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# Electric Vehicle Dynamic Wireless Charging System: Optimal Placement and Vehicle-to-Grid Scheduling

Shiyao Zhang, *Member, IEEE* and James J.Q. Yu, *Senior Member, IEEE*

***Abstract*—Electric vehicle (EV) dynamic wireless charging system has become an emerging application in the area of the intelligent transportation system (ITS). However, an integrated design of EV dynamic wireless charging system requires the considerations of both the economical and technical perspectives of a smart city. Specifically, most of the existing researches unilaterally considers the application of either placement strategy for power tracks (PTs) or dynamic vehicle-to-grid (V2G) scheduling. In this paper, we propose a multi-stage system framework to account for an integrated EV dynamic wireless charging system in a smart city. First of all, an optimal placement strategy for PTs is developed based on city traffic information and EV energy demand. Then, having the optimal locations of PTs through the previous stage approach, the proposed dynamic V2G scheduling scheme is formulated to coordinate the schedules of EVs with the provision of daytime V2G ancillary services. Our simulation results present that the proposed multi-stage system model achieves improvements on both the placement strategy and V2G scheduling scheme. In addition, relatively low economic system costs can be obtained through our proposed model.**

***Index Terms*—Ancillary service, dynamic wireless charging, electric vehicles, vehicle-to-grid scheduling.**

## I. Introduction

In the recent years, wireless charging systems have been widely applied in a smart city. By Internet of Things (IoT) devices, wireless charging systems become a crucial component in intelligent energy management for an urban area [1]. The primary purpose of these systems is to provide convenient and efficient energy services to electric vehicle (EV) customers in a smart city. Compared to traditional wired charging systems where one wired charging pile only serves with a single EV, wireless charging systems can provide energy service to multiple participated EVs in a more flexibly way [2]. Specifically, wireless power transfer (WPT) technique, referring to wireless power transmission empowered by electromagnetic technologies, enables EVs to generally get charged wirelessly via remote devices equipped in the system.

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Shiyao Zhang is with the Academy for Advanced Interdisciplinary Studies, Southern University of Science and Technology, Shenzhen 518055, China (e-mail: syzhang@ieee.org)

James J.Q. Yu is with the Department of Computer Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China (e-mail: yujq3@sustech.edu.cn)

EV wireless charging systems can be categorized into two main types, namely, stationary and dynamic wireless charging systems. Stationary wireless charging systems are operated to transfer energy when EV is parked over fixed couplers, e.g. [3] and [4]. A number of research studies focus on designing the wireless charging schemes under the EV stationary wireless charging system [5], [6], and [7]. For instance, a practical wireless charger prototype in [5] was developed for stationary wireless charging with high efficiency, which improved the compactness of the system. Then, an economic dispatch problem was formulated in [6] for satisfying EV charging demands, which modeled EV mobility as a queuing network. Besides, an optimal charging framework for electric buses was proposed to minimize the system operational cost by considering stationary charging activities at multiple stations in [7]. Nonetheless, the waiting time for EVs to fulfill the charging requirements is relatively long with the stationary solutions. Also, EVs are required to be parked when they are charged to ensure the on-going process of energy transfer services, which limits the EV traveling schedules.

The promising application of dynamic wireless charging systems can indeed tackle with the issues above. Such systems enable EVs to charge while they are in motion over the dynamic charging facilities. There are several studies proposing dynamic wireless charging system models [8]–[13]. In particular, the hardware of dynamic wireless charging systems were investigated in [8] and [9] based on the coil design, whose energy efficiency was illustrated through practical demonstrations. Additionally, EVs can be operated to charge in motion under multiple route plans, whereas power tracks (PTs)-the power supply units-are embedded beneath the traffic roads for energy transfer processes [10]. By having such techniques, dynamic charging protocols can be further applied in dynamic EV charging systems. For instance, the application of dynamic EV charging system for the slow moving traffic conditions was studied and demonstrated in [11]. Furthermore, in [12], a joint model with intelligent routing and EV dynamic charging was proposed to consider the eco-routing scheme while fulfilling the energy requirement of EVs through the system. [13] developed an electric roadway system for long-distance vehicular travels under limited battery capacities and charging rates. However, the placement strategy for PTs in the system is neglected. Moreover, these studies lack the budget constraints on placing PTs.

The design of an integrated dynamic EV wireless charging system requires both the economical and technical analysis

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of the placement strategy of PTs in the city traffic network. Several existing researches have investigated the placement strategy of PTs in a smart city, see [14], [15], [16], and [17] for some examples. In [14], the optimal transmitter coils in a road was designed based on the consistent coupling coefficient. Moreover, [15] investigated the optimal solutions of the charger placement strategy by solving practical issues, such as huge deployment cost and charging delay for different levels. Besides, [16] developed a sequential two-level planning approach for finding the optimal locations to install the dynamic wireless charging facilities. Last but not least, [17] studied the placement strategy related to the EV optimum path selection based on minimizing of the total travel distance or time. Although the existing studies succeed in computing the optimal locations for placing these facilities in relatively large-scale city traffic networks based on the economical and road traffic constraints, they do not involve the effect of EV energy demand on the placement strategy. The available capacity of city energy services is correlated to EV energy demand.

When considering EV energy demand in the city, the interaction between EVs and the smart grid system is critical. The EV charging control scheme is primarily operated by the power grid. Hence, EVs can bring substantially impact of a demand-side management to the grid through dynamic wireless charging. For instance, [18] studied the potential benefit of demand-side management system when considering EV dynamic wireless charging. Besides, EVs are capable of providing different ancillary services to the city smart grid since EV batteries can be regarded as collectively mobile power storage. By considering the vehicle-to-grid (V2G) technique, EVs can be coordinated to return energy to the grid by providing ancillary services. In [19], a coordinated parking system was designed for EVs, as well as supporting V2G ancillary services. Considering the wireless charging with the provision of V2G ancillary services, [20] illustrated that wireless charging can be triggered to fulfill V2G requirements by vehicular communications, e.g. Honda feasibility study [21]. Thus, the provision of daytime V2G ancillary services in EV dynamic wireless charging system can further help stabilize the smart grid [22], [23]. In addition, having the information of daytime driving plans of EVs, the city system operator can easily control a fleet of EVs in providing the daytime V2G ancillary services. Since most of the existing research studies do not consider the provision of V2G ancillary services into EV wireless charging systems, in this work, we consider the provision of V2G ancillary services in dynamic wireless charging system in a smart city.

To bridge the research gaps related to the planning and operation of the current charging systems, in this work, we construct an integrated EV dynamic wireless charging system with the consideration of the facility locations and operations. Specifically, a multi-stage framework for joint optimal placing PTs and V2G scheduling for particular groups of EVs in a city is proposed. The major efforts of this research work are shown as follows:

1) We develop a multi-stage system model to account for EV dynamic wireless charging system in a smart city. This model is more general and practical than the existing studies since the cost-effective approach is developed within the feasible regions.
2) We propose an optimal placement strategy for installing PTs at the first stage, which is based on the city traffic information and energy demand. This contributes to a large economic benefit in the wireless charging system.
3) We formulate the proposed dynamic V2G scheduling framework at the second stage by considering the provision of daytime V2G ancillary services. This helps to understand how EVs and the system operator interact in the energy market.
4) We discuss the merits and effectiveness of the proposed multi-stage system model. We find that through the proposed integrated system, the optimal social welfare of the entire system can be achieved. Furthermore, the effectiveness of the V2G regulation services can also be guaranteed.

