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A Transactive Operating Model for Smart Airport Parking Lots

MAIGHA[1] (Student Member, IEEE) AND M. L. CROW[2] (Fellow, IEEE)

[1]Smart Grids Group, Commonwealth Edison, Chicago, IL 60680-5379, USA

[2]Department of Electrical and Computer Engineering, Missouri University of Science and Technology, Rolla, MO 65401 USA

CORRESPONDING AUTHOR: M. L. CROW (crow@mst.edu)

ABSTRACT Successful adoption of electric vehicles requires adequate and widespread public charging infrastructure to address customer confidence. Technological advancements in smart parking infrastructures and vehicle-to-grid energy transfer have the capability to add value to the vehicle, grid, and electricity markets. As a deferrable load and flexible source, an aggregate electric vehicle fleet can enhance system resilience. In this paper, a long-term airport parking is used as a platform on which transactive business models for electric vehicles have been developed. Different cost components were tested and compared under profit maximization with due consideration with battery degradation costs. Technical details coupled with business propositions have been developed in this paper using a mixed integer optimization implementation. A day-ahead energy transaction portfolio was created considering customer convenience. Results indicate that long-term smart parking can be profitable to all entities while providing significant benefits to the grid.

INDEX TERMS Electric vehicles, transactive operating model, vehicle-to-grid (V2G).

NOMENCLATURE

η_{ch}	Battery charging efficiency (0.92)
η_{dch}	Battery discharging efficiency (0.90)
λ^t	Electricity rate at time instant t
Ψ_i^{rev}	Total revenue of vehicle i during the day
Ψ_i^{deg}	Battery degradation costs for vehicle i during the day
Ψ_i^t	Battery degradation costs for vehicle i at time t
$\Psi_{i,t}^{SOC}$	SOC related battery degradation for vehicle i at time t
$\Psi_{i,t}^{DOD}$	DOD related battery degradation for vehicle i at time t
$B_{i,cap}$	Battery capacity of vehicle i
$B_{i,min}$	Minimum battery capacity for vehicle i
bat_{life}	Battery lifetime in years (10 years or 5000 cycles)
C_{bat}	Battery cost (\$300/kWh)
C_{batdeg}	Total battery degradation costs
C_{labor}	Labor cost for battery replacement (\$ 240)
$C_{i,rev}$	Revenue/cost of vehicle i
$C_{i,rate}$	Charger selection for vehicle i
CF_{max}	Capacity fade (20% of usable battery life)
d	Linear battery degradation cost-intercept (6.41×10^{-6})
$d_{i,arr}$	Arrival day of vehicle i
$d_{i,dep}$	Day of departure of vehicle i
$d_{i,park}$	Number of parking days for vehicle i
DOD	Depth of discharge (80%) at end of lif
E_{bat}^t	Energy stored in the battery at time t.
$E_{i,\Delta t}^{dch}$	Energy discharged in Δt
$E_{i,req}$	Energy required for full charge for vehicle i
$E_{i,sup}$	Total energy supplied to vehicle during parking duration
$f_{i,adm}$	Daily parking fee (\$) for vehicle i
m	Linear battery degradation cost-slope parameter (1.59×10^{-5})
$SoC_{i,avg}^t$	Average SOC of battery of vehicle i at time t
$SoC_{i,arr}$	SOC of battery at time of arrival of vehicle i
t	Time step (1 hr).
$t_{i,delay}$	Delay in providing service to a vehicle
$t_{i,avail}$	Time available before vehicle departure i
$t_{i,req}$	Time required for full charge for i
$t_{i,park}$	Total parking hours for a vehicle
t_{park}^{days}	Total parking days
x	Optimization variable
$x_{i,ch}^t$	Charging power of vehicle i at time t
$x_{i,dch}^t$	Discharging power of vehicle i at time t

I. INTRODUCTION

The increasing penetration of electric vehicles in the automotive market has led to the development of public and private charging infrastructures. Research efforts in the field of drive trains, batteries, and power electronics have made them increasingly affordable. Plug-in electric vehicles (PEVs) may be used not only for travel, but also for providing energy to the power grid. The concept of discharging the electric vehicle energy into the grid is called vehicle-to-grid or V2G. It has been proposed that aggregated PEV fleets may be used for generating profits by transacting energy via electricity markets. Their capability to charge/discharge may be used in the ancillary services market for improving power grid operations, especially with widespread distributed, intermittent renewable energy generation. One of the primary drawbacks in using PEV fleets is that the period in which the vehicles are parked does not often correspond to periods in which it is advantageous to provide ancillary services through V2G. However, airport long term parking structures have numerous characteristics which make them highly suitable for V2G services.

Generally, vehicles remain idle for a continuous period when parked in the airport long-term parking structures. One of the significant costs associated with air travel is the fees associated with personal vehicle parking. Parking fees can be even more significant for close proximity or covered structure parking. However, airport parking structures offer considerable potential for collaboration between electric vehicle owners and structure owner/operators. Some of these uniques features include:

- Unlike residential parking in which the vehicle is only available during the night, long term airport parking lots have the advantage of a large number of vehicles that are available at all hours of the day and night.
- Furthermore, unlike shopping center parking lots where vehicles are only available for short periods of time (typically 1 to 4 hours), airport parking lots have the advantage that vehicles are typically available for longer than 24 hours and usually up to several days with relatively predictable departure times.
- The aggregator can predict the available capacity with a high degree of certainty. This reduces the uncertainty in provision, capacity, and service availability of the asset (EVs).
- Lastly, consumers are able to predict with high confidence when they will retrieve their vehicle, so guaranteeing full state of charge upon exit is achievable.

