several years, two EV fleet collections travel between two sets of origin-destination. The first EV fleet collection starts its travel from node 0 in the traffic network and ends at node 1. In other words, the intended origin-destination for this fleet is 0-1. The second EV fleet collection travels along origin-destination 7-8. Moreover, each EV fleet collection has five vehicles including an electric bus fleet, an electric taxi fleet, and three EV fleets with battery capacities of 4.4 kWh (similar to Toyota Prius), 16 kWh (similar to Chevy Volt and Mitsubishi iMiEV), and 30 kWh (similar to Nissan Leaf), respectively. It should be noted that each fleet consists of 100 EVs. It is also assumed that one kWh supports an EV traveling for five km [47].

Parameter $m_f$, which determines the maintenance cost of each unit of DWC infrastructure, is about 10% of the total fixed and variable costs of construction of DWC infrastructure. According to the report of the U.S. Department of Energy, the average travel cost ($pt_{cf}$) per 100 km of an EV is $2.438 while the average maintenance cost ($mt_{cf}$) per 5000 km of travel is $85. Also, the power losses cost applied in all cases is 4.34 Cents per kWh [30], [32]. To shift the cost to future value, CPI is considered at 5.2%. In addition, the charging rate of each wireless charging infrastructure ($p_s$) is 0.05 kWh/meter [46]. The other parameters to solve the proposed model are shown in Table 1.

To consider the uncertainty of the EV battery level at the origin (i.e., the initial SOC%), we have generated 4525 scenarios and reduced them to 10 scenarios using a backward method. Details of this method are available in [48]. Also, parameter $\sigma_{cf}$ for all EVs is assumed to be 10% of their battery size. To evaluate the proposed method from various aspects, we have simulated and analyzed three different studies for Case A.

#### 1) CASE A (STUD 1)

In the first study, each of the two fleet collections is set to have two fleets of public EVs (buses and electric taxis) and three fleets of personal EVs with battery sizes of 4.4 kWh, 16 kWh, and 30 kWh, respectively. In the first step, to illustrate the importance of using routing to solve the DWC infrastructure location problem, we have solved the location problem for all the routes that an EV fleet can travel from node 7 to node 8. The results are shown in Table 2. It shows that the use of different paths can significantly impact the number and length of power tracks, and battery size. For example, when the vehicle moves from the first route, only one DWC infrastructure with a length of 28m is needed in the path (5-4), while if the vehicle uses the last route, four DWC infrastructures with the total lengths of 84m required in the paths (1-10), (10-2), (2-12), (12-8), respectively.

In addition, the total cost, which is calculated for the mentioned routes are 386302.65$, 441563.44$, 448453.42$, 425462.09$, and 563068.94$, respectively. For instance, using the first route instead of the fourth route can save more than 45% of the total cost. It emphasizes the importance of

#### TABLE 1. Parameters used in case A.

| Parameter       | Value | Parameter       | Value |
|-----------------|-------|-----------------|-------|
| $\eta_f$        | 0.35  | $p_v$ ($$/m$$)  | 40    |
| $\epsilon_f$    | 0.35  | $p_f$ ($$/unit$$) | 3000 |
| $\eta_s$        | 0.2   | $l_{\text{max}}$ (m) | 110  |
| $\epsilon_s$    | 0.1   | $l_{\text{min}}$ (m) | 10   |
| $p_b$ ($$/kWh$$) | 100   | $\epsilon_a$    | 90%   |
| $e_l$           | 10%   |                 |       |
TABLE 2. Results of location problem-solving in different routes.

| Route details | $E_q$ (kWh) | Power track installation link | Length of power track (m) |
|---------------|-------------|--------------------------------|--------------------------|
| $7\to6\to5\to4\to8$ | 1.633 | (5-4) | (28) |
| $7\to6\to10\to9\to8$ | 1.224 | (10-9),(9-8) | (12),(16),(24) |
| $7\to1\to10\to9\to8$ | 1.221 | (10-9),(9-8) | (20),(24),(16) |
| $7\to6\to11\to10\to9\to8$ | 1.873 | (11-6) | (24) |
| $7\to1\to10\to2\to12\to8$ | 1.429 | (1-10),(10-12),(12-8) | (16),(28),(20) |

TABLE 3. Results for case A: battery and track specifications.

| Case A | Public $EV^{(2)}$ Battery size (kWh) | Power track installation link | Length of power track (m) |
|--------|------------------------------------|--------------------------------|--------------------------|
| Study 1 | $EV^{(1)}$ | 2.667 | 6-4 | 28.800 |
| Study 2 | $EV^{(1)}$ | 1.951 | 4-5 | 35.330 |
| Study 3 | $EV^{(1)}$ | 1.951 | 0-4 | 30.000 |
| Total cost including EV battery and DNC costs: $765.355.617$, Average solution time: 601.74s |
| Study 2 | $EV^{(2)}$ | 2.722 | 5-4 | 69.076 |
| Study 3 | $EV^{(2)}$ | 2.622 | 5-4 | 35.748 |
| Total cost including EV battery and DNC costs: $783.999.47$, Average solution time: 855.24s |
| Study 3 | $EV^{(3)}$ | 1.778 | 2-1 | 20.812 |
| Study 3 | $EV^{(4)}$ | 1.778 | 2-7 | 19.200 |
| Total cost including EV battery and DNC costs: $486.162.708$, Average solution time: 973.34s |

FIGURE 6. Bus voltage profiles of PDS for Case A (Scenario 1).

