Deployment Optimization of Dynamic Wireless Electric Vehicle Charging Systems: A Review

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***Abstract*—To alleviate the range anxiety fear of electric vehicle (EV) drivers, dynamic wireless charging (DWC) systems are being developed to supply energy to the EV during its motion, thereby compensating for EV energy consumption and extending the vehicle's driving range. Nevertheless, several challenges are involved in the commercial deployment of on-road DWC systems, particularly with respect to the associated deployment costs and EV energy demand. Accordingly, extensive research is conducted to optimize the deployment of DWC systems within a city infrastructure while addressing the different challenges to encourage mass adoption of EVs and improve their reliability. In this work, a review of current state-of-the-art research into optimizing the deployment of dynamic EV wireless charging facilities is presented, to provide a set of guidelines on the formulation and optimal deployment of DWC systems. In addition, on-the-move V2V energy exchange is also addressed as an additional dynamic charging solution to complement on-road charging systems.**

***Index Terms*—Electric vehicle, dynamic wireless power transfer, lane deployment, location optimization, charging cells.**

I. Introduction

In order to reduce the range anxiety of electric vehicle (EV) users and promote mass adoption of this environment-friendly means of transportation, dynamic wireless charging (DWC) systems are gaining an increasing global interest. This is because DWC systems enable EVs to compensate for their consumed energy during motion without having to stop for frequent recharging and/or battery swapping. This accordingly increases the maximum non-stop trip mileage of the EV, extends its driving range and prevents excessive depletion of the EV batteries thereby prolonging the battery lifetime [1]–[3]. The most common structure of a DWC system utilizes resonant inductive power transfer (RIPT) to transfer electrical energy from a set of primary coils buried under the ground to a secondary coil fitted at the bottom of the EV, separated by an air-gap equivalent to the vehicle-to-ground clearance distance. This is also referred to as Grid-to-Vehicle (G2V) power transfer. In order to ensure optimum energy management and integration of EVs into the city infrastructure, the RIPT circuit level design needs to be complemented with a city-wide deployment optimization framework, to maximize the benefits of this dynamic charging technology. In particular, optimal deployment of EV DWC systems aims to achieve one or more of the following objectives:

- Maximizing the energy received by the EVs in the network,
- Minimizing infrastructure deployment costs,
- Enhancing EV battery performance and lifetime,
- Optimizing charging power levels,
- Minimizing the number of infeasible trips due to EV battery capacity limitations.

Accordingly, several deployment optimization studies have been reported in the literature, of which the On-Line Electric Vehicle (OLEV) project demonstrates one of the earliest commercial deployments [4]–[7]. Other deployment optimization models are also reported in the literature, including driving-cycle based allocation models [8]–[10], traffic flow-based analysis [11]–[13] and deployment at signalized intersections [14], [15]. Vehicle-to-vehicle (V2V) dynamic charging solutions using mobile energy disseminators (MEDs) are also proposed in [16], [17], in which RIPT is employed to dynamically transfer energy between EVs to enable the energy-demanding vehicles to complete their trips without the need to stop for prolonged charging durations. In this work, the authors present a review of current state-of-the-art research into the deployment of dynamic G2V and V2V EV wireless charging solutions, aiming to summarize the different deployment optimization strategies and present a set of guidelines to enable researchers and city planners to formulate and determine the most optimum facilities deployment plan(s).

The rest of this paper is organized as follows: Section II describes the structure of the G2V DWC system addressed in this work in order to accurately define the deployment optimization framework. Section III then presents a detailed review of state-of-the-art G2V DWC system deployment optimization models. This is then followed by a description of V2V dynamic energy exchange solutions in Section IV before the paper is finally concluded in Section V.

II. G2V DWC System Model

The RIPT-based dynamic wireless EV charging system consists of two physically-separated coils that exchange power using alternating magnetic fields, with no direct electrical

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connection between them. The primary coil laid on the ground is connected to the mains grid through rectification, power factor correction and high frequency inversion circuitry. These work together to generate high-frequency alternating magnetic fields that are coupled with the secondary coil fitted at the bottom of the EV. This enables wireless power transfer from the grid to the vehicle; i.e. Grid-to-Vehicle (G2V) power transfer, as shown in Figure 1.

