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Optimal Short-Term Charge/Discharge Operation for Electric Vehicles With Volt-Var Control in Day-Ahead Electricity Market

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ABSTRACT This paper presents a methodology for optimizing the short-term operation of electric vehicle (EV) charging and discharging while considering the potential curtailment of active power due to volt-var control (VVC) prioritizing reactive power output. The proposed approach involves exchanging information between the EV aggregator and the distribution system operator (DSO). This approach allows the EV aggregator to optimize EV charge/discharge schedules while considering voltage-related constraints in the distribution system (DS). Initially, the aggregator shares the optimized schedule with the DSO to estimate the anticipated active power reduction through power flow analysis. Subsequently, the aggregator revises the constraint on active power output to avoid its expected curtailment and performs a second optimization for EV charging and discharging operation. Numerical simulations conducted on a realistic DS model in Japan validate the effectiveness of the proposed method in enhancing profitability in the day-ahead market while ensuring the quality of DS voltage. The results demonstrate an increase in profit by shifting the time of EV charging and discharging based on shared information from the DSO.

INDEX TERMS Aggregator, distribution system, electric vehicle, electricity market, optimization, virtual power plant.

I. INTRODUCTION

THE integration of electric vehicles (EVs) into power systems constitutes a rapidly progressing domain of research, carrying substantial implications for the prospective provision of energy. The merits and obstacles linked to assimilating a substantial quantity of EVs into power systems are intricate and manifold. On one hand, unregulated charging and discharging of an extensive fleet of EVs may engender intricacies in balancing the supply and demand of electricity within bulk power systems. Moreover, this may instigate deviations in voltage on local distribution systems (DSs). Conversely, owing to the EV's capacity for four-quadrant active and reactive power control, regulated charging and discharging of EVs bear the potential to redress these concerns and enhance the operation of power systems with a high share of variable renewable energy (VRE) resources.

Employing active power control of EVs and engaging in the day-ahead electricity market presents an appealing alternative for fortifying the supply and demand balancing in bulk power systems, while also conferring benefits to EV owners. The determination of prices in the day-ahead market generally reflects the balance between electricity supply and demand. In other words, market prices ascend during periods of electricity scarcity and descend during periods of surplus. If arbitrage transactions that capitalize on this fundamental characteristic can be executed by leveraging EV charge and discharge, it will engender a stable operation of the power system for system operators and yield financial gains for EV owners [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. Given the limited capacity of individual EV onboard batteries, they cannot independently participate in the market. This necessitates the aggregation of EVs and the management of charging and discharging for a multitude of EVs that surpasses the minimum capacity constraints of the market. Nonetheless, the simultaneous charge and discharge of EVs will provoke local voltage complications if the EVs are interconnected within the same DS [12].

The local voltage issue triggered by the simultaneous charge/discharge of EVs can be resolved by implementing volt-var control (VVC) on the EVs themselves [13], [14], [15], [16]. However, this approach gives rise to interference between the active and reactive power output. VVC entails the utilization of standardized VVC curves, as defined in [17], [18], and [19] to avert voltage deviations. It enables distributed energy resources (DERs) to independently contribute towards enhancing voltage profiles and obviating the necessity for grid reinforcement. While the prioritization of reactive power injection through VVC is of importance for voltage regulation, it is worth noting that the inverter's capacity is confined by the apparent power (in volt-amperes).

Consequently, the reactive power injection may constrain the active power output for arbitrage transactions, reducing customer profits. Nevertheless, there remains scope for augmented profits, as it facilitates state of charge (SoC) availability during alternative time frames of the day. Therefore, a coordinated optimization of active and reactive power control becomes imperative to augment customer profits while maintaining DS voltage within the specified limits.

Numerous research endeavors have been proposed to achieve coordinated optimization of active and reactive power control for DERs. Most of these studies have focused on exploiting active and reactive power dispatch strategies [20], [21], [22], [23], [24], [25], [35], [36], [37], [38], [39], [40], [41], [42], [43]. While the utilization of optimal dispatch schemes shows promise for EVs that can be fully externally controlled based on pre-determined active and reactive power commands, it becomes challenging to apply such approaches to EVs implementing VVC. These EVs autonomously adjust their reactive power injection according to pre-set VVC curves and the voltage measured at the PCC. Therefore, when the amount of reactive power output is high, the pre-planned active power dispatch may be curtailed.