Aggregated electric vehicle batteries may be used to emulate bulk energy storage systems and can be used for earning profits through energy transactions on the spot market or through energy or ancillary service contracts. There is potential for lucrative models that may increase the PEV utility and value to customers.

We envision a future in which a PEV owner can park at the airport for a significantly reduced fee (or even free) by simply allowing the parking structure owner/operator access to the stored energy in their vehicle battery for short periods of time. We propose an algorithm in which the vehicle owner parks their automobile, plugs it in, enters their expected return date and time, and then returns days later to a fully charged vehicle at little or no parking cost to themselves. We propose to accomplish this through a novel aggregation and control algorithm that buys and sells power on the spot energy market. We believe that both parking structure owner/operators and travelers can benefit through participation.

The parking lot central controller collects individual PEV information such as battery capacity, incoming state-of-charge, and duration of availability. The vehicles are then divided into two groups: a continuous-parking group and a departure-day parking group based on the day the vehicle is scheduled to leave the parking facility. The PEV owner has the option to choose among a standard, or a set of variable, admission fee options and charger types (Type I, II, III). The PEV owner is also requested to specify the minimum energy requirement at the end of its parking period (i.e. how full they want their battery).

Once parked, the battery state-of-charge is controlled by the proposed algorithm. The algorithm maximizes parking lot owner (PLO) profits through continuous charging and discharging of aggregated fleet based on utility price signals, constrained by battery degradation costs. A customer satisfaction index, based on admission fee and revenues earned, is used as a metric for maximizing vehicle utility. The PLO is penalized for any expected energy not served at the time of departure of the EV. The PLO may use a net metering approach to sell electricity at the market price or may add a profit margin. The PLO may act as a player in the ancillary services market to sell the energy discharged from the EVs and thus make additional profits.

With the current advancements in information and communication technology and smart grid applications, electric vehicles can participate in demand response as controllable loads and resources for grid support through unidirectional (grid-to-vehicle) or bi-directional (vehicle-to-grid) energy transactions [1]. Aggregated EV fleets can emulate a bulk energy storage system with the capability of earning profits through energy transactions on the spot market or through ancillary service contracts [2]. They can support intermittent renewable energy integration and provide effective solutions to their ramping requirements. The recent adoption of ramp capability services by MISO and CAISO is a significant step in this direction [3]. Active participation in economic or emergency-based demand response programs and spinning reserves market can provide financial incentives to the customers [4]. The aggregated impact of fleet PEVs can make a compelling case as an active entity in market operations.

Some of the challenges associated with EV parking lots include:

- Dependence of parking lot energy requirement on uncertainty in EV mobility pattern
- Management of grid-to-vehicle (G2V), vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) interactions

- Customer convenience including the impact on battery degradation

In [5], it was established that the parking lot owner and the vehicle owner may benefit simultaneously while maintaining network constraints. The study further showed that it is more beneficial if the parking lot owner participates in the reserve market instead of the energy market. In [6], the authors treat mobility uncertainty by designing a system that uses a trace-based mobility model to account for regular and irregular vehicle arrivals at the parking lots and seek to maximize revenues while maximizing energy transfer to the vehicles. Energy management in G2V, V2G and V2V modes has been explored in [7]. The proposed direct load control policy uses a mix of residential and commercial charging to ascertain economic service to the vehicles while minimizing battery degradation. Reference [8] proposes V2V to develop an 'ad-hoc' mini-grid with vehicles. It suggests a paradigm for optimizing driving experience using a carbon-efficient charging schedule. It is important to note here, that even though EVs are zero-emission vehicles, there are indirect emissions involved based on fuel used for generating electricity [9]. While [4] uses a neural network based stochastic model to predict EV arrivals, [10] proposes a real-time model-predictive control strategy to deal with this uncertainty. The two-stage optimization in [10] predicts the electricity sales price under uncertain solar generation to maximize the revenues.

Even though considerable work has investigated EV charging in the current open literature, business, technical, and economic models for long-term parking facilities have not been given due consideration despite their transactive potential. We propose to bridge this gap while leveraging the ideas in [5]–[10]. Furthermore, a technical construct has been proposed and built around the control and charging paradigm proposed in [11] and [12].

Airport parking structures offer considerable potential for collaboration between EV owners and parking lot operators. In this study, an optimal energy transaction policy to coordinate EV charging and discharging for the mutual benefit of the customer and the parking lot operator has been proposed. Customer satisfaction index and a profit model based on different pricing structures are developed. A novel aggregation and control algorithm that buys and sells at spot energy market has been proposed. It has been shown that both the parking lot owner and the customers can benefit through active engagement. The key contributions of this work include:

- A novel aggregation scheme for long-term EV parking structures,
- A control architecture for optimal energy transactions for the EV fleet,
- A transactive business model for airport parking,
- High customer satisfaction guarantees and mutually beneficial profit models for the principal entities, and
- Understanding the internal charge/discharge dynamics of a fleet in a centralized control architecture.

II. THE BUSINESS MODEL

The dynamics among the principal entities depends on the plans, options, and transactions specifications. Together with subsidiary entities, they complete the model for the parking facility as shown in Fig. 1. The cost and revenue components for the principal entities are summarized in Table 1.