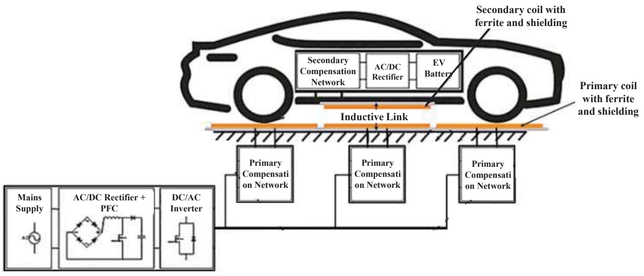

Fig. 1: Dynamic EV charging system using G2V power transfer.

The power received by the EV is then rectified, regulated and supplied to the EV battery to compensate for the energy consumed during the vehicle's motion while contributing to the EV's energy reserve. The relationship between the energy consumed by the EV, the received energy from DWC and the State-of-Charge (SoC) of the EV battery can be simplified as:

$$SoC_f = SoC_i + \left(\frac{E_{DWC} - E_{con}}{E_{max}}\right) \times 100, \tag{1}$$

where SoC_f is the final SoC at the end of the trip, SoC_i is the initial SoC, E_{DWC} is the energy received from the dynamic charging system, E_{con} is the amount of energy consumed by the EV over the same trip, and E_{max} is the maximum EV battery capacity. The received energy, E_{DWC}, is related to the grid power supply, P_{In}, through the efficiency of the DWCS system, η_{DWC} using:

$$E_{DWC} = \int_{\mathbb{C}} \eta_{DWC} P_{In}(t) dt, \tag{2}$$

where $\mathbb{C}$ is the time over which the EV is receiving energy from the primary charging coils. The efficiency of the DWC system , and hence the energy received by the EV are both dependent on the design of the different system components shown in Figure 1, including the design of the primary and secondary coils and their respective compensation networks, and are impacted by the coupling performance of the inductive link and the vehicle's alignment over the primary coils [18]. In addition, accurate estimation of the SoC of the EV battery needs to acknowledge battery temperature, aging, and other factors that affect the battery energy levels. Complete details of the RIPT DWC system design and EV battery SoC estimation methods can be extensively found in [2], [19]–[21] but are beyond the scope of this paper. In this work, a high-efficiency DWC system is assumed to be readily available and the problem at hand is to ensure optimum implementation and deployment of this system within a city infrastructure.

III. State-of-the-Art G2V DWC System Deployment Optimization Models

The optimal DWC system deployment problem can be classified into three main categories based on the corresponding solution space:

- **Macro allocation model**, for city-wide deployments in which standardized driving cycles, such as Urban Dynamometer Driving Schedule (UDDS) and the HighWay Fuel Economy Test (HWFET) [22], and/or metropolitan road network plans are utilized to determine the optimum location of charging coils.
- **Micro allocation model**, in which optimum routes between origin-destination (O-D) pairs are selected for the deployment of charging coils based on route feasibility and traffic conditions.
- **Deployment on signalized intersections**, by utilizing the relatively lower EV speeds at intersections and red-light stopping times to maximize the energy received by the EV. This is also referred to as *quasi-dynamic charging*.

Accordingly, the references highlighted in the introduction of this paper are classified based on these categories and their optimization solutions are discussed in the remainder of this section.

A. Macro Allocation Model

In the macro allocation deployment optimization problem, information on EV speeds and acceleration profiles is obtained from standardized driving cycles over predefined durations, and is used to recommend charging coil deployments at areas of slowest speeds, higher power requirements, etc. In fact, standardized driving cycles, also known as driving schedules, are typically used for vehicle emissions and fuel economy testing due to the nature of the information they carry, yet can be adopted for deployment optimization of DWC systems. This is demonstrated by the authors in [8], [23], in which the UDDS (low power demand, urban driving cycle), as well as other standardized cycles, have been used to determine the optimum locations of the charging coils. A speed-time plot of the UDDS is shown in Figure 2.