TABLE 4. Results for case A: EVs routing for first scenario.

| Case A | $EV^{(1)}$ Details of route | $EV^{(2)}$ Details of route |
|--------|-------------------------------|-------------------------------|
| Study 1 | $EV^{(1)}$ 0-9-4-5-6-7-8-7-1 | $EV^{(2)}$ 7-6-5-4-3-4-8 |
| Study 2 | $EV^{(1)}$ 0-4-5-6-7-8-7-1 | $EV^{(2)}$ 7-6-5-4-3-8-9-8-7 |
| Study 3 | $EV^{(1)}$ 0-4-5-6-7-8-7-1 | $EV^{(2)}$ 7-6-5-4-3-8-9-8-7 |

considering routing in solving the location problem. In the second step, we solve the LPR problem for both fleet collections. The results of the optimization are shown in Table 3 (rows 3-6). As shown in the Table 3 (third column), the optimal sizes of public fleet batteries calculated by the proposed model are much smaller than the conventional battery capacities usually selected for personal plug-in EVs. Note that, the calculated size of public fleet batteries in the proposed method are small and medium-sized, while many automakers use batteries with larger sizes and higher weight (up to 540kg) such as 60 kWh (Chevy Bolt) or 75-90 kWh (Tesla S) for public plug-in fleet [49]. Consequently, the results show that by using DWC technology and with the appropriate placement of wireless charging infrastructures, there can be significant reductions in the sizes and prices of the batteries. The fourth and fifth columns of Table 3 present the calculated optimal installation links and lengths of the power tracks, respectively.

Table 3 shows the routing results of EVs for the first scenario of the first study. Comparing the results obtained for the second fleet collection traveled from node 7 to node 8 (Table 4, Study 1, column 4) and the results of Table 2 (row 1, columns 1) show that solving the LPR problem instead of the location problem allows the best route with the lowest total cost to be selected. Note that, the proposed method determines different routes for different scenarios but the lengths and locations of DWC infrastructures to be installed are the same for all reduced scenarios. Therefore, the calculated optimal lengths and locations of the DWC infrastructures will meet the needs of the EVs with the occurrence of each of the scenarios in the future. Fig. 6 shows the bus voltage profiles/magnitudes of the PDS for Scenario 1 of Case A. Clearly, the wireless charging facilities supply the required electrical energy without any detrimental impacts on the PDS bus voltage regulation. This is a bold advantage of the proposed stochastic model.

2) CASE A (STUDY 2)

In the second study, the effect of transport line traffic on the proposed model is investigated. For this purpose, it is assumed that only 300 EVs per hour are allowed to cross lines 4-5 and 6-5 in the traffic network ($\delta_{pq}$). Other conditions are the same as Study 1. Simulations results of Table 3 show that only three fleets (equal to 300 EVs) per hour could pass through these lines due to the congestion on lines 4-5 and 6-5. Therefore, the routing of fleets 4 and 5 from the first fleet collection and fleets 2 and 4 from the second fleet collection are set differently from other fleets (shaded rows in Table 4).

This diversion has increased the number and length of wireless charging infrastructures from 3 DWC units with
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FIGURE 7. Sioux-Falls traffic network [32] and IEEE 34 bus test feeder [33]. Four EV fleets collections are selected traveling between.

A total transmitter length of 28.8 + 25.33 + 40.5 = 94.633 m (Table 3, Study 1, columns 4 and 5) to four DWC units with a total transmitter length of 35.33 + 69.076 + 21.114 + 50.224 = 175.74 m (Table 3, Study 2, columns 4 and 5). Note that the total cost has increased from $765,355.617 in Study 1 to $783,999.47 in Study 2. Fig. 5 summarizes the optimization results of Study 2 for the first scenario (Tables 2 and 3), including the routes and the battery energy of each EV at the traffic network nodes:

- Vehicles EV_12 (green arrows and fonts), and EV_14 (red arrows and fonts) are traveling between origin-destination 0-1.
- Vehicles EV_21 (blue arrows and fonts) and EV_22 (brown arrows and fonts) are traveling between origin-destination 7-8.

Simulation results of Study 2 show that the proposed model can be employed under traffic forecasts and, to an acceptable extent, prevent traffic network disruption that may occur by installing DWC infrastructure on certain lines.