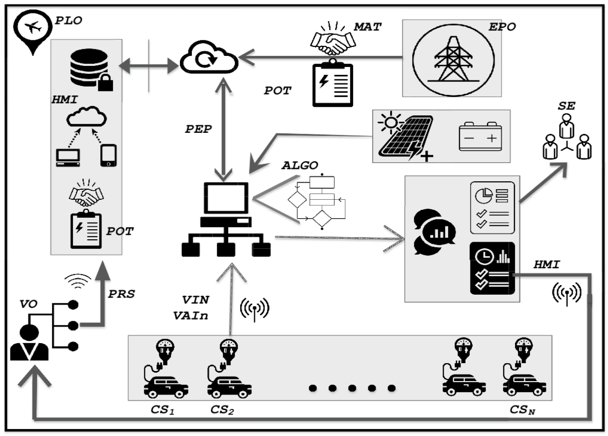

FIGURE 1. **Airport parking lot model.**

A. PRINCIPAL ENTITY PORTFOLIOS

The principal entity portfolio (PEP) defines the major players in the model. The principal entities include electric vehicle owners (EVO), the parking lot operator (PLO), and the energy provider (EPO). The EVO has the authority to choose from and approve the set of operating options for their individual vehicles. These operating options are designed by the PLO in accordance with their market transactions with the EPO. This information regulates the monetary transactions and profits made by each entity and thus determines the energy transaction portfolio for each principal entity.

B. PLANS, OPTIONS, AND TRANSACTIONS

Plans, options, and transactions (POT) determine the major costs incurred and revenues earned by the principal entities. They will be inherently affected by the services the PLO offers to the grid through contractual agreements with the EPO. Certain schemes could be designed to encourage specific behavioral patterns. Table 1 provides a list of cost/revenue components, a subset of which has been used in this study. It is assumed that all contractual agreements between PLO and EPO are enforced.

C. SUBSIDIARY ENTITIES

External businesses can network with the PLO for providing value-added services to the customers. This can improve the value proposition of the smart parking facility. These benefits may take the form of retail coupons, rebates, special services at the airport, etc. Such subsidiary entities (SE) support the infrastructure and may offer mutual benefits by attracting more customers.

TABLE 1. Cost and revenue components for the principal entities.

Vehicle Owner	Parking Lot Operator	Energy Provider
Parking lot Admission Fee Battery Charging Cost V2G Revenues Battery degradation costs Plan violation penalties	Revenues earned through energy transactions Parking fee Penalties on service violation to customer Penalties on contractual violations with the energy provider	Energy transaction costs/revenues Penalties on contractual violations with PLO

III. THE PARKING LOT MODEL

The business model gives the structural and functional framework for the proposed transactive energy paradigm. Successful implementation of the business model requires an understanding of the parking facility characteristics. Although actual PEV arrival/departure times are not known in advance, airport arrival and departure times are predominantly determined by the flight schedules which vary within a known window. Therefore the scheme developed in this paper is based on a prior reservation strategy (PRS) with a buffer window for the arrival time.

A. EV-ENERGY TRANSACTION POTENTIAL

Customers are considered to be prosumers due to their involvement as both producers (V2G) and consumers (G2V). The aggregated EV fleet energy transactions have been optimized by coupling customer and parking lot operator objectives. The bi-directional energy transfer capability of EVs can be used for grid-support in two modes: as a dispatchable source or a controllable load. Since the parking period of each vehicle is known, they can be dispatched as a large energy storage system on demand while serving within their individual battery limits. However, even though this problem appears to be conceptually straightforward, the optimal implementation of the proposed strategies requires an integrated solutions.

B. PARKING RESERVATION SYSTEM

Upon arrival, an EVO would select their charger, enter a retrieval time, and select the option plan for their vehicle. This portal would serve as the human-machine interface that provides the prosumers with analytics on their vehicles, such as vehicle state of charge, energy use, or real-time parking fee.

C. VEHICLE AVAILABILITY INFORMATION

Vehicle owners are requested to register with the PLO and provide their vehicle information. Each vehicle is assigned a unique identification number (VIN) and a charging spot in the parking lot. The Vehicle Availability Information (VAIn)-tuple for vehicle i contains a static block including $\langle B_{i,cap}, C_{i,rate}\rangle$ and a dynamic block $\langle d_{i,arr}, t_{i,arr}, d_{i,dep}, t_{i,dep}, d_{park}, SOC_{i,arr}\rangle$. With customer consent, this information may be stored and used for future forecasting, diagnostics, and analysis by the PLO or its subsidiaries. The vehicle information for this study was emulated using statistical distributions based on certain assumptions as illustrated in Fig. 2. These include:

1) The airport arrival and departure times for the vehicles were randomly sampled from beta probability density functions. This data is generated using the assumption that air traffic is more prevalent during the morning and evening hours.
2) The vehicle state of charge (SOC) on arrival varies between 20% and 50%.
3) The parking period of each vehicle was sampled from a multinomial random distribution. The vehicles may be parked for any period between 1-10 days, with a most probable duration of stay of 3 days.
4) The vehicle battery type was selected from a range of available battery sizes according to the probability distribution of that size [13].

D. COMMUNICATION AND INFRASTRUCTURE DESIGN

C_{PL} represents the total number of parking spots in the facility with a total of CS_{PL} charging stations available. The charging stations are divided into Type I, Type II, and Type III chargers (CS^{I}_{PL}, CS^{II}_{PL}, CS^{III}_{PL} respectively). In this study, it is assumed that the parking lot has sufficient charging spots to serve all the vehicles that arrive, thus $CS_{PL} = C_{PL}$.

The status of each charging spot is encoded as a 3 bit unit shown in Table 3. The first bit represents the charger availability and the next two represent charging, discharging, charged or idle states. The charger status and vehicle status information is stored as shown in Table 2. This information is updated regularly to maintain PLO control.

TABLE 2. Charger status and information encoding.