As observed in Figure 2, the UDDS cycle has a low average speed of around 31.5 km/hr as well as several zero-speed slots in which EVs are expected to be idle, possibly at intersections or during congestion periods. Mapping these zero-speed durations to a city road network suggests the deployment of charging coils at these locations to maximize the received energy by the EV. This is highlighted in [8], in which the author concludes that multiple 10 m-long primary coils are required to cover up to 20% of a UDDS cycle with $P_{In} = 40$ kW in order to extend the driving range of a typical EV by around 87% while maintaining the battery SoC above 20%, assuming that the initial SoC is 100%. On the other hand, the authors in [23] choose to allocate a single 500 m long lane of primary coils to the lowest speed section of

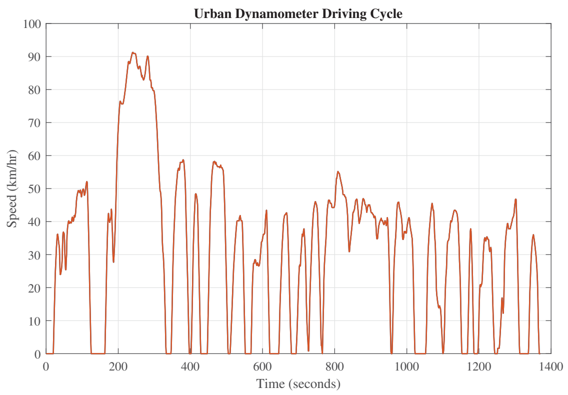

Fig. 2: Speed-time plot of UDDS cycle.

the UDDS cycle to achieve an 85.7% extension in driving range. In addition, the authors in [9] further extended the macro allocation model by including the temporal aspect of the deployment process together with the spatial allocation. This is addressed by incorporating the road lifetime assessment model into the optimization framework, in order to determine the most optimum year at which a particular road can be modified to include charging cells, based on current and expected EV sales and required cost of infrastructure for DWPT system deployment.

Another city wide deployment plan is addressed in [10] in which the authors used mobility records of all public transit vehicles within the city to define the solution space, then design for the optimum deployment that minimizes the total deployment cost by minimizing charging lane length and reducing the number of deployed lanes, while ensuring minimum residual energy is available in the EV battery at each node in the network. The objective function is as follows:

$$\textbf{Minimize} \text{ Cost} = \sum_{i \in N} \omega_0 x_i L_i, \tag{3}$$

subject to:

$$SoC_i \geq \alpha, \tag{4}$$

where N is the set of candidate locations, ω_0 is the unit cost, L_i is the length of the charging segment at location i, x_i is a binary variable to determine whether or not the location has a charging segment, and α is the residual energy threshold.

The authors started with a categorization and clustering process, in which they identified and grouped potential charging cell locations based on a set of attributes, namely vehicle passing speed and visit frequency for each location. A ranking is then allocated to each cluster and candidate locations are identified. Optimum charging cell locations are then selected from the candidate locations such that they provide minimum total deployment cost while ensuring a certain level of expected residual energy is maintained in the EV battery at each location. This energy level is the minimum energy required to reach the next charging location. The clustering-based approach utilized by the authors in [10] helps eliminate unsuitable locations and hence, reduces the solution space of the optimization problem and further simplifies the analysis.

A subset of the city-wide macro allocation model is the deployment optimization for a set of predefined routes with known speed profiles, which is particularly applicable to public transportation electric buses. This is demonstrated by the authors in [4] and [5] to optimize the deployment of wireless charging lanes along the route of the OLEV bus, and is further extended by the authors in [6] and [7] to address a multi-route environment. The optimization objective function is to minimize the total cost of the OLEV project deployment, as shown in the following expression [4]:

$$\textbf{Minimize} \text{ Cost} = k c_b E_{max} \frac{T_t}{T_b} + c_f N + c_v \sum_{i=1}^{N} (x_i^e - x_e^s), \tag{5}$$

where E_{max} is the maximum battery capacity, T_t is the lifetime of the charging track, T_b is the battery lifetime, c_b is the fixed battery cost, c_f is the fixed cost per charging section, c_v is the variable cost depending on the length of the section, N is the number of charging sections, and x_i^s and x_i^e are the starting and ending points of each charging section, respectively.

The cost function in (5) consists of battery cost based on the battery lifetime, fixed infrastructure costs related to the cost of the inverters and other power electronics circuitry, and variable infrastructure costs related to the length of the charging sections. Accordingly, the optimum location of the wireless charging sections is determined along with the optimum bus battery size, using the meta-heuristic Particle Swarm Optimization (PSO) algorithm. A similar optimization scenario is also tackled by the authors in [24] using the heuristic Genetic Algorithm (GA) instead of PSO. In their work, the authors utilized a detailed power consumption model of shared automated electric shuttles (SAES), and expanded the battery cost coefficient c_b into a function of the charging rate of the battery, i.e. C-rate, and the operating SoC window during typical shuttle bus operation on the assigned route. Accordingly, their optimization process revealed that few high-power 100 kW wireless charging segments can be placed along the pre-determined route to provide the required charge-sustained operation with zero charging downtime and reduced battery size by around 36%. The joint optimization of charging coil deployment and bus battery sizing is also addressed in [25] for an eight-route bus network, while including the uncertainty of bus energy consumption and battery depletion rate in a Robust Optimization (RO) model to improve the accuracy of the optimization outcome.

