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RESEARCH ARTICLE

EV Parking Lots for Flexible Energy Sourcing

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ABSTRACT Energy storage is inherently a flexible asset that can be used to reduce renewable energy curtailment and the congestion at its host network, enhance system resilience, and provide ancillary services at peak times. But the cost of technology still hampers the large-scale adoption of storage in power distribution networks. With EV parking lots included in its asset portfolio, a city can take advantage of the power stored in the parked EVs without major capital investments. In this article, we formulate the operation of an EV parking lot from the viewpoint of its owner (i.e., a city or a private entity). The lot works as a market aggregator with operational uncertainties stemming from: (i) random arrival and departure of vehicles, (ii) the SoC of EV batteries at the times of arrival and departure, and (iii) willingness of EV owners to participate. The risks from these uncertainties and market prices of ancillary services impact the bottom line of the lot owner's revenue. For EV owners the excessive up and down cycles of battery is offset by discount offered by the lot owner. We provide an illustrative example and a roadmap to extend this model to take the holistic view of a power distribution network.

INDEX TERMS EV parking lot, V2G control, energy storage system, dynamic capacity, queueing model, market participation, mix-integer linear programming (MILP).

NOMENCLATURE

t	Index of time.
t_0	Initial time slot of the planning horizon.
i	Index of time interval number.
v	Index of electric vehicle (EV).
S_t	Number of occupied spaces at t.
G	General Distribution.
K	Number of parking spaces.
λ_i	Parameter of inter-arrival time exponential distribution.
Δt_i	Duration of time interval i.
n	Auxiliary variable for number of arriving EVs.
m	Auxiliary variable for number of departing EVs.
N_i	Number of EVs arriving in i^{th} interval.
μ_i	Parameter of time-to-stay exponential dist.
μ_i'	EVs departure rate during i^{th} interval.
w_i^j	Expected number of EVs arrived in j^{th} interval and stayed in parking lot till t_{i-1}.
L_i	Number of EVs departing in i^{th} interval.
$\overline{P}_v$	Rated power of EV v.
$\overline{E}_v$	Energy capacity of EV v.
λ_t	Locational marginal price (LMP) at t.
FR_t^{CR}	FR credit at t.
SoC_v^{Int}	Initial SoC of EV v.
SoC_v^{Fnl}	Desired final SoC of EV v.
$f_p(.)$	Day-ahead stochastic planning function.
Reg_t	Aggregated planned FR commitment at t.
P_t^{V2G}	Aggregated planned discharge to grid at t.
P_t^{G2V}	Aggregated planned charge from grid at t.
φ	Discount factor for V2G enabled EVs.
ρ	Performance score.
$RMCCP_t$	Regulation market capacity clearing price at t.
$RMPCP_t$	Regulation market performance clearing price at t.
β_t	Mileage ratio at t.

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$FR_{v,t}$	Committed FR capacity of EV v at t.
N	Number of time steps.
$P_{v,t}^{V2G}$	Planned discharge power of EV v at t.
SB_t^{Rev}	Parking lot owner's sell back revenue at t.
EV_v^{ChCst}	Charging cost of EV v.
t_v^{Int}	Arrival time of EV v.
t_v^{Fnl}	Departure time of EV v.
ϑ_v^{V2G}	Binary variable equal to 1 if EV v gives the V2G permission to the lot owner; and 0 otherwise.
D_v	Demand of EV v.
PE_t^{Cst}	Cost of power purchased from grid to charge EVs at t.
EV_v^{Sve}	Cost-saving of EV v.
EV_v^{DegCst}	Degradation cost of EV v.
γ_v	Fraction of time that battery of EV v is deployed by the lot owner.
T_v^{Xtr}	Extra parking time of EV v.
EV_v^{CapCst}	Capital cost of battery of EV v.
N_v^{Cyc}	Maximum number of cycles that battery of EV v can be charged and discharged.
τ	Planning time horizon.
P_t^{PV2G}	Power flow from PV to grid at t.
N_{EV}	Total number of EVs using parking lot during τ.
$\xi_{v,t}$	Binary parameter equal to 1 if EV v is parked in lot at t; and 0 otherwise.
$P_{v,t}^{PV2V}$	Power flow from PV to EV v at t.
η^c	Battery charging efficiency.
η^d	Battery discharging efficiency.
P_t^{PV}	PV output power at t.
φ^*	Optimal discount factor.
α	Planning risk.
Pr_α	Probability that actual FR capacity becomes less than planned capacity at t given α.
$\hat{\lambda}^{ACap}$	Weighted LMP by aggregated battery capacity.
$\hat{\lambda}^{OSpc}$	Weighted LMP by percentage of occupied spaces.
$\hat{FR}^{CR,ACap}$	Weighted FR credit by aggregated battery capacity.
$\hat{FR}^{CR,OSpc}$	Weighted FR credit by percentage of occupied spaces.
$ACap_t$	Aggregated capacity of EV batteries parked in lot at t.
$OSpc_t$	Percentage of occupied parking spaces at t.

I. INTRODUCTION

A. BACKGROUND AND PROBLEM DESCRIPTION

Cities around the world are slowly transforming to clean energy and targeting net zero residential and commercial communities for 2050. A clear trend is to use a mixed portfolio of renewable energy assets (e.g., solar farms, wind farms and clean Hydrogen) to achieve the net zero goal [1]. The intermittent nature of these renewable sources, however, requires adoption of energy storage in a power grid (both at the distribution and bulk levels). Energy storage is a flexible asset that can help a network to reduce renewable power curtailment and the congestion at peak times, enhance resilience, and be a clean power source for ancillary services [2], [3]. Reduced peak demand and congestion at a network lead to reduced or deferred infrastructure investments, thus helping reduce the overall cost of energy. However, the cost of energy storage of almost every existing technology exceeds its economic benefits, unless the economics of resilience and deferred investments are accurately quantified and included in the cost and benefit analysis [4]. With massive penetration of Electric Vehicles (EVs), cities will allow the construction of public and private EV parking lots. For EV charging, these lots can be sourced by the grid or be co-located with wind or solar farms. In either case, these lots can be valuable sources of flexibility in cities' energy asset portfolios, without major capital investments. These benefits, however, come with challenges too. In particular, a lot owner (which can be public or private) must deal with several sources of uncertainties.

Vehicle to Grid (V2G) technology and FERC order 841 [5] allow large facilities, such as EV parking lots, to participate in the wholesale energy and ancillary service markets [6]. This can generate tangible financial incentives and benefits for EV parking lot industry which is expected to substantially grow with many smart city initiatives around the world. An EV lot follows a Modular Energy Storage Architecture (MESA[1]) where the energy modules are EVs, and each EV space is equipped with a V2G unit. The total energy stored at the parking lot for a duration of time depends on the number of parked vehicles, and varies randomly with arrivals and departures of vehicles and their State of Charge (SoC). The participation of vehicle owners is driven by economic benefits and the risk-averseness of vehicle owners. Thus, not every parked EV will participate, and for the participating ones there may be uncertainties due to unexpected departures or other factors. Technically speaking, we are dealing with an aggregated Energy Storage System (ESS) with total capacity changing randomly over the course of a day. This translates to market risks if the aggregator engages in arbitrage or other ancillary services. This article contributes: (i) by formulating these business risks and (ii) incorporating them in day-ahead planning and operation of the lot. Our formulation covers the economic perspectives of the lot owner and the EV owners.

B. LITERATURE REVIEW

EV integration studies in the literature mainly explore the impacts of EV adoption on demand and the required upgrades in generation, transmission and distribution systems to meet

[1]MESA is an open set of specifications and standards to accelerate interoperability, scalability, safety, quality, availability, and affordability in energy storage systems [7].

the demand [8]. The increased peak load due to plugged-in EVs may overload service transformers causing transformer overheating and subsequent deterioration [9]. EV charging is likely to cause power quality problems, including, under-voltage conditions, voltage and current harmonics, etc. [10], [11], [12]. To mitigate the negative impacts of EV charging, Time-Of-Use (TOU) pricing scheme is proposed in [13] where the utilities incentivize customers to charge their EVs during off-peak hours. Utility-owned smart controls aiming at maximize utility and costumers' benefits are proposed in [14] and [15]. The authors in [16] address the problem of maximizing the profits for the EV owners by selling excess energy to the grid, while in [17] and [18] control algorithms to maximize EV owner's profit from selling power to the grid and participating in the frequency regulation (FR) market are proposed. Yao et al. analyze the EV charging coordination based on price- and incentive-based demand response (DR) programs [19]. Also, the aggregated capacity of batteries in the EV parking lots can be used in the ancillary market. The impact of unit unavailability on system capacity depends on the configuration and series/parallel connections of individual batteries or storage units [20], [21].