Charger Status	Vehicle Status
Charger_ID Charger_type Charger_status [Idle/Engaged] Vehicle_ID Vehicle_status	Charging Discharging Charged Idle

Each charging station is connected with the central controller through a two-way communication channel using an automatic energy metering system. The communication infrastructure may be based on ISO 15118 standard, SAE J2847/1 [14] or AMI communication networks [15]. These standards are designed specifically to allow synergistic development of communication, interoperability, and security protocols for EV-utility interface. Grid-networking protocols

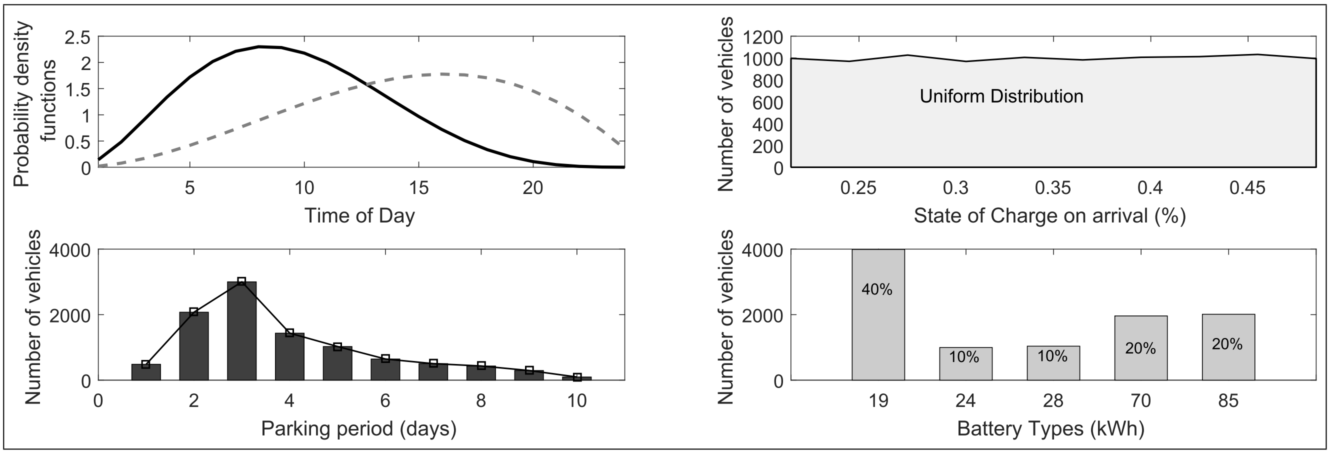

FIGURE 2. Statistical data for a vehicle population of 10000.

TABLE 3. 3-bit unit code for charger status.

Bit-1	Bit-2	Bit-3	Charger Status	Vehicle Status
0	0	0	Available	N/A
1	0	0	Occupied	Charging
1	0	1		Discharging
1	1	0		Charged
1	1	1		Idle

such as IEEE 802.15.4 (Zigbee), broadband over Powerline and HomePlug, ZWave, etc. may be used for this purpose.

E. PARKING LOT CONTROLLER DESIGN

The parking lot controller collects the vehicle information based on the daily reservations and uses this information to categorize the vehicles into two groups 1) departure storage, and 2) parked storage.

The departure battery group has limited V2G capability since these vehicles must be charged to the customer desired SOC (typically at, or near, full SOC) by the end of their specified parking periods. Vehicles scheduled to remain in the structure beyond that day are assigned to parked storage group and have greater resource flexibility because they have no daily hard target SOC. Fig. 3 shows the aggregated battery capacity for the two storage groups. Note that there is a start up period for these results that would not exist in a real-time system. Parked/Departure storage is used to indicate total aggregated battery capacities of the two groups respectively. Parked group includes that are not scheduled to depart at the end of the optimization day. Departure storage aggregates vehicles that are expected to leave the parking facility on the day.

Once the participating vehicles have been categorized into one of the two groups, the parking lot controller optimizes the energy transactions for the aggregated fleet as shown in Fig. 4. Depending on the business strategy adopted, a wide range of objectives might be applicable to the optimization process; they may be classified into 1) PLO-driven, 2) customer-driven, 3) system-driven, or any combination of

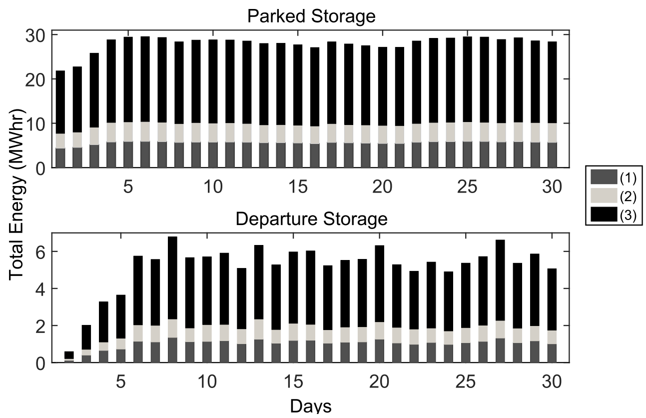

FIGURE 3. Aggregated Parked and Departure Energy Capacity: (1) shows the minimum energy required by the vehicle batteries, (2) shows the initial energy stored in the EVs at the beginning of the day, and (3) represents the maximum aggregated battery capacity for the EVs.

these three categories. Vehicle charging constraints have been adopted from [16]. These business strategies are described in the following sections.