EV battery downsizing, while important for the public transportation network, is difficult to be included in a city-wide optimization model that involves privately-owned EVs with different EV battery capacities and different energy consumption patterns. Accordingly, another city-wide optimization model based on cost minimization is addressed in [26] without attempting to downsize EV batteries. In this work, the author aimed to minimize the capital costs of dynamic charging infrastructure implementation to enable an EV to travel between key destinations in California State, subject to constraints on battery capacity, reserve mileage requirements, and vehicle charging levels. Different combinations of wireless charging power (up to 120 kW) and vehicle range (up to 300 miles) are investigated and the author concludes that to achieve a driving range of 200 miles, a DWC system with 100 kW charging power costs $1 billion less than a 40 kW DWC system. The authors in [27] also define a minimum infrastructure cost minimization objective function and acknowledge the DWC system power ratings yet do not incorporate any battery-related details in the presented analysis.

B. Micro Allocation Model

In contrast to the citywide macro allocation models, other researchers chose to address DWC system deployments in a microscopic scale, by defining the solution space into a set of routes between an origin (O) and a destination (D) and acknowledging traffic conditions along these routes. An O-D road network can be modeled as a directed graph, $\mathfrak{G}$, consisting of $\mathfrak{M}$ nodes and $\mathfrak{L}$ links joining a set of origins $\mathfrak{O}$ to a set of destinations $\mathfrak{D}$. A sample directed graph with a single O-D pair and $M = 3 \times 3$ nodes is shown in Figure 3. The location and direction of the links between each pair of adjacent nodes shall reflect the actual paths in the network. Accordingly, the deployment optimization problem is solved by route optimization, such that the charging sections are placed on the most optimum links to minimize the number of infeasible routes between an O-D pair. A feasible route is defined as a complete path from the origin to the destination that can be completed by an EV while maintaining its SoC above a predefined threshold. The authors in [11] aimed to maximize the number of feasible routes between an O-D pairs subject to a given budget, and define two optimization problems for city planners:

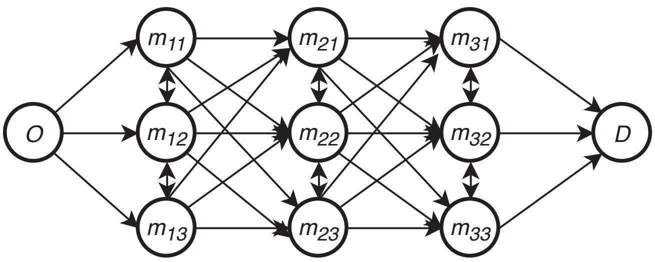

Fig. 3: Sample directed road network graph with a single O-D pair and nine interconnected nodes.

1) For a given minimum EV energy threshold, determine the minimum budget of charging lane deployment, together with the corresponding locations, needed such that the number of infeasible routes is zero. This is equivalent to:

$$\textbf{Minimize}\ \text{Cost} = \sum_{l=1}^{L} c_l x_l, \tag{6}$$

where c_l is the cost of installation of a charging unit along a link, x_l is a binary variable to indicate whether or not the charging unit is installed and L is the total number of links between the O-D pair assuming all routes are feasible.

2) For a given minimum energy and budget constraints, determine the optimal installation locations to minimize the number of infeasible routes and hence reduce the range anxiety problem of drivers within the network. This is equivalent to:

$$\textbf{Maximize}\ \text{Feasible Routes} = \sum_{r=1}^{R} \delta_r w_r y_{lr}, \tag{7}$$

where r is the index of the route (consisting of multiple links L), δ_r is the normalized travel demand along the route, w_r is a binary variable to indicate whether or not the EV completes the route with its SoC above the defined threshold and y_{lr} is a binary variable to indicate whether or not link l belongs to route r. The authors use δ_r to omit road segments that have low traffic demand from the set of feasible routes, thereby reducing the solution space of the optimization model.