Apart from that, the authors in [22] propose a robust algorithm based on a receding horizon linear problem for the EV aggregator considering EV constraints, price uncertainties, and battery aging that is compensated by a utilization index. By employing a real travel database, Giordano et al. propose a day-ahead optimization of EVs fleet charge in [23], while considering the arrival and departure times forecasts and the energy required for the next trip. Moreover, in [24], a linear optimization model to maximize the revenues obtained by a V2G EV aggregator is developed considering grid services in the UK electricity market, while in [25], a linear planning model that aids EV aggregation investors for the purpose of ancillary service markets is proposed where the number of targeted EVs and the best incentives to the EV owners are also determined. An aggregate of EVs is modeled as a virtual battery in [26] considering the stochastic number of connected EVs and their initial SoCs. Further, the economic behavior of an EV aggregator is evaluated in [27], where wholesale electricity market participation impacts on locational marginal prices and power dispatch patterns are explored. A multi-timescale response capacity evaluation model of EV aggregator is proposed in [28], where EV owners' responsive willingness based on psychology model, as well as charge-discharge states and SoCs are established. In [29], Wang et al. propose a state-space method to develop a reduced EV aggregator model at the system level to describe the response characteristics of many EVs and to realize frequency regulation.

To the best of our knowledge, there is a major gap in understanding how an EV aggregator facility should operate in a distribution network. Moreover, the cost and benefit of such a facility for its owner, EV owners, and distribution network requires investigation.

C. CONTRIBUTION AND PAPER STRUCTURE

Our proposed model integrates multiple revenue streams stemming from the dynamic aggregated capacity achieved from the EV batteries, which turns the parking lot to be an aggregated dynamic ESS while characterizing the stochasticities of the EVs behaviors. Moreover, the cost and benefit analysis of such a facility for its operator/owner, EV owners, and distribution network requires more investigations. The technical approach presented here for an EV aggregator behaving as an ESS is sufficiently generic as long as the following system-level assumptions are met:

- The parking lot is owned and operated by an independent entity.
- One or more storage modules may be owned by a single individual.
- Modules become *available* and *unavailable* according to independent and time-dependent stochastic processes.
- SoC for a module at the time of availability is random, and a required level of charge must be met prior to its unavailability.
- The parking lot owner has full access to the modules during the time periods that they are available as long as the SoC at the time of unavailability is met.

There are also assumptions with respect to modules including:

- Type and size of modules might be different.
- Each storage module is stochastically degradable, and the parameters for the degradation processes are known a priori.

Finally, there are financial assumptions to be considered as well, including:

- The parking lot owner acts as an aggregator in the market and can offer market products, such as FR and/or peak load shaving. These transactions are hidden from the module owners and are between utility and the parking lot owner.
- A module owner decides to engage in a transaction with the parking lot owner based on compensation and degradation risks.
- Individual owners must pay a premium to participate.

In summary, the main contributions of this paper can be listed as follows:

- Developing a comprehensive, integrated day-ahead planning model for a parking lot owner who uses a queueing formulation to compute EV population at different times and a stochastic optimization model with objectives of maximizing the stacked up revenue streams from the FR market, energy arbitrage, and EVs charging fees constrained by EV owners' compensation agreements for degradation costs.
- Driving the stochastic behavior of the aggregated storage by random arrivals and departures of EVs, random arrivals and firm departures SoCs, and whether an EV owner is willing to participate by compromising

TABLE 1. Summary of literature review highlighting the scope and contribution of this paper.

Reference	Queueing Model*				EV Aggregator Revenue◇			EV Owner Cost-Benefit•		
	Rand. Arr. Time	Rand. Arr. SoC	Rand. Dep. Time	Rand. EV Pop.	FR	Arbitrage/DR	EV Ch. Cost	Opt. Discount	Rand. Bat. Deg. Cost	Req. Dep. SoC
[17]					√		√			√
[19]	√	√	√			√	√			√
[22]	√	√	√			√	√		√	√
[23]	√		√			√	√			√
[24]	√			√	√	√	√			
[25]					√		√	√	√	
[26]	√	√		√						
[27]						√	√			√
[28]	√	√	√			√		√		√
[29]	√	√	√							√
[30]	√	√	√			√			√	√
[31]	√	√	√			√	√		√	√
Current Model	√	√	√	√	√	√	√	√	√	√

*Rand., Arr., Dep., and Pop. denote random, arrival, departure, and population respectively.
◇FR, DR, and Ch. represent frequency regulation, demand response, and charging respectively.
•Opt., Bat., and Req. symbolize optimal, battery, and requested, respectively.

between the optimized discount received and the cost of overstaying in the parking lot that is reflected as the battery degradation cost.

The rest of the paper is structured as follows. Section II includes preliminaries and Section III gives the day-ahead planning and operational model. Section IV gives experimental results and summarizes our findings. Finally, conclusions are drawn in Section V followed by the future extensions.

II. PRELIMINARIES

A. THE HOLISTIC VIEW OF THE FRAMEWORK

The facility owner aims at maximizing his/her revenue by optimally controlling bi-directional power flow in the facility, constrained by vehicle owners' permissions. A vehicle owner's decision is partially dependent on what s/he receives in return, either as a discount for the use of the facility or as an expedited payback. The vehicle owner needs to weigh this return against battery degradation. For the lot owner to participate in the market, the facility must plan in day-ahead depending on vehicle queues. Here, a queueing model is developed that explains vehicle arrivals and departures, and the number of vehicles in the facility. The results from this model are fed into a day-ahead planning model which also takes into account day-ahead and regulation market capacity and performance clearing prices, i.e. RMCCP and RMPCP respectively (see Fig. 1; Day-ahead stochastic planning block). The day-ahead model assumes optimal operational control for each of the multiple scenarios that are generated according to the stochastic inputs. We also formulate planning risks and risks to the distribution network due to the underlying stochasticity of the facility (Fig. 1; Distribution network impact-assessing model block). The optimal operational control model governs bi-direction power flow in the facility and works closely with the facility and vehicle owner's revenue model. Fig. 1 illustrates the holistic view of the proposed approach.

B. THE QUEUEING MODEL

The initial SoC of an EV battery is a random variable that follows truncated normal distribution bounded from below, with mean and variance as functions of the vehicle's arrival time. EVs that arrive earlier have higher mean value and lower variance. It is assumed that EVs should reach to the owner-defined SoC upon departure. Between arrival and departure times, an EV can be part of the lot's modular energy storage system if the V2G permission is granted by the EV owner. The facility has a finite number of parking spaces for EVs. We assume that the facility is empty at the beginning of the day when $t_0 = 0$, i.e. $S_{t_0} = 0$. EVs arrive according to a general stochastic process and occupy parking spots for a random period each; this time also follows a general probability distribution. Underlying arrival distributions change with time of the day, and time-to-stay distributions vary from one EV to another. Further SoC levels at arrival and departure times depend on individual vehicles characteristics. From a queueing point of view, this parking facility works as a $G/G/K/0$ queue, where the first two G's are general distribution designations for inter-arrival time and time-to-stay of vehicles, respectively. K is the number of parking spaces and the capacity of the facility. We assume an exponentially distributed inter-arrival times with a time-dependent parameter λ_i for the i^{th} time interval. The probability of n vehicle arrivals during the i^{th} time interval is then given by:

$$\mathbb{P}\{N_i = n\} = \frac{[\lambda_i.\Delta t_i]^n}{n!} e^{-\lambda_i.\Delta t_i} \quad \forall n = 0, 1, \ldots, K \tag{1}$$

and the expected umber of arrivals during this interval is:

$$\mathbb{E}[N_i] = \sum_{n=0}^{K} \frac{[\lambda_i.\Delta t_i]^n}{(n-1)!} e^{-\lambda_i.\Delta t_i} \tag{2}$$

where Δt_i is the duration of i^{th} interval. Moreover, the time to stay of any EV, which arrives during the i^{th} interval, is assumed to be a random variable that follows an exponential distribution with the mean value $1/\mu_i$. Let μ_i' be the vehicle departure rate from the facility during the i^{th} interval from the perspective of an outside person. This time-dependent departure rate is the function of time to stay of EVs, which arrived during prior intervals. μ_i' can be calculated by the weighted average of the times to stay of all vehicles that are