The rest of this paper is organized as follows. Section II presents and illustrates our multi-stage system model. In Section III, we formulate an optimal placement strategy for PTs in a city. By receiving the optimal placement strategy for installing PTs, the dynamic V2G scheduling, is then proposed in Section IV. In Section V, we conduct the performance evaluation of the proposed system model. Finally, we conclude this work in Section VI.

## II. System Model

This section presents four essential parts of the multi-stage framework, including the road network of a smart city, EVs, PTs, and system overview. The details of each component are illustrated as follows.

### A. Road Network

The road network is developed to represent the physical connections from one location to another inside a city. For ease of representation, the road network is modeled by a directed graph $G(\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ denotes the set of nodes to indicate the intersection points among different road segments. In addition, $\mathcal{E}$ represents the road paths connecting the nodes. We define $d_{ij}$ as the travel distance from Node $i$ to Node $j$ for every road segment $(i, j) \in \mathcal{E}$. Note that, if Node $i$ and Node $j$ are not adjacent, the travel distance $d_{ij}$ may not be equal to $d_{ji}$ due to the different routing plans. To evaluate the shortest distance for traveling from the departure point to the destination point, we adopt Dijkstra's algorithm to obtain the routing plans for the vehicles. Furthermore, inside a city, both wired and wireless charging stations are located in the city road network. The wired charging stations refer to the set of actual parking garages or parking lots with the installations of wired chargers. For the wireless charging stations, there are two main types, stationary wireless charging stations and dynamic wireless charging systems. The former is similar to the wired charging stations but with wireless charging pads installed at parking spaces while the latter one refers to the installations of PTs over the road paths in the city network. In this work, since we focus on the design of the EV dynamic wireless charging system and the charging protocols

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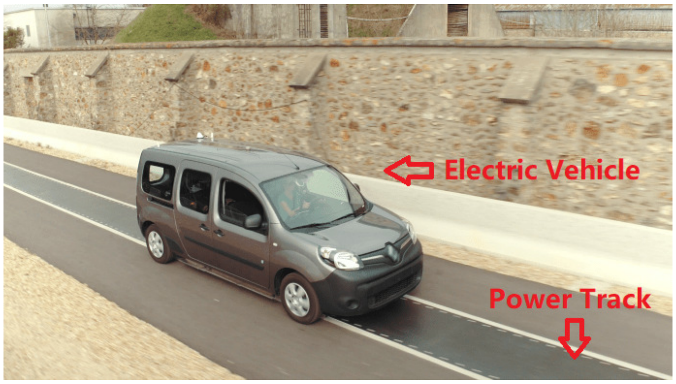


Fig. 1. Qualcomm's dynamic charging technology [26]

are different for EV wired and wireless charging, we only consider the installations of PTs in the city road network.

### B. Electric Vehicles

Considering their mobility behavior, EVs, known as vehicles with batteries equipped, can collectively be considered as a large city mobile energy storage. Due to the quick start and fast response characteristics of EV batteries, they can follow power control signals to provide various types of ancillary services in the city [22], such as frequency regulation service. The power control signals are defined as the coordination commands from the system operator so as to control the subordinate EVs. Specifically, the system operator broadcasts a uniform control signal to optimize and report the subordinate EV charging/discharging schedules. The purpose of frequency regulation service is to keep the grid frequency close to the nominal value to maintain the stability of the smart grid. By considering the EV batteries in the smart grid, a group of EVs is capable to collectively bring in a substantial capability for providing the frequency regulation service.

### C. Power Tracks

PTs refers to an energy supply unit of roadway powering systems. One of the real testbeds of PTs is shown in Fig. 1, i.e., Qualcomm's dynamic charging technology. Fundamentally, PTs are based on the near-field electromagnetic induction-based WPT technique. It consists of two main types, namely, magnetic induction and electrostatic induction [24], which is determined by different power levels and gap separations. PTs are typically installed on the road segments of a city road network, and they enable the WPT technique for EVs to both charge and discharge wirelessly. The set of PTs in a city is denoted by $\mathcal{K}$. Each PT $k \in \mathcal{K}$ is embedded beneath every road segment $(i, j) \in \mathcal{E}$. According to [25], a single standard coil-set for SAE J2954 charging standard is applied for the WPT Power Class 1 and 2 to 7.7kW.

### D. System Overview

The overall system involves interactions between two crucial smart systems in a smart city, namely, the intelligent transportation system (ITS) and the smart grid. ITS mainly deals with the mobility of vehicles in a city, while the smart grid system tackles with the charging operations of EVs. Through the information sharing between these two smart systems, the coordination of EVs can be associated with joint mobility and charging operations. Specifically, under this system, EVs can jointly complete their own travel plans and fulfill the charging requirements.

Consider a simplified scenario given in Fig. 2 which shows a travel plan of a particular EV $n$. We set a specific routing plan from initial point to Point j. In the beginning, an EV with around 50 % battery level at the initial point. When it arrives at Point i, it depletes around 25 % battery level since it involves multiple driving schedules in a relatively long distance. In order to complete the remaining of EV's schedules, it can choose to travel over the road segment with PTs installed with joint charging and moving. For instance, as Fig. 2 shown, PT k is used to placed between Point i to Point j. Here, we consider the case that PT k is relatively long and EV participates various driving schedules during these two points. By having such implementation, EV can fulfill around 25 % battery level. Besides the scheduling operation of EVs in a smart city, to better facilitate such implementation, efficient placement strategies for PTs are needed based on the information of the traffic networks and EV conditions.

The proposed multi-stage system model consists of two main stages: I) optimal placement strategy for PTs and II) dynamic V2G scheduling. The flowchart of the system model is shown in Fig. 3. Initially, the system operator collects and analyzes the traffic information from ITS and energy demand from the smart grid, respectively. Then, the system operator carries to perform optimal placement strategy for installing PTs on the road segments at Stage I. The PT placement solutions can be obtained by considering the city road networks, flows of EVs, and EV energy demands. Making use of the optimal placement solutions for PTs at Stage I, the EV dynamic V2G scheduling scheme is thus proposed at Stage II. Meanwhile, EV customers have their preferences on participating in dynamic V2G scheduling or only performing vehicle traveling. In addition, the provision of daytime V2G ancillary service can further be deployed to stabilize the stability of the city smart grid. The final commitment of V2G ancillary service is reported to the smart grid so as to verify the effectiveness of the provision of the daytime ancillary services. For this multi-stage system framework, the utilization of PTs can help EVs both complete their travel plans and charging plans in a joint and efficient manner. The dashed lines shown in Fig. 3 indicate the information flows occurred in this system while the solid arrows represent the system operation flows.