For both problems, the authors in [11] performed a computational evaluation of the objective functions for a given directed graph with 26 nodes using a simplified SoC estimation similar to that in (1). Results revealed significant improvements, i.e. reduced deployment costs and increased feasible routes, in contrast to other heuristics that forcefully install charging units in mostly visited links and/or in centralized links.

On the other hand, the authors in [12] chose to allocate charging sections such that the trip time is minimized between an O-D pair while ensuring that the EV completes the trip without fully depleting its battery. The authors in [13], however, located their charging sections based on an objective function that maximizes the captured flow, i.e. maximizes the number of paths that an EV can take between an O-D pair without running out of energy. The interaction between traffic flow patterns and the location of the charging facilities is incorporated by applying the stochastic user equilibrium principle to describe the routing choice behavior of EV drivers based on the availability of charging cells. This is also acknowledged in [12] in which network equilibrium between traffic flow and demand is set as a constraint to ensure that all feasible paths are utilized and considered for charging lane deployments. Accordingly, both [12] and [13] aimed at placing the charging sections at locations of maximum traffic flow to ensure maximum utilization of the charging infrastructure.

C. DWC System Deployment at Signalized Intersections

As the macro allocation model recommends regions of slowest speed for charging lane deployment, traffic intersections are strong candidates for the optimal deployment problem. Nevertheless, the microscopic model emphasizes the importance of route feasibility, which is assessed based on the traffic flow and other route conditions between O-D pairs. Accordingly, an integration of both allocation models is evident in quasi-dynamic charging system deployments at signalized intersections, in order to benefit from the relatively lower vehicle speeds and pre-known traffic conditions to maximize the energy received by the EVs while controlling traffic signal timings.

Optimal deployment at signalized intersections is addressed by the authors in [14] where they proposed an optimal combination of traffic signal timings and wireless charging infrastructure locations based on traffic conditions to maximize the charging energy while reducing traffic delay by controlling signal timings. In order to model the road network and incorporate traffic conditions, the modified cell transmission model (CTM) is used where a lane is discretized into a number of cells of equal width and the cells are classified based on their location on the signalized intersection. This is shown in Figure 4. Accordingly, each cell is assigned a

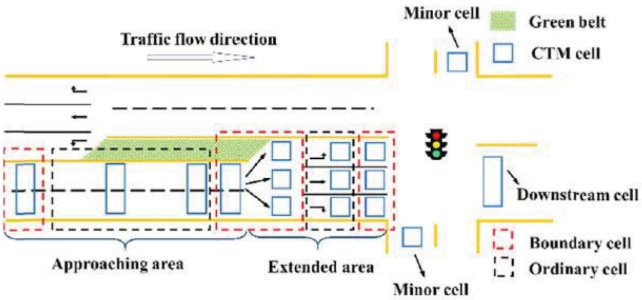

Fig. 4: Modified cell transmission model (CTM) adopted in [14].

binary variable to determine whether or not charging coils are required, and traffic flow in and out of each cell is used to determine the optimum signal timings. The optimization model is hence a mixed integer, non-linear programming (MINLP) model with continuous and discrete constraints. The authors started by choosing a set of feasible signal timings then using traffic flow and traffic density information with signal timings to solve a binary programming model to determine charging cell locations. Accordingly, the authors filtered these locations to create a Pareto set of possible solutions and eliminated solutions with larger delay and smaller energy, ultimately reaching a single optimal solution. By utilizing traffic flow and density information, the authors acknowledged the distribution of vehicles along the road and aimed to meet their energy demand by adjusting traffic signal timings with optimal charging cell locations.

On the other hand, without utilizing the CTM, the authors in [15] also addressed quasi-dynamic charging at signalized intersections, by defining their optimization problem to maximize the total energy transferred to all EVs by optimizing the green signal times and the length of the charging lanes placed at the intersections. However, instead of incorporating actual traffic flow data in a hybrid genetic and PSO optimization algorithm similar to the authors in [14], the authors in [15] utilized traffic simulations and queue counting techniques on the Simulation of Urban MObility (SUMO) simulator [28] to obtain information on received energy for different lane lengths and green signal timings and used it to define the solution space for the optimization objective function.