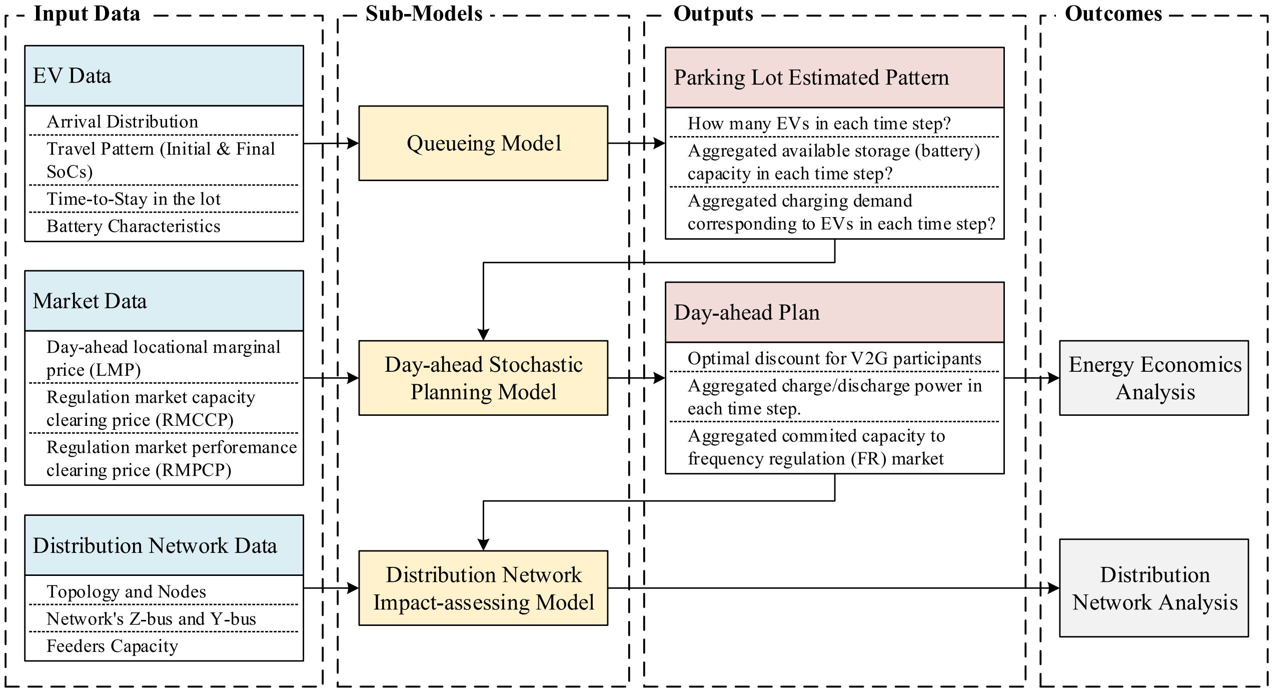

FIGURE 1. Schematic diagram of the proposed framework.

at the facility, and is given by:

$$\mu_i' = \frac{\sum_{j=1}^{i-1} w_j^i.\mu_j}{\sum_{j=1}^{i-1} w_j^i} \quad \forall i \tag{3}$$

where weight w_j^i is the expected number of vehicles which arrived in the j^{th} interval and remained in the facility till t_{i-1}:

$$w_j^i = \lambda_j.\Delta t_j.e^{-\mu_j.(t_{i-1}-t_j)} \quad \forall i, j \tag{4}$$

Then the probability of n vehicles departing the facility during the i^{th} interval given m vehicles are in the parking lot at the time t_{i-1} is:

$$\mathbb{P}\{L_i = n | S_{t_{i-1}} = m\} = \frac{[m.\mu_i'.\Delta t_i]^n}{n!}.e^{-m.\mu_i'.\Delta t_i} \tag{5}$$

$\forall i, \forall n = 0, 1, \ldots, m$ where $S_{t_{i-1}}$ is the number of occupied spaces at the time t_{i-1}. The expected number of departing vehicles during the i^{th} interval is then given by:

$$\mathbb{E}[L_i | S_{t_{i-1}} = m] = \sum_{n=0}^{m} \frac{[m.\mu_i'.\Delta t_i]^n}{(n-1)!}.e^{-m.\mu_i'.\Delta t_i} \quad \forall i \tag{6}$$

Expected number of EVs in the parking lot at the end of i^{th} interval is given by:

$$\mathbb{E}[S_{t_i}] = S_{t_{i-1}} - \mathbb{E}[L_i | S_{t_{i-1}}] + \mathbb{E}[N_i] \quad \forall i = 1, 2, \ldots, 24 \tag{7}$$

III. DAY-AHEAD PLANNING AND OPERATIONAL CONTROL

In order to estimate potential market benefits, an economic dispatch model is developed under the PJM fast regulation market (RegD) rules [32]. The facility owner commits the maximum capacity in peak-priced hours while ensuring that sufficient capacity is available to provide both regulations up/down (discharging/charging) services. For demonstration purposes, we use 2016 PJM day-ahead regulation market data for capacity and performance clearing prices [33]. For the wholesale arbitrage, the facility owner may charge EV batteries when the electricity price is low and sell it back to the grid when the price is high, while the EV SoC demands are met.

A. DAY-AHEAD PLANNING MODEL

FR capacity commitment and net injected power, i.e. aggregate charge minus aggregate discharge, must be considered in the day-ahead planning which is scheduled based on the number of EVs, S_t, types of batteries reflecting EVs' rated power and energy capacities, $\overline{P}_v$ and $\overline{E}_v$ respectively, and initial and final desired SoCs of the batteries, denoted by SoC_v^{Int} and SoC_v^{Fnl} respectively, at any time step t and for all EVs indexed by v in the parking lot. Moreover, market variables such as electricity price, i.e., LMP (λ_t), and FR credit (FR_t^{CR}) could influence the planning. These input variables are stochastic, hence stochastic optimization is applied. The outputs of the model are optimal discount factor assigned to EVs (for V2G permission), aggregated planned capacity for FR commitment (at each time step), aggregated amount of electricity required to charge EVs, and aggregated amount of discharged electricity during each time step. Fig. 2 depicts the functional diagram of the day-ahead stochastic planning model.

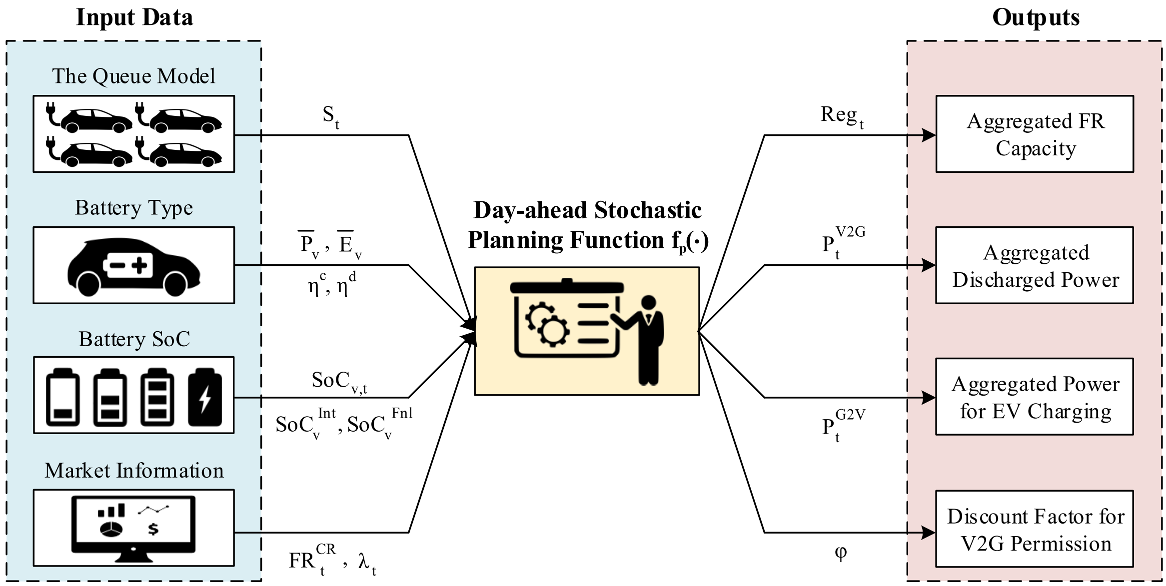

FIGURE 2. Day-ahead stochastic planning model's functional diagram.