## III. Optimal Placement Strategy for Power Tracks

As discussed in Section II-D, the first stage problem is to investigate the optimal placement strategy for installing PTs on the city road networks. The problem formulation is shown as follows. The related parameters and variables are presented in Table I.

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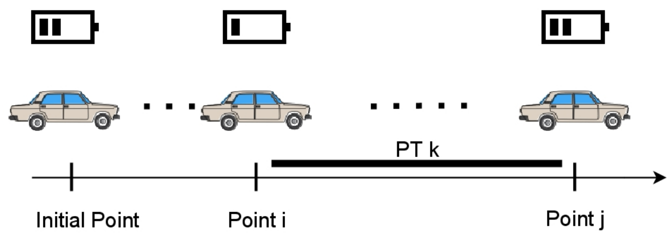


Fig. 2. A time slot conversion example.

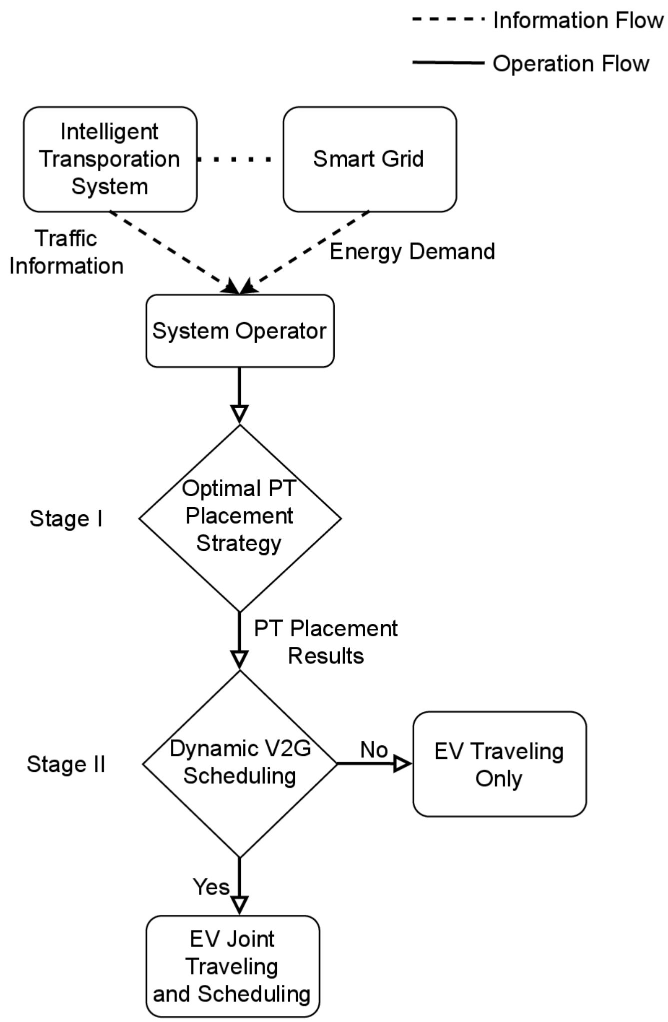


Fig. 3. Proposed system model.

TABLE I
TABLE OF NOTIFICATIONS IN PROPOSED OPTIMAL PLANNING STRATEGY.

| | |
|---|---|
| $\mathcal{V}$ | Index set of nodes |
| $V$ | Total number of nodes |
| $\mathcal{E}$ | Index set of road paths |
| $\mathcal{K}$ | Index set of PTs |
| $\mathcal{N}$ | Set of EV groups |
| $x_{ij}^k$ | Binary variable for placing PT $k$ at path $(i,j)$ |
| $\mathcal{L}_s^n$ | Departure point for EV $n$ for each route |
| $\mathcal{L}_d^n$ | Destination point for EV $n$ for each route |
| $P^k(t)$ | Power demand of PT $k$ at Time $t$ |
| $E_{\min}$ | Minimum required energy for EVs' charging operations |
| $\psi_k$ | Installation cost for PT $k$ |
| $d_{ij}$ | Physical distance for path $(i,j)$ |

### A. Placement Strategy Constraints

We first define a binary variable $x_{ij}^k$ to indicate that PT $k \in \mathcal{K}$ is installed at the road path $(i,j)$, as follows:

$$x_{ij}^k = \begin{cases} 1 & \text{if PT } k \text{ is installed at path } (i,j) \in \mathcal{E} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

In the EV dynamic wireless charging system, each PT is designed to be installed on the city road segments. To ensure that an EV arrives at the final destinations fulfilling the energy requirements, the case of wireless charging through the PTs are required during the traveling period. To let EV charge in motion, there is at least one PT installed on the city road segments. This can be ensured by having:

$$\sum_{k,i,j} x_{ij}^k \geq 1 \tag{2}$$

By considering the vehicular routes in the city, the network flow model needs to be implemented. The utilization of this model is to ensure the feasibility of installing each PT on road path $(i,j)$, which further elaborates the potential placement of PTs by following the bi-directional traffic flow on this road path. Hence, for PT $k \in \mathcal{K}$, the relation between the number of incoming paths and the number of out going paths can be guaranteed by

$$\sum_{i \in \mathcal{V}} x_{ij}^k - \sum_{i \in \mathcal{V}} x_{ji}^k = \begin{cases} 1 & \text{if } j = \mathcal{L}_d^n, \mathcal{L}_s^n \neq \mathcal{L}_d^n \\ -1 & \text{if } j = \mathcal{L}_s^n, \mathcal{L}_s^n \neq \mathcal{L}_d^n \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $\mathcal{L}_s^n$ and $\mathcal{L}_d^n$ represent the departure and destination point for EV $n \in \mathcal{N}$ at each route. Also, the first two conditions ensure the directional placement of PTs on road paths, which are based on the traffic flows of the road network. The last condition ensures no PT installation on this road path since the number of incoming edges is equal to number of outgoing edges.

In addition, the energy demand of PTs in the wireless charging system is directly related to the amount of energy needed for charging all participated EVs in the city. Let $P^k(t)$ be the power demand of PT $k$ at Time $t$. Hence, during the time period $\mathcal{T}$, the city energy demand is associated with the utilization of PTs, which can be expressed as

$$\sum_{t,k,i,j} x_{ij}^k P^k(t) \Delta t \geq E_{\min}, \ \forall k \in \mathcal{K}, t \in \mathcal{T}, (i,j) \in \mathcal{E} \tag{4}$$

where $E_{\min}$ denotes the minimum energy required for charging all participated EVs in the city.

### B. Formulation of Optimal Placement Strategy

The proposed optimal placement strategy of PTs is developed based on the demand for EVs traveling and charging. Different from other existing formulations of charging station placement strategies, we incorporate the energy demand of EVs in (4), so as to link the case of scheduling EVs with the

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provision of daytime V2G ancillary services at the second stage. For the first stage, the purpose is to investigate the efficient strategy for placing PTs in the road segments of the entire city. Here, we assume that the travel pattern of every EV is known after the execution of Stage I. To approach it, the control objective of this problem aims to minimize the budget for placing the PTs in the city area while satisfying the energy requirements. The budget function is associated with the placement costs for PTs in the city, which can be expressed as:

$$C_{\text{Placement}} = \sum_{k \in \mathcal{K}, (i,j) \in \mathcal{E}} \psi_k d_{ij} x_{ij}^k \tag{5}$$

where $\psi_k$ represents the installation cost for a single PT on each road segment.