1) MAXIMIZE PLO PROFITS

This objective seeks to maximize the parking lot owner's profits. This strategy generates revenues by selling maximum energy to the power grid (during high price periods) and buying energy from the grid to charge the vehicle fleet during the low-cost periods of the day. It also seeks to avoid any penalties based on contractual violations with the ESO or the customer. The PLO may buy/sell at the wholesale rate by transacting energy between the vehicles and the EPO. This profit may be shared between the PLO and the EVO. The total costs incurred/revenues earned by the customer are given by Ψ_i^{rev} in:

$$\Psi_i^{rev}(x) = \sum_{t=1}^{t_{i,avail}} \left(\frac{x_{ch,i}^t}{\eta_{ch}} - x_{dch,i}^t \cdot \eta_{dch} \right) \left(\lambda^t\right) \tag{1}$$

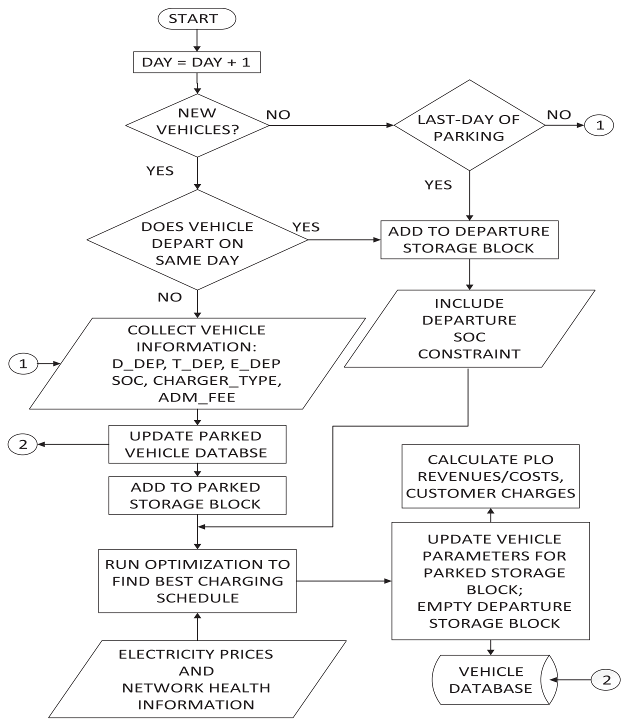

FIGURE 4. **Flowchart for parking lot control algorithm.**

2) MINIMIZE BATTERY DEGRADATION

One of the major challenges associated with V2G is battery degradation during cyclic charging/discharging of the battery that may adversely affect the automotive life of the battery. Because numerous charge/discharge cycles can degrade the battery, an additional objective is to minimize battery damage, thus protecting EVO interests. Simple linear approximations for SOC and DOD related degradation costs have been adopted from [17] and [18]:

$$\Psi_i^{deg}(x) = \sum_{t=1}^{t_{i,avail}} \Psi_i^t = \sum_{t=1}^{t_{i,avail}} \Psi_{i,t}^{SOC(x)} + \sum_{t=1}^{t_{i,avail}} \Psi_{i,t}^{DOD} \tag{2}$$

$$\Psi_{i,t}^{SOC} = C_{bat} \frac{m \cdot SOC(x)_{avg,t} - d}{8760\, CF_{max} \cdot bat_{life}} \tag{3}$$

$$\Psi_{i,t}^{DOD} = \frac{C_{bat} \cdot B_{i,cap} + C_{labor}}{bat_{life} \cdot B_{i,cap} \cdot DOD} E(x)_{i,\Delta t}^{dch} \tag{4}$$

$$x = \begin{cases} x_{ch,i}^t, & \text{if } \upsilon_i^t = 1 \text{ (charging mode)} \\ x_{dch,i}^t, & \text{if } \upsilon_i^t = 0 \text{ (discharging mode)} \end{cases} \tag{5}$$

where

$$SOC_{avg,t+1} = SOC_{avg_t} + \frac{x_{i,ch}^t + x_{i,dch}^t}{B_{cap}} \tag{6}$$

$$E_{i,\Delta t}^{dch} = E_{t-1}^{bat} - E_t^{bat} \tag{7}$$

The binary variable υ_i^t ascertains either charging or discharging mode at each time instance t for each vehicle i (5).

3) OPTIMIZE VEHICLE UTILITY

The major aspects of vehicle utility include:

- Maximize utilization of the battery capacity during the entire parking period, while
- Minimizing battery degradation costs, and
- Maximizing energy transaction profits.

The PLO seeks to maximize its profit by optimizing vehicle utility.

4) CUSTOMER SATISFACTION INDEX (CSI)

A customer satisfaction index may be defined for each customer based on 1) total costs incurred including any portion of the PLO profit shared with the EVO, 2) total expected energy served by the PLO, and 3) the SOC at time of departure. This index is defined as a weighted sum of three components 1) total costs $C_{i,total}$, 2) expected energy served $E_{i,SOC}$, and 3) delay in service $T_{i,delay}$ due to inadequate SOC at time of departure. The weight w_k where $k \in \{1, 2, 3\}$ is a user defined ratio based on external priorities.

$$CSI_i = w_1 C_{i,total} + w_2 E_{i,SOC} + w_3 T_{i,delay} \tag{8}$$

$$C_{i,total} = 1 - \frac{(C_{i,rev} + f_{i,adm} + C_{i,batdeg})}{f_{i,adm}} \tag{9}$$

$$E_{i,SOC} = \frac{E_{i,sup}}{E_{i,reqd}} \tag{10}$$

$$T_{i,delay} = 1 - \frac{t_{i,delay}}{t_{i,park}} \tag{11}$$

IV. MODEL DEVELOPMENT

The airport parking lot is modeled as a structure that has predictable (within set variances) arrival and departure of vehicles. A minimum of 500 vehicles are available at any time during the 30 day consideration period. The number of vehicles arriving or departing the parking lot on any day is selected randomly based on the probability distribution shown in Fig. 2. After the vehicle information is obtained through the parking reservation system, the scheduling controller runs the optimization under the constrained scenarios generated using the PLO-defined single or multiple objectives. This optimization for day d is completed using the information available by 23:59 hours on day $d - 1$. The obtained profiles Ω are appended to the VIN and sent over the communication channels to the assigned charging station. Once the vehicle is parked in a designated spot, its energy transaction profile follows the pattern stored at the corresponding charging station. On completion of the parking period, the energy transactions are evaluated and the financial logs are updated.