The following equation explains the inputs and outputs of our proposed stochastic day-ahead planning function $f_p(.)$:

$$\left[\{Reg_t;\forall t\},\{P_t^{V2G};\forall t\},\{P_t^{G2V};\forall t\},\varphi\right]=f_p\Big(\big[\{S_t;\forall t\},\{\lambda_t;\forall t\},\{FR_t^{CR};\forall t\},\{SoC_v^{Int};\forall v\},\{SoC_v^{Fnl};\forall v\}\big]\Big) \tag{8}$$

where $\{Reg_t;\forall t\}$ is the time series of the aggregated planned capacity for FR; $\{P_t^{V2G};\forall t\}$ and $\{P_t^{G2V};\forall t\}$ are the time series for the aggregate planned discharged and charged power for the parking lot; and φ is the optimally planned discount factor for the V2G enabled EVs. To capture the stochasticity of input variables, a Monte-Carlo (MC) simulation is implemented to generate sample paths according to the stochastic input distributions, one of which is vehicle arrival process characterized by the queueing model of Section II-B. An optimal day-ahead plan for a given path in Monte-Carlo simulation is calculated using the revenue optimization model described next. The plans for randomly generated MC paths are then aggregated into statistical distribution of output variables in the planning phase.

B. OPERATIONAL CONTROL MODEL

The objective function includes revenue and cost terms, and constraints are driven by market, demand type and other factors. We start with the main sources of revenue:

1) FR CREDIT

FR credit in PJM RegD market is based on the capability offered and the performance provided, where the former is related to the hourly integrated regulation capacity, while the latter is related to how fast ESS responses to regulation signals [32]. The integrated committed capacity, Reg_t, receives credit FR_t^{CR} at time t which is calculated as:

$$FR_t^{CR}=Reg_t\times\rho\times(RMCCP_t+\beta_t\times RMPCP_t) \tag{9}$$

where $RMCCP_t$ and $RMPCP_t$, both in \$/kWh, are adopted from PJM [33]. ρ is a score between 0 to 1 indicating a unit's performance in following the regulation signal. Since battery storage response is quick, this performance score is close to 1. Reg_t is also defined as:

$$Reg_t=\sum_{v=1}^{S_t}FR_{v,t} \tag{10}$$

where $FR_{v,t}$ is the committed capacity to FR market from EV v during time step t, and β_t is PJM mileage ratio [32].

2) SELL BACK ENERGY TO THE MAIN GRID

The facility owner's benefit as a result of selling energy to the main grid in time step t is calculated as:

$$SB_t^{Rev}=\lambda_t\times P_t^{V2G} \tag{11}$$

where P_t^{V2G} is the aggregated discharged electricity from EVs at time t, and λ_t is day-ahead locational marginal price (LMP) adopted from PJM 2016 data [34].

3) CHARGING EVs

The facility sells electricity to the EVs for battery charging. We assume that EV pays to the parking lot operator the average price during the time it is parked in the facility. Moreover, EVs which give the V2G permission to the parking lot operator pay less. The amount of money that EV v pays to the operator, denoted by EV_v^{ChCst}, is formulated as:

$$EV_v^{ChCst}=\left(1-\varphi\times\vartheta_v^{V2G}\right)\times\overline{\lambda_v}\times D_v \tag{12}$$

where $\overline{\lambda_v}$ and D_v are the average price in \$/kWh during the EV v parking time, and EV v demand in kWh, respectively. ϑ_v^{V2G} is a binary variable equal to 1 if EV v gives the V2G permission to the facility operator, and 0 otherwise. φ is also a variable between 0 and 1 and represents the discount factor offered by the operator to the EV owners in exchange for V2G permission. The only daily operation cost element for the facility is the cost of buying electricity from the main grid to charge EV batteries. Here we assume PJM hourly day-ahead LMP as a unit price of electricity. This cost element is then formulated as:

$$PE_t^{Cst} = \lambda_t \times P_t^{G2V} \quad \forall t \tag{13}$$

where PE_t^{Cst} and P_t^{G2V} are cost of purchasing electricity in \$ at time t and the amount of electricity purchased at time t, respectively. EV owners may make cuts in their cost of charging EV's battery if they give the V2G permission to the operator. Thus, EV v's cost-saving, denoted by EV_v^{Sve}, is modeled as:

$$EV_v^{Sve} = \varphi \times \overline{\lambda_v} \times D_v \tag{14}$$

The cost element related to the EV owner is the excessive degradation of battery due to V2G permission. We assume that battery degradation is proportional to the extra time that EV is parked in the lot. The time that a vehicle stays in the lot in excess of time it needs for charging can be considered as committed capacity to the FR market. Deploying EV battery in FR market or arbitrage during this extra time causes the excessive degradation, which results in an earlier replacement of EV battery. We convert this degradation to a dollar value by equation (15) below.

$$EV_v^{DegCst} = \gamma_v \times T_v^{Ext} \times \frac{\overline{P}_v}{2\overline{E}_v} \times \frac{EV_v^{CapCst}}{N_v^{Cyc}} \quad \forall v \tag{15}$$

In (15), T_v^{Ext} is the extra parking time corresponding to EV v; $\overline{P}_v$ and $\overline{E}_v$ are respectively the rated capacity in kW and the energy capacity in kWh of battery in EV v. The expression $T_v^{Ext} \times \frac{\overline{P}_v}{2\overline{E}_v}$ models the number of full cycles the battery may have during the extra time. γ_v is the fraction of time that battery in EV v is deployed by parking operator. EV_v^{CapCst} is the capital cost of battery in EV v and N_v^{Cyc} is the maximum number of cycles that battery could be charged and discharged. Equation (15) illustrates the portion of battery capital cost that can potentially be used for V2G permission. We assume that the EV monitoring system is smart enough to estimate the degradation cost in (15) and the revenue in (14) as a result of V2G permission. As such, EV owner gives V2G permission if $EV_v^{Sve} > EV_v^{DegCst}$, i.e.:

$$\vartheta_v^{V2G} = \begin{cases} 1 & \text{if } EV_v^{Sve} > EV_v^{DegCst} \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

C. THE FACILITY OWNER'S OPTIMIZATION PROBLEM

The facility owner's problem aims at maximizing the revenue subject to V2G permissions from EV owners. In the case the facility has renewable generation such as Photovoltaic (PV), the objective function is formulated as:

$$\textbf{Max} \sum_{t=1}^{\mathcal{T}} \left(FR_t^{CR} + SB_t^{Rev} - PE_t^{Cst} + \lambda_t \times P_t^{PV2G} \right) + \sum_{v=1}^{N_{EV}} EV_v^{ChCst} \tag{P1}$$

where P_t^{PV2G} is the power flow from PV to the main grid during time step t. As mentioned before, P_t^{V2G} and P_t^{G2V} are integrated power flow due to discharging or charging, and are given by $\sum_{v=1}^{N_{EV}} P_{v,t}^{V2G}$ and $\sum_{v=1}^{N_{EV}} P_{v,t}^{G2V}$, such that $P_{v,t}^{V2G}$ and $P_{v,t}^{G2V}$ are the power flows from EV v to the main grid during time step t and vice versa. Moreover, the quantity allocated to the FR market reduces the maximum power flow for charging and discharging as:

$$P_{v,t}^{V2G} + FR_{v,t} \leq \xi_{v,t} \times \overline{P}_v \quad \forall v, t \tag{17}$$
$$P_{v,t}^{G2V} + P_{v,t}^{PV2V} + FR_{v,t} \leq \xi_{v,t} \times \overline{P}_v \quad \forall v, t \tag{18}$$

where $\xi_{v,t}$ is a binary parameter equal to 1 if EV v is parked in the lot during time step t, and 0 otherwise; $P_{v,t}^{G2V}$ is the power flow from the main grid to EV v during time step t; and $P_{v,t}^{PV2V}$ is the power flow from the PV to EV v during time step t. In addition, the SoC of the EV battery is limited by its capacity minus the allocated capacity to the FR market, which is modeled as:

$$FR_{v,t} \leq SoC_{v,t} \leq \overline{E}_v - FR_{v,t} \quad \forall v, t \tag{19}$$

and the SoC of EV v battery at time step t is formulated as:

$$SoC_{v,t} = SoC_{v,t-1} + \eta^c \left(P_{v,t}^{G2V} + P_{v,t}^{PV2V} \right) - \frac{P_{v,t}^{V2G}}{\eta^d} \tag{20}$$

over $\forall v$, $t \in [t_v^{Int} + 1, t_v^{Fnl}]$. η^c and η^d are the battery charging and discharging efficiencies; and t_v^{Int} and t_v^{Fnl} are the arrival and departure times of EV v, respectively. The initial SoC of an EV battery is random and depends on the arrival time. We assume that if an EV stays long enough at the parking lot, the owner will request for the full charge. Further, power flow form EV to the grid and the capacity allocation to the FR market is allowable according to the EV owner permission. Therefore:

$$0 \leq P_{v,t}^{V2G} \leq \vartheta_v^{V2G} \times \overline{P}_v \quad \forall v, t \tag{21}$$
$$0 \leq FR_{v,t} \leq \vartheta_v^{V2G} \times \overline{P}_v \quad \forall v, t \tag{22}$$
$$0 \leq P_{v,t}^{G2V} \leq \overline{P}_v \quad \forall v, t \tag{23}$$
$$0 \leq P_{v,t}^{PV2V} \leq \overline{P}_v \quad \forall v, t \tag{24}$$
$$0 \leq P_{v,t}^{PV2V} \leq P_t^{PV} \quad \forall v, t \tag{25}$$
$$0 \leq P_t^{PV2G} \leq P_t^{PV} \quad \forall t \tag{26}$$

where P_t^{PV} is the PV output power generated during time step t depending on the PV rated capacity and solar irradiance

Algorithm 1 `Optimal Discount Factor`

1: Initialize $k \leftarrow 1$.
2: **while** $k \leq 101$ **do**
3: $\quad \hat{\varphi}_k \triangleq \frac{k-1}{100}$
4: $\quad$ **Solve** Problem (P1) **such that** $\varphi = \hat{\varphi}_k$
5: $\quad Obj_k \triangleq$ Optimal objective function value in (P1) in iteration k
6: $\quad k \leftarrow k+1$ and **go** to step 2.
7: **end while**
8: $\varphi^* \triangleq \text{argmax}_{\hat{\varphi}_k}\, Obj_k$
9: **return** φ^*

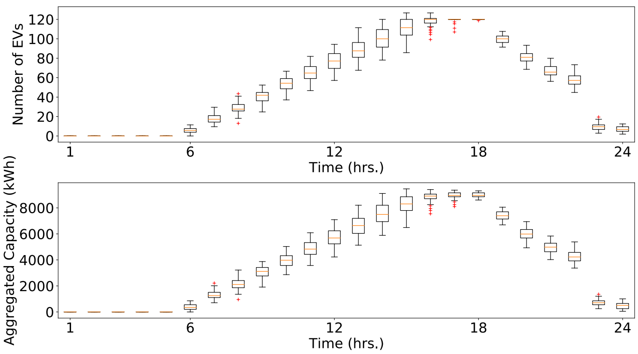

FIGURE 3. Top) Number of EVs parked in the lot, bottom) aggregate capacity of batteries.

at time t [35]. Finally, the parking lot operator's problem is summarized as:

$$\begin{aligned} &\textbf{Solve} \quad \text{P1} \\ &\textbf{s.t.} \quad \text{Constraints } (9) - (26). \end{aligned}$$

Relation (16) makes the proposed optimization problem non-linear. To solve this mix-integer nonlinear programming (MINLP) problem, we iteratively solve the model for different values of φ, where $\varphi \in [0, 1]$, until the convergence is reached at φ^*. In each iteration, the problem is converted to a mix-integer linear programming (MILP) problem by assigning a value to φ and determining the V2G binary variable according to (16) (see Algorithm 1). The equivalent MILP problem is solved by using the YALMIP toolbox in MATLAB platform [36]. It is worth mentioning that the algorithm can be carried out on a daily basis as well, which yields different hourly optimal discount factors.

IV. NUMERICAL EXPERIMENTS

We start with day-ahead planning examples. We illustrate results for a commercial parking lot with 120 parking spaces. EV arrivals are assumed to be *Markovian*. The capacity of batteries and their initial and final SoCs are randomly generated according to their stochastic distributions while market information, viz. FR credit and electricity prices, are unchanged. Fig. 3 depicts the boxplots for the number of EVs parked in the lot and the aggregated capacity of batteries based on 100 MC sample paths. The parking lot is almost

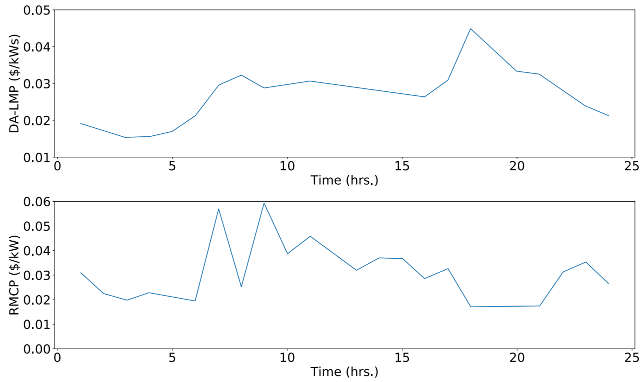

FIGURE 4. Top) Day-ahead locational marginal prices (DA-LMP), bottom) regulation market clearing prices (RMCP).

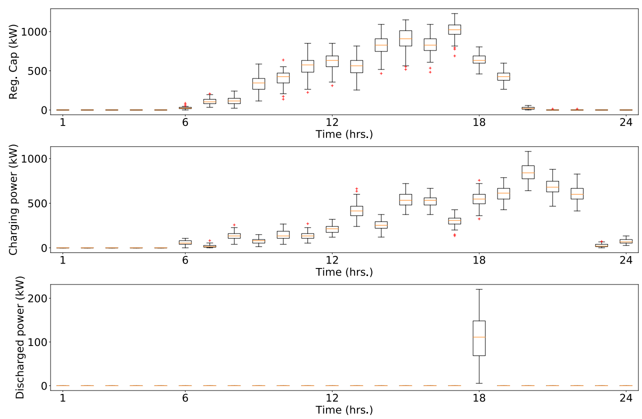

FIGURE 5. Top) FR capacity, middle) Elec. power required for charging, bottom) Elec. Power to discharge.

fully-occupied during 4-6 PM. The market data remains fixed for all scenarios as given in Fig. 4. Then, the optimal plans are calculated for each sample path, and results from all paths are compiled into distributions.

Fig. 5 shows the Reg. Cap, charging and discharging power over 24-hour. It is observed that the optimal decisions during the planning phase is highly sensitive to the market values. Although there is relatively more available capacity at 4 PM compared to 3 pm, FR committed capacity is less at 4 pm. This is due to the higher RMCP value at 3 pm compared to 4 pm. Analogous to the other example, as shown in Fig. 5 at the bottom, selling to the grid is an optimal decision at 6 PM when the electricity price is high. The day-ahead plan is estimated by taking the average over all scenarios. The planned capacity for FR participation and net demand are shown in Fig. 6.

The following sources of uncertainty exist in the planning phase. If the FR market participants are called for regulation service but fail to provide the requested capacity due to overestimation in planning phase, they get penalized by the market operator. Thus, there is a risk associated with the day-ahead plan calculated as the probability that the actual capacity for FR participation

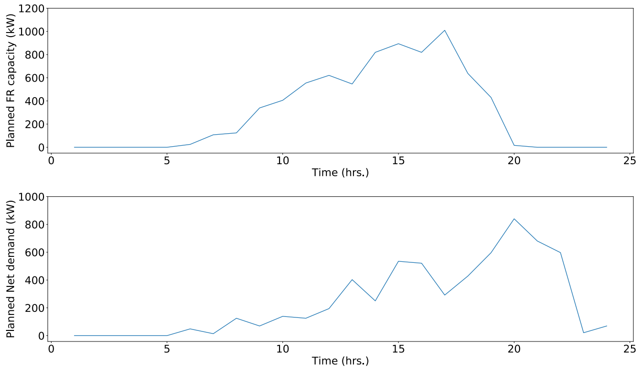

FIGURE 6. Top) Planned FR capacity, bottom) planned net injected power.