By incorporating the operational constraints into the proposed optimal placement problem, the optimization problem is formulated as follows:

$$\textbf{minimize} \; C_{\text{Placement}} \tag{6a}$$

$$\textbf{subject to} \quad (1) - (4) \tag{6b}$$

The proposed optimal placement problem in (6) is formulated as a mixed-integer linear programming (MILP). Although this problem is NP-hard, many commercial solvers, such as gurobi and mosek, can be utilized to efficiently provide approximate solutions. The utilization of these solvers can provide an approximate solution to the problem in an efficient manner [27]. There are metaheuristics methods like evolutionary algorithms that can solve the proposed problem. Nonetheless, mosek can guarantee a provable upper and lower bounds for the global optimal solution, therefore is preferred in this work. In addition, the sub-optimal solution can be converged through a finite number of steps.

## IV. Dynamic Vehicle-to-Grid Scheduling

As discussed in Section II-D, based on the optimal solution of Stage I, we develop the optimal wireless charging/discharging strategies for the participating EVs in the city at the second stage. The problem formulation is presented in the following. The related parameters and variables are presented in Table II.

### A. Wireless Charging/Discharging Constraints

The system operation of dynamic V2G scheduling depends on the planning strategy for power tracks installed in the city road paths. We first define the time-varying route plan of EV $n$ as $y_n^*(t)$ at Time $t$, which corresponds to the optimal placement strategy $x_{ij}^{k*}$ that is developed from Stage I. Otherwise, without the prior information about the PT placement strategy, the charging/discharging schedule cannot be determined. Meanwhile, the optimal travel plan of each EV is also gained so that the amount of periods between every EV and in-touch PTs is known. In the second stage, we make use of these two information to schedule the dynamic wireless charging for the particular groups of EVs that users prefer to participate. The rest of EVs are regarded as the group that only considers traveling in a road network without wireless charging/discharging. During the participation time period $\mathcal{T}$, the participating electric vehicles must fulfill the system requirements related to charging/discharging behaviors. In addition, since we consider the provision of daytime ancillary services in the city region, the stability criterion of the city smart grid system should also be achieved. The operation bounds for charging and discharging powers of EV $n$ follow:

TABLE II
Table of notifications in proposed dynamic V2G scheduling.

| | |
|---|---|
| $y_n^*(t)$ | Time-varying route plan of EV $n$ at Time $t$ |
| $\mathcal{T}$ | Index set of timeslot |
| $N_T$ | Total operation time period |
| $N_{EV}$ | Total number of EVs |
| $P_n(t)$ | Active power of EV $n$ at Time $t$ |
| $P_{n,\text{dch}}$ | Discharging power limit of EV $n$ |
| $P_{n,\text{ch}}$ | Charging power limit of EV $n$ |
| $SOC_n(t)$ | State-of-charge of EV $n$ at Time $t$ |
| $\Delta t$ | Length of a time slot. |
| $Cap_n$ | Installed battery capacity of EV $n$. |
| $\eta_{\text{ch}}$ | Charging efficiency |
| $\eta_{\text{dch}}$ | Discharging efficiency |
| $d_{ij}^n(t)$ | Travel distance of EV $n$ for path $(i,j)$ at Time $t$ |
| $v_{ij}^n(t)$ | Travel velocity of EV $n$ for path $(i,j)$ at Time $t$ |
| $\theta_{ij}^n(t)$ | Delay parameter for path $(i,j)$ at Time $t$ |
| $\beta_n$ | Unit energy consumption of EV $n$ |
| $SOC_{n,\text{ini}}$ | Initial state-of-charge of EV $n$ |
| $SOC_{n,\text{req}}$ | Charging requirements of EV $n$ |
| $SOC_{n,\min}$ | Lower bound of state-of-charge for EV $n$ |
| $SOC_{n,\max}$ | Upper bound of state-of-charge for EV $n$ |
| $P_{\text{tot}}(t)$ | Total active power of the city area at Time $t$ |
| $P_{\text{reg}}(t)$ | Regulation signals at Time $t$ |
| $\alpha_n$ | Unit cost for operating EV $n$ |
| $\gamma_n$ | Charging/discharging cost for EV $n$ |
| $\xi$ | Reward for providing daytime regulation service |

$$P_{n,\text{dch}} \le P_n(t) y_n^*(t) \le P_{n,\text{ch}}, \; \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{7}$$

where $P_{n,\text{dch}} \le 0$ and $P_{n,\text{ch}} \ge 0$.

Then, when EV $n$ participates in dynamic scheduling operation at each time slot, it performs charging/discharging activity as it is connected with the power tracks. Hence, the state-of-charge (SOC) of each participated EV $n \in \mathcal{N}$ at Time $t$ can be calculated by:

$$SOC_n(t + \Delta t) = SOC_n(t) + \frac{\Delta t}{Cap_n} \eta(P_n(t)) P_n(t), \; t \in \mathcal{T} \tag{8}$$

where $Cap_n$ represents the battery capacity of EV $n$, and $\eta(\cdot)$ denotes the energy efficiency of the charging/discharging power of each EV, which is calculated by:

$$\eta(P_n(t)) = \begin{cases} \eta_{\text{ch}} & P_n(t) \ge 0, \\ \frac{1}{\eta_{\text{dch}}} & P_n(t) < 0, \end{cases} \tag{9}$$

where $\eta_{\text{ch}}, \eta_{\text{dch}} \in (0, 1]$ represents the charging and discharging efficiencies of each participated EV $n$, respectively.

Since EVs are traveling in the city area, we define the travel distance of EV $n$ from Point $i$ to Point $j$ as $d_{ij}^n$. Then, the time-

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varying energy consumption of the battery level of EV $n$ at Time $t$ can be expressed as:

$$SOC_n(t + \Delta t) := SOC_n(t) - \frac{\beta_n}{Cap_n} d_{ij}^n(t) \tag{10}$$

where $\beta_n$ denotes the unit energy consumption factor of EV $n$.