For the 30 day period, the number of vehicle arrivals/departures, trip duration, arrival SOC, and arrival/departure times were sampled from the data shown in Fig. 2. Locational marginal prices for a node in the Midwest Independent System Operation (MISO) region were selected as the test case data [20]. Figure 5 shows a comparison between the hourly fluctuation of prices during the months of June and January that were selected to account for seasonal variations.

Three cases have been simulated for the months of January and June:

- *Case 0:* Traditional parking lot without charging capabilities

TABLE 4. Monthly revenues for a parking lot with Type III chargers ($).

	Month	Revenue/Cost	Battery Degradation Costs	Total Costs
Case 1: Charging only	June	19,968	1,988	19,968
	Jan	21,588	199	2,158
Case 2: Transactive	June	$-263,621$	1,801	$-261,820$
	Jan	$-133,081$	15,810	$-131,500$

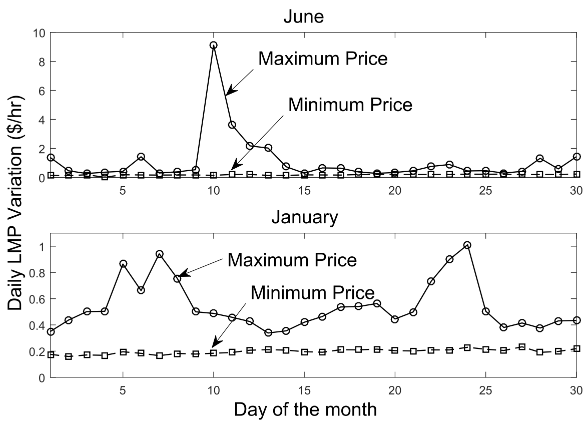

FIGURE 5. Daily maximum and minimum LMP variation for a node in the MISO region (June/Jan) [20].

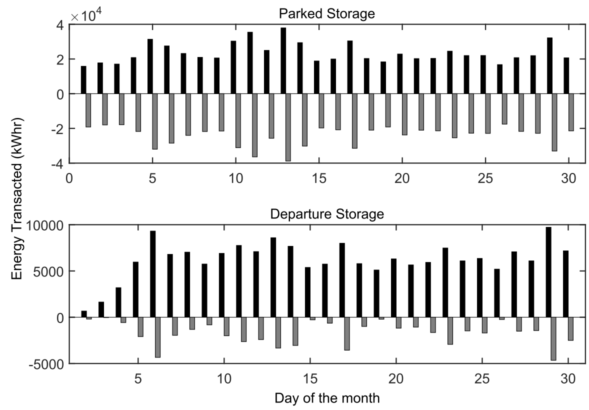

FIGURE 7. Energy transacted by parked and energy storage blocks (Type III chargers) during the month.

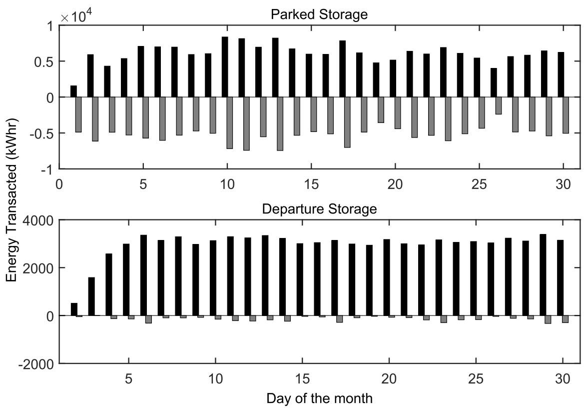

FIGURE 6. Energy transacted by parked and energy storage blocks (Type I chargers) during the month.

- *Case 1:* Parking lot with charging capability (only)
- *Case 2:* Smart parking lot for maximizing PLO revenue through active energy transactions

A standard (base case) daily parking fee (f_{adm}) and two additional fee structures are analyzed: 1) a SOC dependent fee (f_{adm}^{SOC}), and 2) a usable capacity dependent fee (f_{adm}^{cap}).

$$f_{adm} = t_{park}^{days} \times fee_{\$/day} \tag{12}$$

$$f_{adm}^{SOC} = (1 - SOC_{arr}) \times t_{park}^{days} \times fee_{\$/day} \tag{13}$$

$$f_{adm}^{cap} = \frac{(B_{i,cap} - B_{i,min})}{B_{i,cap}} \times t_{park}^{days} \times fee_{\$/day} \tag{14}$$

The standard daily parking fee (f_{adm}) is the per vehicle fee that would normally be charged. If the vehicle is parked less than 24 hours, the parking fee is pro-rated linearly. Covered vehicle parking in metropolitan areas can range from \$15 to upwards of \$30 per day.