In contrast to controlling the signal timings, the authors in [29] utilized existing red traffic light durations to determine the Waiting Queue Length (WQL) and use that to represent the charging demand of EVs at the intersection. On the other hand, the charging supply is represented by the Wireless Charging lane Length (WCL) and the optimization problem aimed to determine the optimal length of charging lanes that need to be deployed to minimize the charging lane installation costs while minimizing the gap between charging energy supply and demand. Accordingly, the authors used real traffic datasets to define the charging demand in an urban area and build the corresponding charging lane deployment plan to meet this demand while ensuring minimum construction costs.

IV. V2V DWC System Deployment Model

The on-the-move V2V energy exchange is another approach proposed in the literature to reduce range anxiety of EV drivers by offering a dynamic charging solution. This utilizes city busses, with high-capacity batteries, to wirelessly supply power to vehicles in demand for charging energy, thereby operating as Mobile Energy Disseminators (MEDs). In this model, the primary coil is fitted in front of the MED bus and the secondary coil is at the back of the EV. RIPT is employed to enable the energy exchange between the two vehicles. This is shown in Figure 5.

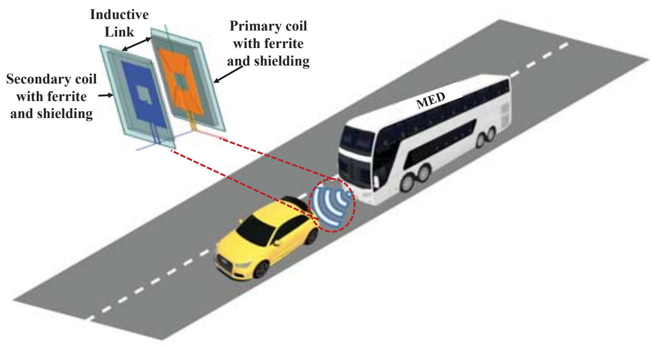

Fig. 5: Dynamic EV charging system using V2V power transfer.

In [16], the authors utilized mobile energy disseminators (MEDs) to optimize the route taken by EVs to reach from source to destination. Accordingly, the optimization problem is a restricted shortest path problem in which the optimum path from Node A to Node B is selected based on the presence of MEDs on a road segment where the additional distance required to meet MEDs and the predicted total travel time are minimized. The weight function used for path selection then consists of three main components: travel distance, travel time and EV energy consumption along the path. The optimization objective is to minimize the weight, W assigned to each road segment j, along the route of the EV i, as follows:

$$\textbf{Minimize} \sum_{ij} W_{ij}, \tag{8}$$

in which

$$W_{ij} = F(E_{ij}, T_{ij}, D_{ij}), \tag{9}$$

where E_{ij} is the energy consumption of vehicle i along road segment j, T_{ij} is the corresponding travel time and D_{ij} is the corresponding travel distance.

On the other hand, the authors in [17] also utilized MEDs for route optimization by minimizing the total travel time for every EV while utilizing both MEDs and static charging stations. Yet, they did not consider minimizing the travel distance or energy consumption as an objective of the optimization problem. Instead, their work focused on minimizing the travel time by acknowledging the additional time required to use the path that has an MED as well as the charging time and the waiting time on static charging stations. The EV energy level was used as a constraint that determines whether the path is feasible or not.

The concept of Mobile Energy Disseminators requires effective V2V energy exchange and accurate coordination between the MED and the EV to maintain front-to-rear distance and avoid accidents. Nevertheless, the utilization of MEDs helps to minimize the number of infeasible trips by addressing urgent on-the-move EV energy demand without the need for excessive investments in infrastructure transformation to accommodate the charging lanes. MEDs are hence expected to offer faster time-to-market (TTM) than deployments of DWC systems, although challenges in authentication, billing and effective energy distribution may be faced by the MED operators.

V. Conclusions

In this work, a review of the deployment optimization frameworks of different dynamic wireless EV charging solutions are presented. On one hand, different on-road charging unit deployment optimization models are described and categorized based on the solution space of the optimization problem and the associated variables. State-of-the-Art research findings into DWC G2V facilities deployment models are explained with relevant details of the respective optimization objective functions. In addition, V2V energy exchange solutions are also highlighted as complementary dynamic charging solution that supports the infrastructure G2V energy transfer model. Nevertheless, further research is required into the integration of static and dynamic, G2V and V2V EV charging solutions to ensure effective penetration of EVs into the transportation industry, maximize returns on infrastructure investments and eliminate EV owners' anxiety.

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