For the travel velocity from Point $i$ to Point $j$ at Time $t$ over the road segment $(i, j) \in \mathcal{E}$, we denote it as $v_{ij}^n(t)$ for EV $n$. In practice, the real-time traffic conditions of the city network may affect the EV actual routing plans. Once the immediate changes in road condition happened, the travel velocity of EV $n$ is indeed influenced. Hence, we define the delay parameter $\theta_{ij}(t)$ to indicate whether the sudden traffic congestion occurred over the road segment $(i, j)$ at Time $t$ or not. The delay parameter is related the time-varying travel speed of the road segment for EV $n$, Then, we have

$$d_{ij}^n(t) = (v_{ij}^n(t) - \theta_{ij}(t))\Delta t, \ \forall n \in \mathcal{N}, (i, j) \in \mathcal{E} \tag{11}$$

Apart from completing the routing plans for each EV $n$, it also fulfills the energy requirement of charging/discharging scheduling through the connections of wireless power tracks. The energy requirement is associated with the required SOC level of each EV $n$. Let $SOC_{n,\text{ini}}$ be the initial SOC of EV $n$ at the source location and $SOC_{n,\text{req}}$ be the required SOC level of EV $n$, respectively. Suppose $SOC_n(N_T)$ be the final SOC of EV $n$ at the end of the total time period, and then, the fulfillment of the charging requirement before reaching the destination is denoted by

$$SOC_n(N_T) \geq SOC_{n,\text{ini}} + SOC_{n,\text{req}}, \ \forall n \in \mathcal{N} \tag{12}$$

Furthermore, for the charging/discharging operation of each EV $n$, over-charging and deep-discharging scenarios, should be avoided. Therefore, the operational bounds of SOC at Time $t$ should follow

$$SOC_{n,\text{min}} \leq SOC_n(t) \leq SOC_{n,\text{max}}, \ \forall n \in \mathcal{N} \tag{13}$$

where $SOC_{n,\text{min}}$ and $SOC_{n,\text{max}}$ denote the lower and upper bound of SOC of EV $n$, respectively.

Before the problem formulation of the proposed dynamic V2G scheduling, the following assumptions are adopted in this paper:

1) Each EV reports its own travel plans with charging requirement during the participation period.
2) Frequency regulation service is zero-energy service, since the expectation of the required energy is zero for a relatively long time period.

The related studies have adopted the first assumption frequently, see [28], [29], and [30], while the second assumption is related to the forecast errors of the grid power upon frequency regulation requests [31].

### B. *Formulation of Dynamic Vehicle-to-Grid Scheduling*

The proposed dynamic V2G scheduling framework is formulated to consider the V2G scheduling problem. The V2G scheduling is associated with the operation of the dynamic wireless charging system on handling all participated EVs when traveling inside the city area. By considering the system operation, the operational cost related to managing the participated EVs traveling inside the city area is needed to be considered. It is affected by the route plan of EV $n$, which directly affects the value of $d_{ij}^n(t)$ at time $t$. Hence, this cost function can be expressed as

$$C_{\text{Operation}} = \sum_{n \in \mathcal{N}, t \in \mathcal{T}, (i,j) \in \mathcal{E}} \alpha_n d_{ij}^n(t) \tag{14}$$

where $\alpha_n$ indicates the unit operational cost for managing EV $n$ in the city area.

Furthermore, besides the system operational cost, the proposed scheduling scheme involves V2G scheduling of the participated EVs during the time period $\mathcal{T}$. The mechanism of V2G scheduling incurs the cost of charging/discharging activities of EVs. In addition, the provision of daytime V2G ancillary services can be implemented to further keep the system's stability. In this work, we study the V2G scheduling with the daytime frequency regulation service to alleviate the active power fluctuations of the city smart grid, in order to keep the grid frequency within a stable region. Hence, for the proposed dynamic V2G scheduling, during the total period $\mathcal{T}$, the control objective is to minimize the charging costs of the participated EVs while generating the reward for providing daytime V2G regulation service in the city smart grid. This reward is directly associated with the quality of the V2G regulation service. Therefore, the cost function for V2G scheduling is formulated as follows

$$C_{\text{Charging/Discharging}} = \sum_{n \in \mathcal{N}, t \in \mathcal{T}} \gamma_n P_n(t) - (R - \xi \sum_{t \in \mathcal{T}} (P_{\text{tot}}(t))^2) \tag{15}$$

where $\gamma_n$ denotes the individual charging/discharging cost for EV $n$, and $R$ is the base reward for providing the daytime regulation service in the city area with the penalty factor $\xi \in (0, 1]$ to investigate the regulation performance. $P_{\text{tot}}(\mathcal{T})$ denotes the total active power profile of the city smart grid, which is calculated by

$$P_{\text{tot}}(\mathcal{T}) = P_{\text{reg}}(\mathcal{T}) + P_A(\mathcal{T}) \tag{16}$$

where $P_{\text{reg}}(\mathcal{T})$ denotes the regulation signals of the city smart grid. $P_n(\mathcal{T})$ indicates the active power profile of EV $n$. In addition, $P_A(\mathcal{T})$ presents the aggregated active power of the participated EV $n$ in the city area, which is also obtained by

$$P_A(\mathcal{T}) := \sum_{n \in \mathcal{N}} P_n(\mathcal{T}) \tag{17}$$

To sum up, the optimization problem for dynamic V2G scheduling is formulated as follows:

$$\textbf{minimize} \ C_{\text{Scheduling}} = C_{\text{Operation}} + C_{\text{Charging/Discharging}} \tag{18a}$$

$$\textbf{subject to} \quad (7) - (13) \tag{18b}$$

*Lemma 1*: The objective function (18) is convex.

*Proof*: As shown in (18), the objective function includes two parts, namely, $C_{\text{Operation}}$ and $C_{\text{Charging/Discharging}}$. For function $C_{\text{Operation}}$, it belongs to an affine function. Then, since $C_{\text{Charging/Discharging}}$ is a quadratic function, it's strictly convex.

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Therefore, it follows that the summation of an affine function and a convex function is convex such that the objective function (18) is convex. ■

*Lemma 2*: The feasible set of (18) is convex.

*Proof*: The feasible set of (18) is associated with the constraints (7), (12), and (13). The region of (7) is apparently convex by definitions. Then, we first transform (12) to

$$\sum_{t\in\mathcal{T}} \eta(P_n(t))P_n(t)\Delta t \geq \frac{Cap_n}{\Delta t}(SOC_{n,\text{req}} - SOC_{n,\text{ini}}) \quad (19)$$

Also, Constraint (13) can be transformed as follows:

$$\sum_{t\in\mathcal{T}} \eta(P_n(t))P_n(t)\Delta t \geq \frac{Cap_n}{\Delta t}(SOC_{n,\text{min}} - SOC_{n,\text{ini}}) \quad (20)$$

$$\sum_{t\in\mathcal{T}} \eta(P_n(t))P_n(t)\Delta t \geq \frac{Cap_n}{\Delta t}(SOC_{n,\text{max}} - SOC_{n,\text{ini}}) \quad (21)$$

We assume that there exist two points $P_{n,1}(\mathcal{T})$ and $P_{n,2}(\mathcal{T})$ satisfying the region of (19) and there exist $\lambda_1, \lambda_2 \in [0, 1]$ to satisfy $\lambda_1 + \lambda_2 = 1$. First of all, we define:

$$P_{n,3}(\mathcal{T}) = \lambda_1 P_{n,1}(\mathcal{T}) + \lambda_2 P_{n,2}(\mathcal{T}) \quad (22)$$

Then, the following inequality holds:

$$\eta(P_{n,3}(t)P_{n,3}(t) \geq \lambda_1\eta(P_{n,1}(t))P_{n,1}(t) + \lambda_2\eta(P_{n,2}(t))P_{n,2}(t) \quad (23)$$

The inequality constraint (23) indicates that $P_{n,3}(\mathcal{T})$ also satisfies (19). Since the region of (19) is equivalent to (12), we prove that the feasible set defined by (12) is convex. Similarly, the feasible set of (20) and (21) are also convex recursively through different timeslots. To conclude, the feasible region defined by the constraints (7), (12), and (13) is convex so that the feasible set of (18) is convex. ■

*Theorem 1*: The formulated problem in (18) is a convex optimization problem.