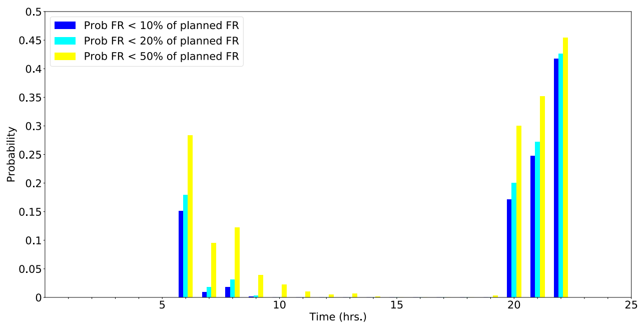

FIGURE 7. FR planning risk during different hours of the day.

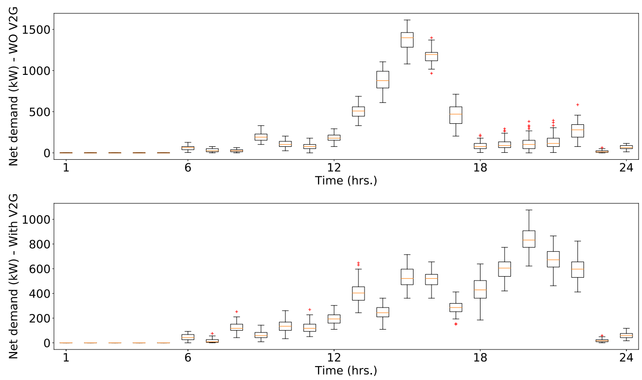

FIGURE 8. Parking facility net demand: Top) Case I: Without V2G, bottom) Case II: With V2G.

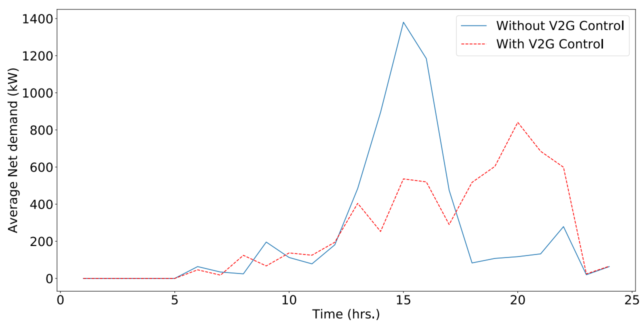

FIGURE 9. Average net demand profile.

becomes less than the planned capacity, i.e. $Pr_\alpha = Pr\,(\text{Actual FR Cap} < \alpha\%\text{ of Planned FR Cap})$ where α is the planning risk. Fig. 7 depicts the planning risks over 24-hour period. As illustrated in Fig. 7, the risk related to the FR planning capacity is negligible during the peak time when the parking lot is almost fully-occupied. However, FR planning based on the average scenario has a higher risk during the off-peak hours (6-8 AM and 8-10 PM). The uncertainty of the ESS planned capacity can also have voltage fluctuation effects on the distribution network that it is connected to. Such an uncertainty can be dampened, and adversarial effects can be eliminated if the distribution network includes conventional energy storage.

V2G integration can reduce the peak demand of the parking lot and this can be a major source of savings to the lot owner. Consider the commercial lot with 120 parking spaces. Two V2G scenarios are analyzed, i.e. Case I and Case II. In Case I, the V2G system is not enabled and EVs only consume electricity to charge their batteries, while in Case II, V2G is active which enables the lot's owner to send electricity back to the main grid. Fig. 8 shows the facility net demand in Cases I and II over all EV arrival scenarios in the MC simulation. As depicted in Fig. 8, the peak demand in Case II is much lower compared to the Case I. The reason is the flexibility in charging and discharging of batteries due to bi-directional V2G technology. The facility operator can manage the power flow in a way to reduce peak demand which results in lower electricity cost. Also, Fig. 9 shows the average net demand profile of the lot node for Cases I and II. From Fig. 9, it can be observed that using V2G system reduces the peak demand by almost 40%.

In order to demonstrate the impacts of parking facility peak-hours and the number of EV parking spots on the ESS valuation, the following case studies are investigated:

- *Case 1*: A commercial lot with 80 EV parking spaces.
- *Case 2*: A commercial lot with 120 EV parking spaces.
- *Case 3*: A residential lot with 80 EV parking spaces.
- *Case 4*: A residential lot with 120 EV parking spaces.

Note that the peak hours for Cases 1 and 2 are assumed to be around noon and for Cases 3 and 4 during night. Fig. 10 shows the average aggregated capacity of batteries parked in the facility and the percentage of occupied parking spaces for the commercial and residential lots. From Fig. 10, the commercial lot is almost fully occupied during noon times, however, the peak hour in a residential lot is during the night time. In terms of the average parking times, for the residential lot, vehicles usually arrive during the evening time and stay in the lot until the next morning. Thus, as shown in Table 2, on average, EVs stay in the residential lot for a longer duration.

Multiple scenarios for each case are simulated, each of which corresponds to various hourly LMP, RMCCP, and RMPCP profiles. Fig. 11 depicts the average LMP and FR market clearing price which are fed into the simulated scenarios. Moreover, for each scenario, the arrival and stay times

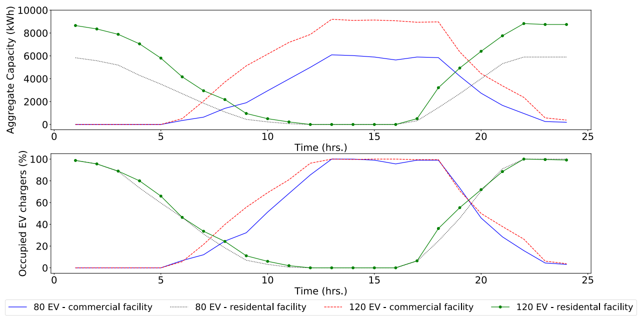

FIGURE 10. Top) dynamic storage aggregated capacity (kWh), bottom) percentage of occupied EV parking spaces.

TABLE 2. Parking lot characteristics.

Case Study	Average number of EVs coming into the facility in a day	Average parking duration for EVs (hrs.)
Case 1	193	4.33
Case 2	295	4.73
Case 3	80	10.62
Case 4	120	11.07

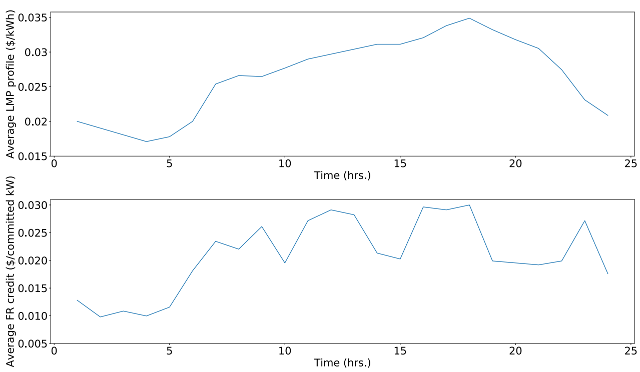

FIGURE 11. Top) average hourly LMP, bottom) average hourly FR credit.

TABLE 3. Optimal average discount factor and annual revenues for all 4 case studies.

Case Study	Case 1	Case 2	Case 3	Case 4
Average φ^*	45%	56%	60%	67%
FR credit ($)	48,868	90,744	51,180	53,753
Sell-back revenue ($)	199	393	1,016	2,501
EV charging revenue ($)	24,203	28,141	11,445	12,047
Total net benefit ($)	27,496	55,568	39,255	46,647

of EVs are randomly generated according to the queueing model. We also assume two battery capacities, 60 kWh and 90 kWh, with equal probabilities. All chargers are considered to be level-2 with 15 kW power rating and 90% charging and discharging efficiencies. Utilizing the proposed optimal operational control model, the dollar amounts obtained from different sources for each of illustrative cases are summarized in Table 3. Note that for annual net benefit calculation, the cost of electricity to charge EVs is also included.