V. RESULTS AND DISCUSSION

A 30 day parking lot model was simulated for PLO profit maximization. This convex optimization problem (mixed-integer linear problem) was solved using Gurobi [19] considering the fleet arrival/departure times and energy needs. The results further reflect the battery degradation costs observed using the corresponding arg min. A comparison of the Case 1 and Case 2 with respect to the base case (Case 0) is summarized in Table 4 for the case in which all EVs use Type III chargers. The two operating paradigms are 1) charging only and 2) transactive. This assumption is made to provide a level comparison between the two operating paradigms. In the Total Costs category, a negative cost indicates that a profit is being generated. This table implies that without some level of transactive operation, the PLO would be forced to charge EV owners an additional fee to offset the costs of providing the charging service. However, with transaction operation, the PLO would make a profit. However, without profit sharing with the EV owners, there is no incentive for them to participate in the transaction market operations. The basic premise of the proposed algorithm is to find a profit sharing model such that the EV owner is sufficiently incentivized to park in the parking structure and allow their vehicle to participate in the transactive scheme.

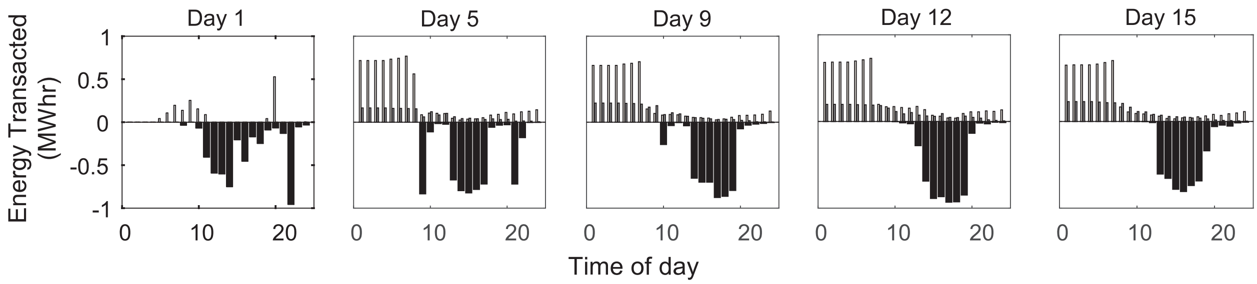

FIGURE 8. **Hourly energy transactions (Type I chargers) for a 5-day sample.**

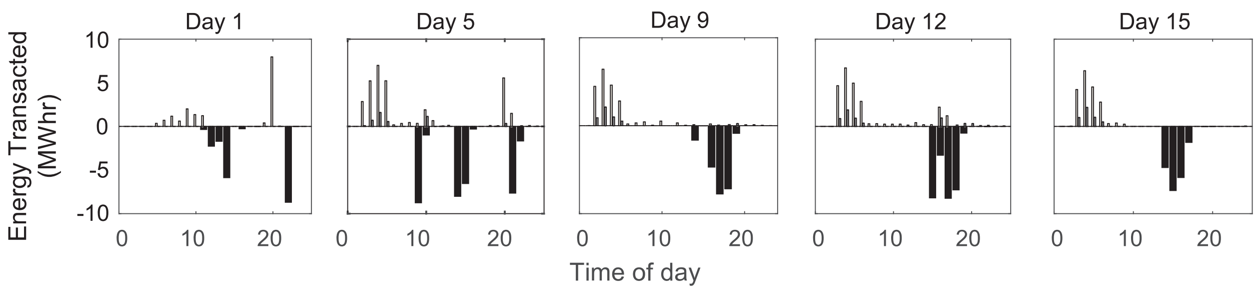

FIGURE 9. **Hourly energy transactions (Type III chargers) for a 5-day sample.**

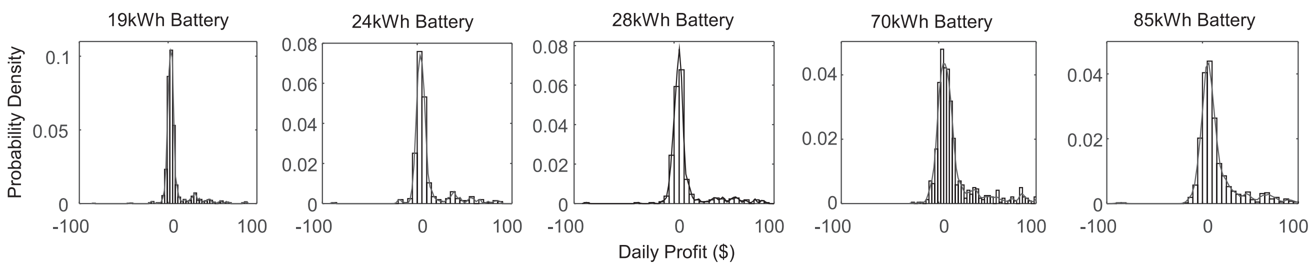

FIGURE 10. **Probability density functions for variation in charging fee by battery type.**

To ascertain the impact of the type of charger on the algorithm behavior, the transactive scheme was applied to a structure with Type I chargers only and Type III chargers only. These results are summarized in Figures 6 and 7 respectively.

The total energy transacted by the PLO during the month of June in Case 2 is shown in Figs. 6 and 7 for slow (Type I) chargers and fast (Type III) chargers respectively. As expected, these results indicate that the EVs using slow chargers resulted in lower cumulative energy transactions in comparison to those with fast chargers. Therefore, for maximizing vehicle utility, fast chargers would be more beneficial than the slow chargers. Furthermore, more energy was transacted by the parked storage group as opposed to the departure storage group, primarily because of the departure SOC requirement.