*Proof*: According to [32], we use the proofs to Lemmas 1 and 2 to prove that the formulated problem in (18) is a convex optimization problem. ■

The proposed V2G scheduling is developed in a centralized manner so that the system operator broadcast the power control signals to the participated EVs when receiving the traffic and energy information. Considering the communication between the system operator and the participated EVs, the number of EVs connected may cause the communication burden and the incast issue among the communication nodes simultaneously. Hence, we need to define the communication overhead, which is denoted as

$$CO = D \cdot m \cdot N_T(N_{EV} + 1) \quad (24)$$

where $D$ denotes the size of a one-dimensional control variable, $P_n(\mathcal{T})$, and $m$ is the number of iterations performed by using the solver.

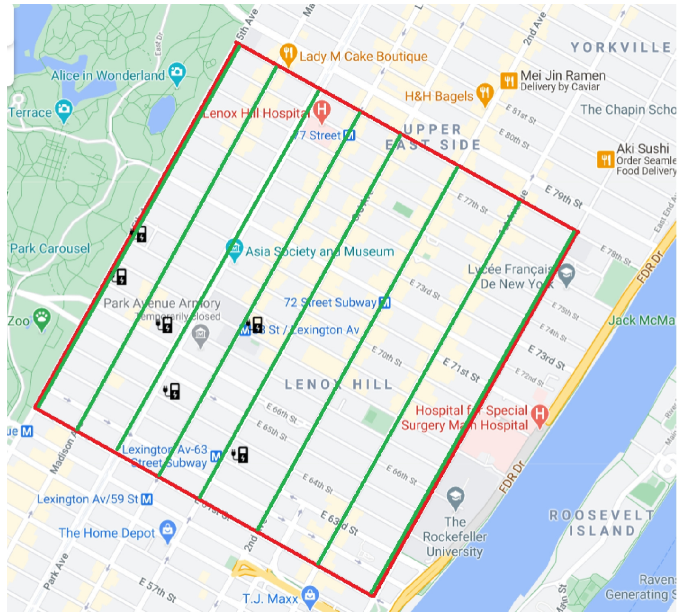


Fig. 4. Google map of Manhattan in New York city.

## V. Performance Evaluation

In this section, we assess the performance of the proposed multi-stage system. First of all, we present the simulation setup. Then, we conduct the scenarios for comparison in simulation, as well as relevant performance metrics. After that, we test the proposed system on its effectiveness and effect to the city smart grid. Then, we investigate the economic feasibility of the proposed model. Finally, we further examine the impact of fleet size to the system.

### *A. Simulation Setup*

In the simulation, we evaluate the performance of the proposed model in Manhattan of New York city shown in Fig. 4. The investigated area (approx. $1300\,\text{m} \times 870\,\text{m}$) is captured inside the red bounding box. In this area, there are totally 324 nodes and 378 road paths. The installation cost of one PT with the length of 75 m is set to \$40,000 per 100 meters following [33]. To capture the EV mobility patterns, the operational period is considered from 8:00 a.m. to 10:00 a.m., which can be divided into $N_T = 120$ slots with $\Delta t = 1$ minutes. During this time period, each EV performs multiple travel plans, and the time gap for resting between two consecutive routing plans is set to 1 min. The unit operation cost $\alpha_n = \$3.75$ per 100 km, which follows [34]. Furthermore, in this work, we investigate a specific daytime V2G ancillary service, namely V2G regulation service. In order to present the effectiveness of such service, during the investigated time period, we use the regulation signal data on 1 September 2017 [35] with a forecast error $e(t) \sim N(0, 0.3)$ [28]. In addition, we set the base regulation reward to \$40 per MWh following the PJM market standard [36]. The regulation capacity of the Manhattan area is set to be 300 kW following [37].

The settings for EVs are shown in the following. Considering EVs traveling in the urban area, the unit energy

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consumption $\beta_i$ of each EV is set to 20 kWh per 100 kilometers. The averaged driving speed of each EV is set to be 20 mph without sudden congestion conditions. In this work, we consider two types of EV groups with $N_{EV} = 200$, Chevrolet Volt with 18.4 kWh [38], and Nissan Leaf with 40 kWh [39]. Here, we assume the entire two groups of EVs participating dynamic V2G scheduling so as to present the desired system performance. The charging standard follows SAE J2954 under the WPT Power Class 1 and 2 [25]. Based on the standard, we limit the discharging and charging power to -7 kW and 7 kW, respectively, and the charging/discharging efficiency is set to 0.9. According to [29], we model the SOC settings of EVs based on the uniform distribution. In particular, the initial SOC of EV $n$ follows U[30%, 40%], and the charging requirement of EV $n$ follows U[0%, 20%]. The safety condition of the charging/discharging mechanism is considered where the minimum and maximum SOCs follow U[10%, 20%] and U[90%, 99%], respectively. Besides, the charging price is set to $0.59 per kWh, which is in accordance with the actual price in Manhattan. The simulation is conducted in MATLAB Release 2017a through the mosek optimization solver under the yalmip toolbox.

### B. *Scenarios for Comparison*

For evaluating the effectiveness of the proposed system model, we consider three different scenarios in comparison, which are shown as:

1) S1: proposed dynamic V2G scheduling under optimal placement strategy
2) S2: proposed dynamic V2G scheduling under fixed placement strategy
3) S3: optimal V2G scheduling at fixed charging stations

The proposed dynamic V2G scheduling under optimal placement strategy for PTs is denoted by S1. In S1, we perform different vehicular route patterns under 100 random cases to generate the optimal placement strategy. S2 presents the proposed dynamic V2G scheduling under a fixed placement strategy. Specifically, for the fixed placement strategy, we consider that there exist the following two fixed placement strategies, namely, “S2 with Main Roads” and “S2 with Full Roads”. The former indicates that the PTs are only installed at the main roads, including 5th Avenue, Park Avenue, Lexington Avenue, 3rd Avenue, 2nd Avenue, 1st Avenue, and York Avenue, which are shown as the green roads in Fig. 4, while the latter one presents the case that all road segments are placed equipped with PTs. These main roads are the crucial intersected segments of multiple junctions with dense vehicular flows. Different from the previous two scenarios, S3 only considers V2G service provided at the wired charging stations located in the city area. In this case, we deploy the optimal V2G scheduling framework in [37], and the exact locations of the six charging stations in the Manhattan area can also be found in Fig. 4. In this scenario, we set the parking cost of these wired fast-charging stations to $5 per hour following the actual Manhattan parking cost.