We note that the overall income is small for these examples, but these numbers can significantly increase with the lot capacity and market prices of ancillary services. There may also be credits for clean energy and reduced carbon footprints that are not considered here. The net benefit can be significantly increased if the parking lot is powered by its own or a community owned solar farm.

Furthermore, the following observations are noted:

1) Capacity commitment of the commercial lot in the FR market is more valuable than the residential lot due to the higher FR credit during the day times (see Fig. 10; bottom). Also, the capacity requirement for the FR during the day is more than the night, thereby, commercial lot can make more revenue in the FR market.
2) Selling back electricity to the grid is more beneficial for the residential lot due to the higher variation in the hourly LMPs during night times (see Fig. 10; top). The facility operator can charge EVs when the electricity price is low and discharge to the grid when the price is high. Also, EVs are parked for a longer duration in the residential lot leading to more opportunities for arbitrage.
3) Since φ^* in the residential lot is higher than the commercial lot, the lot owner's revenue from charging the EVs in the residential lot is less than the commercial lot.
4) Commercial lot generates more revenue from the FR market than selling electricity to the grid; by discharging to the grid, the lot operator must recharge the batteries to the full SoC per EV owners' requests. This problem can go away if the lot is co-located with a solar farm and receives its power from that farm. Around 40% electricity peak reduction was observed for the commercial lot with V2G-enabled charging stations. This reduces the power loss in the distribution network and defers the needs for the T&D capacity upgrades.

As discussed, LMP and FR credit affect the parking lot owner's revenue. In order to consider these pricing elements during the peak-hours of the parking lot, here we define four new terms via (27)-(30) in the following, namely weighted LMP by aggregated battery capacity, $\hat{\lambda}^{ACap}$, weighted LMP by percentage of the occupied spaces, $\hat{\lambda}^{OSpc}$, weighted FR credit by aggregated battery capacity, $\hat{FR}^{CR,ACap}$, and weighted FR credit by percentage of the occupied spaces, $\hat{FR}^{CR,OSpc}$, respectively. Thus we have:

$$\hat{\lambda}^{ACap} = \sum_{t=1}^{24} ACap_t \times \lambda_t \tag{27}$$

$$\hat{\lambda}^{OSpc} = \sum_{t=1}^{24} OSpc_t \times \lambda_t \tag{28}$$

$$\hat{FR}^{CR,ACap} = \sum_{t=1}^{24} ACap_t \times FR_t^{CR} \tag{29}$$

$$\hat{FR}^{CR,OSpc} = \sum_{t=1}^{24} OSpc_t \times FR_t^{CR} \tag{30}$$

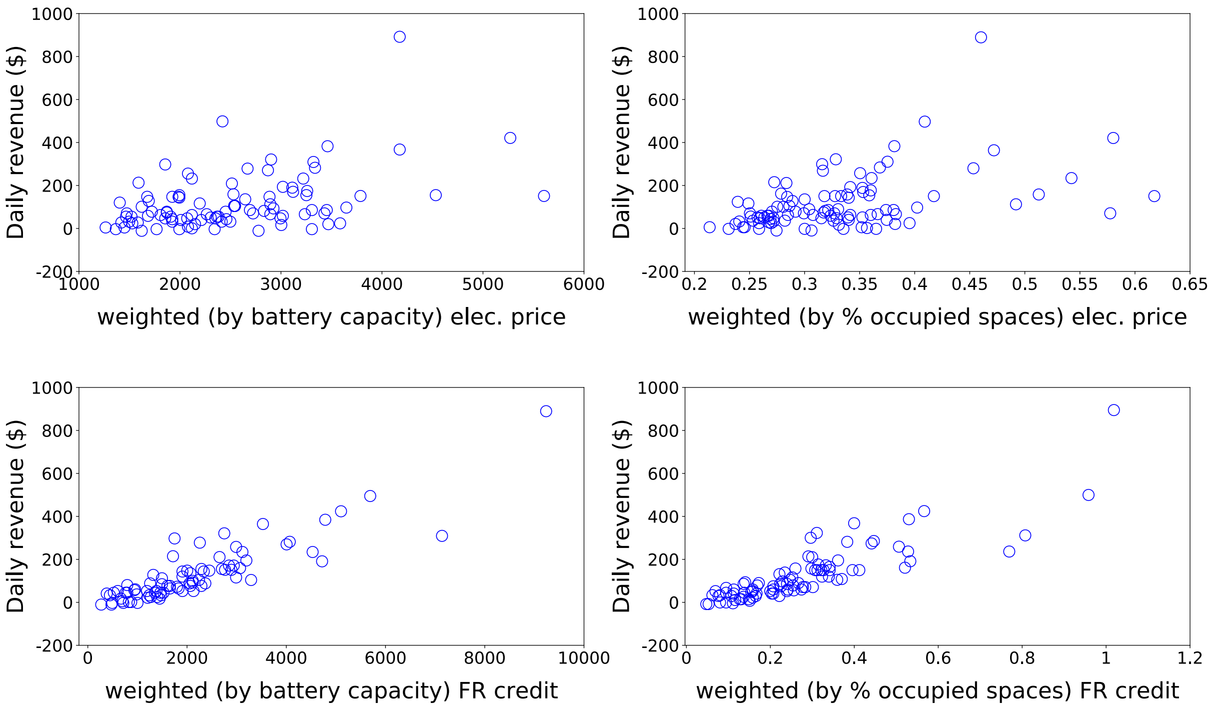

FIGURE 12. Correlation analysis of the daily revenue with respect to weighted LMP and FR credit.

where $ACap_t$ and $OSpc_t$ denote the aggregated capacity of batteries parked in the parking lot and the percentage of occupied parking spaces at time t, respectively. Fig. 12 shows the correlation between these four new factors and the daily revenue of the parking lot. As can be observed from Fig. 12, the parking lot owner's daily revenue has a strong correlation with the weighted FR credit for both weighted capacity and occupied spaces. However, Fig. 12 does not show a strong correlation between LMP and daily value. Table 4 presents the correlation value between these four factors and the daily value of the parking lot.

Analysis of the daily parking lot owner's revenue for all of the four cases reveals that the LMP and FR credit during the peak-hour of the parking lot has an impact on its value. Moreover, it has been illustrated that FR credit has the most significant impact on the evaluation process. In other words, high FR credit during the busy hours of the parking lot causes high value for the parking lot operator. Furthermore, more capacity for EVs in the parking lot results in more revenue for the parking lot operator. As part of this analysis, it has been observed that with the current state of the energy and regulation markets, commercial parking lots with noon-time peak are more beneficial from the parking lot operator's point of view. The reason is the high regulation market clearing price during the day-time, which coincides with peak-hours of the commercial parking lots. Moreover, V2G capability can reduce the peak electricity demand by almost 40%, which leads to power loss reduction in the distribution network and defers the needs for the capacity upgrade. From the EV owners' perspective, the discount they receive from the

TABLE 4. Correlation coefficient values.

Factor	Correlation with daily revenue
$\hat{\lambda}^{ACap}$	0.45
$\hat{\lambda}^{OSpc}$	0.46
$\hat{FR}^{CR,ACap}$	0.89
$\hat{FR}^{CR,OSpc}$	0.87

parking lot operator compensates for the additional battery degradation cost. Also, EV owners (same as all rate-payers in the distribution network) could benefit from the lower electricity tariff-rate, which is expected because of the peak reduction in the utility grid.

V. CONCLUSION AND FUTURE WORK

This paper presented an integrated framework which optimally plans for the charge and discharge of EVs in a parking lot to maximize the parking lot owner's benefits. The economic benefit to EV owners through reduced parking fees or discounted charging fees was also taken into account, which compensated the additional degradation of the vehicle battery. We showed that the proposed model is capable of quantifying the impacts of such parking lot on the power distribution network, where approximately 40% power peak reduction was observed for the commercial parking lot with V2G-enabled charging stations. This reduces the power loss in the distribution network and defers the needs for T&D capacity upgrades. The analysis also revealed that, with the current state of energy arbitrage and regulation market, commercial parking lots are more beneficial from the parking lot operators' point of view compared to the residential parking lots, which are occupied during the night time. The reason is the higher regulation market clearing price during the noon-time, which coincides with peak-hours of the commercial parking lots.