Some studies focus on both active power dispatch and reactive power control in accordance with standardized VVC curves [26], [27], [28], [44], [45], [46], [47], [48]. Reference [26] proposed a local voltage control scheme incorporating piecewise linear VVC, significantly relaxing the constraints on convergence conditions. Reference [27] presented a distributed optimal power flow (DOPF) scheme that encompasses standard piecewise-linear VVC and active power curtailment of PV systems, considering three distinct fairness perspectives. Additionally, [28] integrated standard VVC into the OPF framework to enhance the hosting capacity of PV systems in the DS. In [44], an ADMM-based distributed three-block algorithm for DER coordination over alternative current (AC) OPF with VVC constraints was proposed. In [45], distributed volt-var-watt control was introduced to improve the fairness of inverter active power curtailment. Reference [46] proposed a hierarchical voltage control framework that coordinates diverse devices with different response times, incorporating voltage stability constraints into droop slope optimization to mitigate oscillation risks. Reference [47] presented a DOPF method with VVC and dynamic inverter reactive current control, which reduces voltage deviation and PV curtailment. Reference [48] integrated local piecewise volt-var and volt-watt droop functions into a multi-period DOPF formulation, demonstrating reduced voltage deviation and improved net load smoothing with BESS.

However, these methods employing OPF are optimized from the DSO's standpoint. When the optimization targets EVs, it becomes challenging for the DSO to account for and optimize all of them, as the objective functions and constraints of optimization vary for each EV owner.

Moreover, these studies fail to consider the potential reduction in active power due to the reactive power output of VVC. Consequently, if VVC prioritizes reactive power control when managing the day's active power as per the schedule submitted to the day-ahead market, unanticipated active power curtailment may occur, leading to customer losses in the day-ahead market. While this outcome is inevitable from a voltage control standpoint, integrating information on active power curtailment induced by reactive power output from VVC into the optimization process is anticipated to alleviate profit loss.

This paper's main contribution is to propose a methodology for optimizing EV charge and discharge operation while considering the anticipated curtailment of active power when prioritizing the reactive power output of VVC. Furthermore, by performing optimization at the level of each individual EV rather than from the DSO's perspective, it is feasible to tailor the optimization to a variety of specific objectives and constraints, all while satisfying voltage requirements.

To estimate the expected active power curtailment, the EV aggregator must know the voltage in the DS, as it serves as a determining factor for reactive power output. The voltage can be calculated through power flow analysis using DS information encompassing DS topology, control device configurations, and power profiles of all customers (not solely those under contract with the aggregator). Therefore, the aggregator shares information with the distribution system operator (DSO) in our proposed approach. The aggregator shares the optimized EV charge and discharge schedule with the DSO, enabling the latter to derive the projected curtailment of active power based on power flow calculations. Subsequently, the aggregator revises the constraints based on the shared information and re-performs the optimization process. Thus, an elaborate communication network is deemed unnecessary given the restricted nature of the exchanged information and its lack of urgency. The effectiveness of the proposed method is assessed using a real DS model in Japan, focusing on customer profit, active power curtailment, and DS voltage.

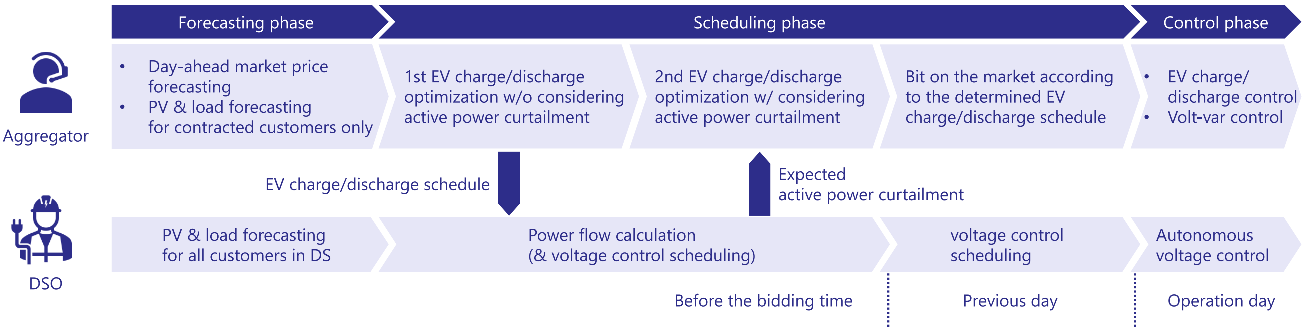


FIGURE 1. Framework of charge/discharge management of aggregated EVs. The aggregator enhances the optimization of the EV charge/discharge schedule through information sharing with the DSO to consider anticipated active power curtailment resulting from the prioritized provision of reactive power by VVC, which can be derived via power flow calculation.