### C. *Performance Metrics*

We evaluate the variance of the total power profile $P_{tot}$ of the Manhattan area as one important performance metric. The variance function of the active power profile of the city smart grid is expressed as

$$\begin{aligned}\text{Var}(P_{tot}(\mathcal{T})) &= \frac{1}{N_T}\sum_{t\in\mathcal{T}}\left((P_{tot}(t) - \frac{1}{N_T}(\sum_{t\in\mathcal{T}}(P_{tot}(t))\right)^2 \\ &= \frac{1}{N_T}\sum_{t\in\mathcal{T}}(P_{tot}(t))^2 - \frac{1}{N_T^2}(\sum_{t\in\mathcal{T}}P_{tot}(t))^2\end{aligned} \tag{25}$$

A smaller variance value indicates a better performance in providing the daytime V2G regulation service, which also presents that the active power fluctuations of the city smart grid can be better flattened.

### D. *Simulation Result*

*1) Effectiveness of Proposed System Model:* The effectiveness of the proposed multi-stage system framework is evaluated based on the quality of the daytime V2G regulation service provided in the city area. The quality of this service is reflected by the total active power profile of the city smart grid. During the complete time period, the regulation signals of the system refer to the active power mismatches between power generations and demands, which is shown by the blue solid line in Fig. 5. In this figure, we can observe that our proposed model (S1) outperforms the two baseline approaches, including “S2 with Main Roads” and S3. The reason is that EVs perform dynamic wireless charging only in motion of the main roads in S2, while for S3, EVs are operated to charge within the short parking period at the charging stations. These two scenarios cannot thoroughly smooth the active power fluctuations of the entire period, which are shown as the magenta dashed line (S2) and the green triangle-solid line (S3) in Fig. 5. Comparing the cases of “S2 with Full Roads” and “S2 with Main Roads”, “S2 with Full Roads” yields a better performance. The reason is that “S2 with Full Roads” enables all road segments placing PTs so that when EVs are traveling inside a road network, they always contact with PTs to perform wireless charging/discharging. However, for the case of “S2 with Main Roads”, EVs can only perform dynamic V2G scheduling when they are traveling over the main roads. Besides, “S2 with Full Roads” performs better than S1 because this scenario does not consider the economical constraints on installing PTs. Hence, our proposed model can not only provide a relatively high quality of V2G regulation service but also satisfy the economical budget constraints on installation costs. Furthermore, a similar result can be presented in Table III, which shows that S1 has a relatively low variance value so that better performance on the provision of the daytime V2G regulation service is obtained.

Besides, we further study the satisfaction of EV dynamic charging of the proposed system model. Note that we define $ROE$ as the ratio of the energy requirement, which is calculated by

$$ROE = \begin{cases} \frac{E_C}{E_{\text{req}}} & E_C < E_{\text{req}}, \\ 1 & E_C \geq E_{\text{req}}, \end{cases} \tag{26}$$

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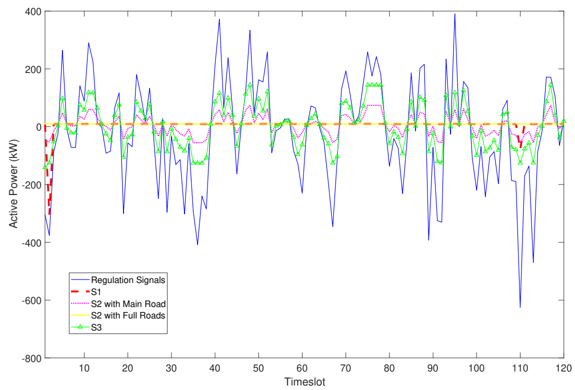


Fig. 5. Comparison of different scenarios in active total power profile.

TABLE III
COMPARISON OF DIFFERENT APPROACHES IN VARIANCE OF TOTAL POWER PROFILE

| Scenarios | Variance ($\mathrm{k}^2\mathrm{W}^2$) | ROE |
|---|---|---|
| Regulation Signals | $3.31 \times 10^5$ | - |
| S1 | $8.78 \times 10^2$ | 1 |
| S2 with Main Roads | $1.58 \times 10^3$ | 0.9501 |
| S2 with Full Roads | $9.75 \times 10^{-1}$ | 1 |
| S3 | $6.09 \times 10^3$ | 1 |

where $E_C$ denotes the actual charged energy from EVs and $E_{\text{req}}$ is the required energy of EVs. When $ROE = 1$, it holds that the charging requirement of each EV $n \in \mathcal{N}$ is satisfied. From Table III, we can observe that S1, "S2 with Full Roads", and S3 have $ROE = 1$ on average, which means that they can fulfill the EV charging requirements so as to indicate the satisfaction of EV customers. "S2 with Main Roads" only complete 95.01% of the charging requirements averagely due to insufficient charging with limited PTs.

*2) Effect of City Smart Grid:* From the previous results, the active total power profiles of different scenarios are gained. We further study the system's effect, especially the impact of different scenarios on the grid frequency. Table IV presents the effect of the grid frequency under different approaches. Note that we utilize a frequency standard of 50 Hz for the grid. Based on its operating requirements, the stable region of this system is within $[49.5, 50.5]$ Hz, which presents a tolerance bound at 1%. According to Table IV, we can observe that S1 and "S2 with Full Roads" can both satisfy the stability criteria of the city smart grid system, while the other two scenarios cannot keep the system stable. Indeed, S1 can keep the system stable for the entire time period except for a few minor spikes. Therefore, our proposed multi-stage system model can better guarantee the stability of the smart grid.

*3) Economic Feasibility:* In this part, we evaluate the economic feasibility of the proposed multi-stage system model in comparison of the baseline approaches. Note that for S3, we utilize the actual capital cost of installing the charging stations at the specific locations. The cost of every single port at fast-charging stations is approximately \$51,000 [40]. Meanwhile, we presume that all participated EVs are assigned at least once to the fast-charging stations for charging during the total participation time period. Based on the settings, we can obtain the economical aspects of different scenarios. The result is shown in Table V. By comparing different placement strategy, S3 develops the highest installation costs while "S2 with Main Roads" requires the lowest. For the case of "S2 with Main Roads", it only involves the PT placements at critical junctions of the road network that are mentioned in Section V-B. The reason is that S3 requires all roads to place PTs, which leads to the highest capital costs. When considering the service quality for providing the daytime V2G regulation service, S1 can contribute to cost-effective benefits by considering the efficient dynamic V2G scheduling scheme with relatively low installation costs. Hence, S1 can guarantee both economical and technical benefits to the entire system.

In addition, we further investigate the averaged cost per EV on dynamic V2G scheduling scheme. The result is presented in Table VI. Clearly, S1 achieves a relatively low cost on EV wireless charging scheme, which reflects that it can better encourage EV customers to participate dynamic V2G scheduling. Besides, owing to the best performance in smoothing the active power fluctuations of the city smart grid, "S2 with Full Roads" yields a better result than S1 when the entire system do not consider the budget constraint on placing PTs. This result is consistent with the solutions shown in Section V-D1, which further indicates the effectiveness of S1 for both economic and technical aspects of the entire system.