The extension of the above model to multiple EV parking lots can benefit cities, especially in under-privileged communities, where brown fields can be transformed into clean energy and income generating lots. The collective flexibility offered by a network of EV parking lots (as modeled here) can significantly mitigate and reduce the peak loads that are anticipated due to high market penetration of EVs. At the same time, these lots can help stabilize LMPs at times of peak loads, hence, reducing for additional T&D infrastructure investments. Moreover, developing an integrated model that accommodates different EV classes, including Level-1, Level-2, and DC fast charging (DCFC), is in order as our very close future work.

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REFERENCES

[1] S. Bouckaert, A. F. Pales, C. McGlade, U. Remme, B. Wanner, L. Varro, D. D'Ambrosio, and T. Spencer, "Net zero by 2050: A roadmap for the global energy sector," IEA, Paris, France, Tech. Rep. 01781941, 2021.

[2] F. Angizeh, A. Ghofrani, E. Zaidan, and M. A. Jafari, "Resilience-oriented Behind-the-Meter energy storage system evaluation for mission-critical facilities," *IEEE Access*, vol. 9, pp. 80854–80865, 2021.

[3] F. Angizeh, A. Ghofrani, E. Zaidan, and M. A. Jafari, "On evaluation of onsite energy storage for various end-use facilities with utility bill management, arbitrage, and frequency regulation opportunities," in *Proc. IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (ISGT)*, Feb. 2021, pp. 1–5.

[4] *New Jersey Energy Storage Analysis (ESA): Responses to the ESA Elements of the Clean Energy Act of 2018. Rutgers*, The State University of New Jersey, State New Jersey Board Public Utilities (NJBPU), Trenton, NJ, USA, 2019.

[5] *Electric Storage Participation in Markets Operated by Regional Transmission Organizations and Independent System Operators*. U.S. Federal Energy Regulatory Commission (FERC), Washington, DC, USA, 2016, p. 139.

[6] C. Guille and G. Gross, "Design of a conceptual framework for the V2G implementation," in *Proc. IEEE Energy Conf.*, Nov. 2008, pp. 1–3.

[7] *MESA—Open Standard for Energy Storage*. Accessed: 2017. [Online]. Available: http://mesastandards.org/mesa-device

[8] J. Taylor, J. W. Smith, and R. Dugan, "Distribution modeling requirements for integration of PV, PEV, and storage in a smart grid environment," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2011, pp. 1–6.

[9] S. W. Hadley, "Evaluating the impact of plug-in hybrid electric vehicles on regional electricity supplies," in *Proc. iREP Symp.-Bulk Power Syst. Dyn. Control-Revitalizing Oper. Rel.*, Aug. 2007, pp. 1–12.

[10] A. Dubey, S. Santoso, and M. P. Cloud, "Understanding the effects of electric vehicle charging on the distribution voltages," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Apr. 2013, pp. 1–5.

[11] R.-C. Leou, C.-L. Su, and C.-N. Lu, "Stochastic analyses of electric vehicle charging impacts on distribution network," *IEEE Trans. Power Syst.*, vol. 29, no. 3, pp. 1055–1063, May 2014.

[12] M. K. Gray and W. G. Morsi, "Power quality assessment in distribution systems embedded with plug-in hybrid and battery electric vehicles," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 663–671, Mar. 2015.

[13] Y. Gao, C. Wang, Z. Wang, and H. Liang, "Research on time-of-use price applying to electric vehicles charging," in *Proc. IEEE PES Innov. Smart Grid Technol.*, May 2012, pp. 1–6.

[14] J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 365–375, Jan. 2015.

[15] Z. Li, Q. Guo, H. Sun, S. Xin, and J. Wang, "A new real-time smart-charging method considering expected electric vehicle fleet connections," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 3114–3115, Nov. 2014.

[16] C. Hutson, G. K. Venayagamoorthy, and K. A. Corzine, "Intelligent scheduling of hybrid and electric vehicle storage capacity in a parking lot for profit maximization in grid power transactions," in *Proc. IEEE Energy Conf.*, Nov. 2008, pp. 1–8.

[17] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 65–72, Jun. 2010.

[18] W. Shi and V. W. S. Wong, "Real-time vehicle-to-grid control algorithm under price uncertainty," in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Oct. 2011, pp. 261–266.

[19] L. Yao, W. H. Lim, and T. S. Tsai, "A real-time charging scheme for demand response in electric vehicle parking station," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 52–62, Jan. 2017.

[20] I. Serban and C. Marinescu, "A look at the role and main topologies of battery energy storage systems for integration in autonomous micro-grids," in *Proc. 12th Int. Conf. Optim. Electr. Electron. Equip.*, May 2010, pp. 1186–1191.

[21] D. C. Erb, O. C. Onar, and A. Khaligh, "Bi-directional charging topologies for plug-in hybrid electric vehicles," in *Proc. 25th Annu. IEEE Appl. Power Electron. Conf. Expo. (APEC)*, Feb. 2010, pp. 2066–2072.

[22] D. F. R. Melo, A. Trippe, H. B. Gooi, and T. Massier, "Robust electric vehicle aggregation for ancillary service provision considering battery aging," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1728–1738, May 2018.

[23] F. Giordano, F. Arrigo, C. Diaz-Londono, F. Spertino, and F. Ruiz, "Forecast-based V2G aggregation model for day-ahead and real-time operations," in *Proc. IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (ISGT)*, Feb. 2020, pp. 1–5.

[24] P. Meenakumar, M. Aunedi, and G. Strbac, "Optimal business case for provision of grid services through EVs with V2G capabilities," in *Proc. 15th Int. Conf. Ecol. Vehicles Renew. Energies (EVER)*, Sep. 2020, pp. 1–10.

[25] A. Aldik, A. T. Al-Awami, E. Sortomme, A. M. Muqbel, and M. Shahidehpour, "A planning model for electric vehicle aggregators providing ancillary services," *IEEE Access*, vol. 6, pp. 70685–70697, 2018.

[26] S. Agheb, Z. Y. Dong, and G. Ledwich, "Aggregation of electric vehicles for emergency frequency control of two-area interconnected grid," in *Proc. IEEE PES Innov. Smart Grid Technol. Eur.*, Oct. 2020, pp. 196–200.

[27] D. Toquica, P. M. De Oliveira-De Jesus, and A. I. Cadena, "Power market equilibrium considering an EV storage aggregator exposed to marginal prices—A bilevel optimization approach," *J. Energy Storage*, vol. 28, Apr. 2020, Art. no. 101267.

[28] X. Xu, K. Li, F. Wang, Z. Mi, Y. Jia, and Y. Jing, "A multi-timescale response capability evaluation model of EV aggregator considering customers' response willingness," in *Proc. IEEE Ind. Appl. Soc. Annu. Meeting*, Oct. 2020, pp. 1–10.

[29] M. Wang, Y. Mu, Q. Shi, H. Jia, and F. Li, "Electric vehicle aggregator modeling and control for frequency regulation considering progressive state recovery," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 4176–4189, Sep. 2020.

[30] A. Mehrabi and K. Kim, "Low-complexity charging/discharging scheduling for electric vehicles at home and common lots for smart households prosumers," *IEEE Trans. Consum. Electron.*, vol. 64, no. 3, pp. 348–355, Aug. 2018.

[31] A. Mehrabi, H. S. V. S. K. Nunna, A. Dadlani, S. Moon, and K. Kim, "Decentralized greedy-based algorithm for smart energy management in plug-in electric vehicle energy distribution systems," *IEEE Access*, vol. 8, pp. 75666–75681, 2020.

[32] (2012). *PJM Manual 11: Balancing Operations*. [online]. Available: http://www.pjm.com/~/media/documents/manuals/m11.ashx

[33] *PJM Ancillary Services*. [online]. Available: https://www.pjm.com/markets-and-operations/ancillary-services.aspx

[34] *PJM Data Minor 2, Day-Ahead Hourly LMPs*. [online]. Available: https://dataminer2.pjm.com/feed/da_hrl_lmps/definition
[35] F. Angizeh and M. Parvania, ''Stochastic risk-based flexibility scheduling for large customers with onsite solar generation,'' *IET Renew. Power Gener.*, vol. 13, no. 14, pp. 2705–2714, Oct. 2019.
[36] J. Lofberg, ''YALMIP: A toolbox for modeling and optimization in MATLAB,'' in *Proc. IEEE Int. Conf. Robot. Autom.*, Sep. 2004, pp. 284–289.

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