Figures 8 and 9 show a sample 5-day hourly variation of energy bought and sold by the parking lot outfitted with Type I and Type III chargers respectively. The Type I chargers result in lower, contiguous energy transactions, whereas Type III chargers lead to non-contiguous, higher transactions. This result can help in understanding the regulation capability of a smart parking lot. The charge and discharge cycles typically follow the pattern of discharging energy to the grid (V2G) in the afternoon and charging (G2V) at night when electricity prices are low. Note that at any time instant (1 hr time step for optimization algorithm) some vehicles may be charging while others are discharging. This result may be counter-intuitive, but it is a product of the optimization process that balances SOC needs, battery degradation, arrival, and departure times across the entire population of vehicles.

Fig. 10 shows the probability density functions of the daily profit for each battery type for the month of June obtained from the population data set described earlier. A similar pattern was observed for other months of the year. These probability distribution functions highlight a few trends. All of the distribution functions indicate a typical profit margin. This margin is in addition to the base case (case 0) daily fee that would normally be charged. This indicates that the parking lot owner could easily decrease the nominal daily fee, thereby

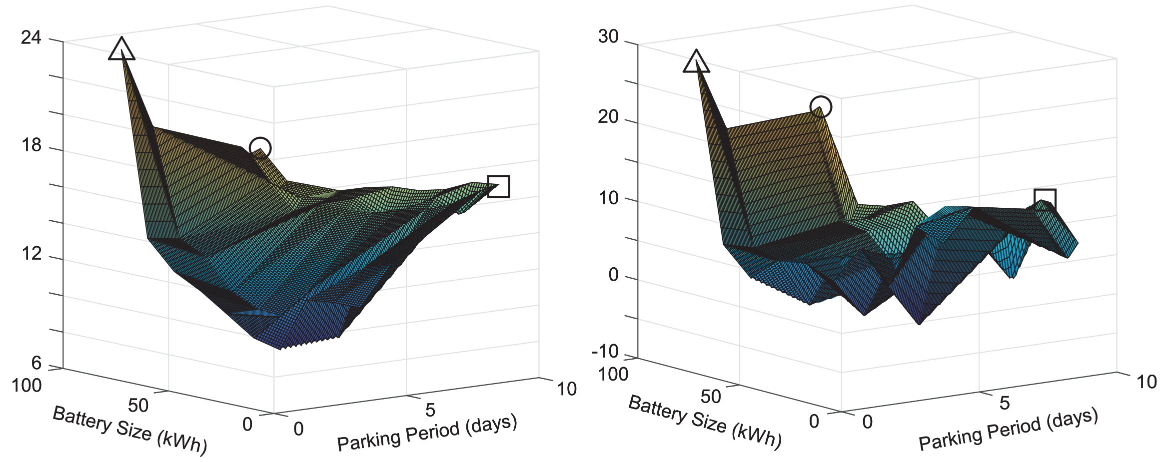

FIGURE 11. **Daily parking fee variation for the months of January and June.**

incentivizing vehicle owners to park in the structure, and still maintain a healthy profit margin. The profits are more likely to be larger for vehicles with large batteries since they are more likely to have significant transactive participation. There are a small number of vehicles however, for which the profit margin is negative. This situation is caused by vehicles parked for short periods that require significant charging. In the case of large battery/short duration, it would make sense to charge the vehicle owner a surcharge for vehicle charging. However, in all other cases, the profits could be used to incentivize vehicle owners to participate (i.e. by giving them a parking fee discount) while still maintaining a significant profit for the parking lot owner.

Figure 11 shows the aggregation of all vehicles and costs for June and January. Each of these figures represent the variation in daily "break-even" parking costs with change in parking period and battery size. These results are based on a base case parking fee of \$20/day. There are several notable trends illustrated in this figure. Note that the largest daily cost occurs for vehicles with large batteries parked for short periods of time (black triangle). This is because these batteries typically only charge due to their short duration in the parking structure and they cannot participate in V2G. Thus a surcharge for charging may be required. However, as the parking length increases, the average daily cost decreases as the benefits from the transactive algorithm begin to dominate (black circle). For small batteries however, the opposite situation arises; as the small batteries participate in the transactive market, the battery degradation costs become apparent the longer the vehicles are parked (black square). Note however, that in all cases except the large battery/short duration, the daily fees are less than \$20/day, and in the month of June, they actually become negative, indicating large profits can be realized.

VI. CONCLUSION

This paper discusses a detailed business model for smart airport parking facilities. The transactive capabilities of a large EV fleet were leveraged to find an optimal charge/discharge paradigm that maximizes vehicle utility, enhances customer experience and provides profits to the parking lot owner. This work provides a framework that may be used to design a business model for any long-term parking facility. Further, the impact of the choice of charger type and hourly price variation has also been discussed. The day-ahead algorithm may be utilized to assess the daily energy transaction capability of the parking lot and provide the customer with impact-assessment of various POT schemes. Uncertainties due to price changes, driver behavior and renewable energy will be explored in future extensions of this work.

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MAIGHA received the B.Tech. degree in electrical engineering from GBPUAT, Pantnagar, India, in 2002, and the Ph.D. degree in electrical engineering from the Missouri University of Science and Technology, Rolla, USA, in 2017. She was an Assistant Software Engineer at TCS, India, for 2.7 years. She was a Post-Doctoral Researcher with Clemson University, Charleston, USA. She is currently serving as a General Engineer with the Smart Grids Group, Commonwealth Edison, Chicago. Her research interest is in the area of microgrids, smart inverters, distributed energy resources, and electric vehicles.

M. L. CROW (S'83–M'90–SM'94–F'10) received the B.S.E. degree from the University of Michigan, Ann Arbor, and the Ph.D. degree from the University of Illinois, Urbana–Champaign. She is currently the F. Finley Distinguished Professor of electrical engineering with the Missouri University of Science and Technology. Her research interests include computational methods for dynamic security assessment and the application of power electronics in bulk power systems.