*4) Impact of Fleet Size:* We further analyze the impact of the EV fleet size on the performance of the V2G scheduling scheme. In particular, we consider five different sizes of EV fleets, including 50, 100, 200, 300, and 400 EVs. The simulation result is shown in Table VII. As the size of the fleet increase, the variance of the active total power profile reduces dramatically. Additionally, the lower variance of the total power profile indicates a more stable grid operation. Besides, in the same table, we can observe that the operation cost related to V2G scheduling decreases when raising the size of the EV fleet. It apparently reflects that the better performance on alleviating the active power fluctuations can let EV customers pay less and receive more rewards on providing the daytime V2G regulation service in the city smart grid. Furthermore, we further study the communication overhead related to different fleet size. Suppose the size of one-dimensional control variable $D = 8$ bytes, and then the results for average communication overhead $CO$ are 0.098 MB, 0.194 MB, 0.386 MB, 0.578 MB, and 0.770 MB for these five cases individually, which follows (24).

*5) Comparison of Different Placement Strategy:* In this part, we further investigate the effectiveness of the proposed optimal placement strategy for PTs. The performance metrics consist of the total budget cost on placing PTs and requirement ratio that is calculated by $\frac{E_{total}}{E_{min}}$ where $E_{total}$ denotes the total EV energy demands. In addition, a higher requirement ratio indicates better performance in fulfilling the EV energy demands. Note that the baseline placement strategy follows the formulations from several existing approaches, such as

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TABLE IV
THE EFFECT OF GRID FREQUENCY UNDER DIFFERENT SCENARIOS

| | Performance Metrics | | | |
|---|---|---|---|---|
| Scenarios | Average (Hz) | Variance (Hz$^2$) | Maximum (Hz) | Minimum (Hz) |
| Regulation Signals | 50 | 30.58 | 59.11 | 39.89 |
| S1 | 50 | 0.06 | 50.03 | 47.43 |
| S2 with Main Roads | 50 | 24.09 | 59.55 | 41.31 |
| S2 with Full Roads | 50 | $7.13 \times 10^{-9}$ | 50.01 | 49.99 |
| S3 | 50 | 3.15 | 53.27 | 46.75 |

TABLE V
ECONOMIC FEASIBILITY OF DIFFERENT SCENARIOS.

| Scenarios | $C_{\text{placement}}$($USD) |
|---|---|
| S1 | $6.00 \times 10^6$ |
| S2 with Main Roads | $4.08 \times 10^6$ |
| S2 with Full Roads | $1.02 \times 10^7$ |
| S3 | $1.28 \times 10^7$ |

TABLE VI
IMPACT OF DIFFERENT SCENARIOS ON EACH EV.

| Scenarios | Averaged Cost per EV ($USD) |
|---|---|
| S1 | 19.86 |
| S2 with Main Roads | 37.33 |
| S2 with Full Roads | 8.01 |
| S3 | 25.13 |

[17]. Based on [17], we change the objective function (5) to $\sum_{k\in\mathcal{K},(i,j)\in\mathcal{E}}(t_{ij}x_{ij}^k)$, which means that the objective aims to minimize the time spent on traveling around the entire routes. In the meantime, we do not consider (4) for this formulation. The comparison result is presented in Table VIII. Although the baseline approach achieves a lower budget cost on placement strategy, the energy demand cannot satisfy the demand of all participated EVs in the captured area of Manhattan. Nonetheless, our proposed placement strategy can meet the requirement of the EV energy demand with a relatively low budget cost on placing PTs. Therefore, the effectiveness of the proposed placement strategy is guaranteed.

TABLE VII
IMPACT OF DIFFERENT SIZE OF EVS THROUGH S1.

| Number of EVs | Variance (k$^2$W$^2$) | $C_{\text{Scheduling}}$($USD) |
|---|---|---|
| 50 | $7.58 \times 10^3$ | $9.03 \times 10^5$ |
| 100 | $1.95 \times 10^3$ | $2.35 \times 10^5$ |
| 200 | $8.78 \times 10^2$ | $9.56 \times 10^4$ |
| 300 | $5.02 \times 10^2$ | $1.51 \times 10^2$ |
| 400 | $3.95 \times 10^2$ | $1.18 \times 10^2$ |

TABLE VIII
COMPARISON OF DIFFERENT PLACEMENT STRATEGY.

| Metrics | Proposed Strategy | Baseline Strategy |
|---|---|---|
| Budget Cost ($USD) | 7,929 | 4,914 |
| Requirement Ratio | 90.0% | 35.8% |

## VI. CONCLUSIONS

In this paper, we propose a multi-stage system framework to develop a novel EV dynamic wireless charging system in a smart city. The multi-stage system jointly considers optimal placement strategy for installing PTs in a city road network and dynamic V2G scheduling. In the first stage, we formulated an optimal placement strategy for PTs based on the city traffic information and energy demands. Once the optimal locations of PTs are obtained, the proposed dynamic V2G scheduling scheme is developed in the second stage to coordinate the EV schedules as well as provide daytime V2G ancillary services to the city smart grid system. Simulation results indicate that our proposed multi-stage system model outperforms the baseline approaches with relatively low capital costs for the system installations. In addition, the frequency of the city smart grid can be further stabilized owing to the provision of daytime V2G regulation service. Besides, the impact of the different sizes of the EV fleets on the system is investigated. For future work, we can extend several following parts into the proposed integrated system model. First of all, since this work does not consider the coexistence of both wired and wireless charging mechanisms for EVs, we will develop a general EV charging system that accounts for both wired and wireless charging schemes. Then, we will investigate the effect of this approach on the city power grid due to the different EV patterns on performing wired and wireless charging mechanisms. Furthermore, the proposed multi-stage system framework can be implemented with by considering real-time traffic conditions of the city road networks.

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**Shiyao Zhang** (S'18–M'20) received the B.S. degree (Hons.) in electrical and computer engineering from the Purdue University, West Lafayette, IN, USA, in 2014, the M. S. degree in electrical engineering (electric power) from University of Southern California, Los Angeles, CA, USA, in 2016, and the Ph.D. degree from the University of Hong Kong, Hong Kong, China. He is currently a Post-Doctoral Research Fellow with the Academy for Advanced Interdisciplinary Studies, Southern University of Science and Technology. His research interests include smart energy systems, intelligent transportation systems, optimization theory and algorithms, and deep learning applications.

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**James J. Q. Yu** (S'11–M'15–SM'20) is an assistant professor at the Department of Computer Science and Engineering, Southern University of Science and Technology, Shenzhen, China, and an honorary assistant professor at the Department of Electrical and Electronic Engineering, the University of Hong Kong. He received the B.Eng. and Ph.D. degree in electrical and electronic engineering from the University of Hong Kong, Pokfulam, Hong Kong, in 2011 and 2015, respectively. He was a post-doctoral fellow at the University of Hong Kong from 2015 to 2018. He currently also serves as the chief research consultant of GWGrid Inc., Zhuhai, and Fano Labs, Hong Kong. His general research interests are in smart city and urban computing, deep learning, intelligent transportation systems, and smart energy systems. His work is now mainly on forecasting and decision making of future transportation systems and basic artificial intelligence techniques for industrial applications. He is an Editor of the IET SMART CITIES journal.