3) CASE A (STUDY 3)
The third study is simulated to show the trade-off between the EV battery size and the length of the DWC infrastructure. The difference between this study and Study 1 is that all personal EV battery sizes are set to 4.4 kWh. Simulation results are presented in Table 4. Note that:

- As expected, the decrease in the EV battery sizes has caused the DWC infrastructures to increase from three DWC units with 94.633 meters of power tracks in Study 1 to five DWC units with 137.316 meters of power tracks in Study 3.
- Despite the 45% increase in the total length of the DWC infrastructures, the total cost has been significantly reduced from $765,355,617 to $486,162,708 which shows a 36% reduction.
- The reduction in total cost (due to reduction in EV battery sizes) suggests that the well-designed DWC systems can be cost-effective options for both public and personal EV fleets.

Since the size of public EV batteries in this study is smaller than in Study 1, despite the lack of traffic restrictions, different routes have been determined by increasing the number and length of DWC infrastructures for two fleets from each fleet collection.

B. SIoux-Falls 24 Node Traffic Network Coupled With IEEE 34 Node Test Feeder

The Sioux-Falls traffic network is coupled with the IEEE 34 bus test feeder (Fig. 7) and used to evaluate the performance of the proposed model in a more extensive traffic network and a more complex power distribution system. This traffic network has 76 direct links and 24 nodes and is based on the urban traffic network of Sioux-Falls city in South Dakota [40]. The coupled power distribution system is the IEEE 34 bus test feeder with 34 buses and 33 lines. Information about this system, including lines and buses data, is available in [50]. The base values of the system are 500 MVA and 13.5 kV. In this case, four fleet collections, each consisting of 5 fleets with 100 EVs are selected to travel between origins-destinations 0-23, 19-3, 12-1 and 6-11.

We have investigated the uncertainty of EV battery level at the origin (initial SOC%) by generating 5140 scenarios and reducing them to 10 scenarios by backward method of [30]. To use more battery capacity of each EV, parameters $\delta$ and $\nu$ are set to be 5% for all vehicles. The rest of the parameters, including the weighting factors of objective function are the same as Case A. To consider the traffic conditions in the transportation network, it is assumed that vehicle congestions in links 10-13, 11-2 and 17-6 are such that only 300, 400, and 300 EVs per hour can cross these links, respectively. Also, each fleet collection includes a public transportation fleet and four EV fleets with a battery capacity of 5.4 kWh, 6.2 kWh, 16 kWh, and 30 kWh. Note that the proposed model determines the optimal battery capacity of the public fleet. After solving the proposed stochastic scenario-based model for Case B, the optimal battery size of the public fleet and the allocated DWC infrastructure specifications are calculated and listed in Table 5. The optimization results of Table 5 show that in Case B, seven DWC units with a total length of 416.393 meters of power tracks and total cost of $2,024,751.02 are allocated in the traffic network links. Also, the average solution time of this case study was about 1719.078 Seconds.

There is an additional cost in the result of case B compared to the results of case A. The reason for this difference is the

| Battery size (kWh) | Power track installation link | Length of power track (m) | Power track installation link | Length of power track (m) |
|-------------------|-------------------------------|---------------------------|-------------------------------|---------------------------|
| EV_11             | 5.098                         | 2-3                       | 81.616                        | 11-2                       | 74.376                    |
| EV_12             | 8.737                         | 3-4                       | 30.240                        | 13-2                       | 39.440                    |
| EV_13             | 5.098                         | 5-4                       | 87.736                        | 17-15                      | 83.920                    |
| EV_14             | 5.142                         | 9-10                      | 19.529                        |                           |                           |

Total cost including EV battery and DWC costs: $2,024,751.02.
Fig. 8 summarized results of the first scenario for Case B, including the routes and the EV battery energy levels at each traffic node of the South Dakota traffic network. These results indicate that EVs with different battery capacities and different initial battery SOCs can benefit from the installed DWCs. As with Case A (Fig. 6), the bus voltage profiles of PDS for this case, shown in Fig. 9, are within the regulation limit of 1 p.u that confirms the optimal allocation and sizing of DWC infrastructure does not have detrimental effects on the power quality of PDS.

V. CONCLUSION

A novel stochastic scenario-based method is proposed for optimal allocation and sizing of EV DWC infrastructures that considers traffic in the transportation network as well as losses and voltage profiles of the PDS. It provides a platform on real coupled electricity and transportation systems, which allows all types of EVs to use DWC technology. Simulation results for two real coupled traffic and power networks show that the proposed method can increase the tendency to use DWCs due to significant reduction in EV battery size and cost, longer driving range, and elimination of charging downtime. Furthermore, the proposed method allows investors to produce EVs at a lower cost and increase their revenues with agreements to manage traffic in the transportation network without detrimental impacts on the electricity network. Therefore, the proposed method will be beneficial to all stakeholders including EV drivers and investors as well as transportation and electricity network provider.
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