The subsequent sections of this paper are organized as follows: Section II outlines the proposed scheme for EV charge and discharge management. Section III provides detailed explanations regarding the optimal operation aspect of the proposed method, which relies on information sharing between the EV aggregator and the DSO. Section IV conducts numerical simulations utilizing a real DS model in Japan to evaluate the efficacy of the proposed method. Lastly, Section V presents the concluding remarks.

II. OUTLINE OF EV CHARGE/DISCHARGE MANAGEMENT

EV charge/discharge management is conducted using the framework shown in Fig. 1. The primary players in our proposed approach are the EV aggregator and the DSO, where the aggregator and DSO are responsible for forecasting, scheduling, and control, respectively.

The aggregator oversees the charging and discharging activities of EVs, aiming to optimize profits within the day-ahead electricity market. The aggregate capacity of EVs managed by the aggregator must surpass the required capacity to partake in the market. In this context, we presume that the aggregator contracts with customers who possess both EVs and residential PV systems within a DS. The aggregator is also free to charge and discharge the EVs unless it interferes with the customers' driving requirements. However, the aggregator does not manage the PV systems.

On the other hand, the DSO is responsible for maintaining voltage within the DS through voltage control devices. As charging and discharging numerous EVs simultaneously pose challenges to voltage maintenance, employing voltage control mechanisms within the EVs themselves proves to be a cost-effective solution, potentially obviating the need for extensive investment in DS reinforcement. Consequently, we also assume the implementation of VVC in all customers' EV supply equipment (EVSE).

Implementing VVC in EVSEs may potentially result in a reduction of customers' profitability, as the prioritization of reactive power output leads to curtailment in active power output. Let S represent the apparent power rating of the grid-timed inverter within EVSE. The active and reactive power outputs at time t, denoted as p_t and q_t respectively must adhere to the following constraint:

$$S \geq \sqrt{p_t^2 + q_t^2}. \tag{1}$$

The constraint stipulates that active power curtailment should be implemented when there is an escalation in the magnitude of prioritized reactive power output in the control phase, as illustrated in Fig. 1. For aggregators participating in the day-ahead market, aiming to capitalize on arbitrage opportunities, the active power curtailment that is not anticipated in the scheduling phase, which takes place up to the day before the control phase, results in an opportunity loss in expected profitability.

It presents a formidable challenge for aggregators to discern the potential occurrence of active power curtailment and devise charge/discharge strategies for EVs with VVC prioritizing reactive power output to avert active power curtailment by themselves. This complexity arises because the reactive power output of VVC is contingent upon the voltage at the PCC, which varies based on the status of DS configuration and all customers connected to the same DS, including those not under contract with the aggregator. The aggregator will be accessible to its customers' PV generation and electricity consumption data. However, access to other customers' data within the same DS, as well as DS data encompassing network topology and control device configurations, crucial for voltage calculations, is unavailable. Conversely, the DSO typically possesses all the requisite data for voltage calculations.

Henceforth, our proposed methodology aims to exchange information between the aggregator and the DSO in EV charge/discharge operation to prevent profit loss attributable to the inverter's apparent power capacity concern. The schematic representation of the energy management framework for aggregated EVs, encompassing three stages: forecasting, scheduling, and control [29], [30], [31], is depicted in Fig. 1. During the forecasting phase, the aggregator predicts the day-ahead market price as well as the profiles of PV generation and load for contracted customers. Simultaneously, the DSO forecasts the PV and load profiles for all customers within the DS. Progressing to the scheduling phase, the aggregator first optimizes the EV charge/discharge schedule without considering potential active power curtailment for all contracted customers, utilizing forecasted data. Subsequently, the optimized schedule is communicated to the DSO. The DSO then evaluates the potential for active power curtailment among the contracted customers in the initial schedule by conducting a power flow calculation (PFC) and communicates the findings back to the aggregator. Taking the DSO's information into account, the aggregator adjusts the constraints of the optimization problem and re-conducts the EV charge/discharge optimization to preempt the anticipated active power curtailment. Finally, during the control phase, the EVs are regulated in accordance with the ultimately determined charge/discharge schedule. The subsequent section will elaborate on the scheduling phase. As aforementioned, the volume of data to be exchanged is exceedingly scant and lacks the necessity for prompt action, thus rendering an elaborate communication infrastructure superfluous for the deployment of the proposed methodology. It is also superior from an implementation standpoint because it is not optimized from the DSO's perspective, as is the case with DOPF utilized in previous studies. This allows the EV owner to implement an optimization that freely incorporates their own objectives and constraints.

III. OPTIMAL CHARGE/DISCHARGE OPERATION FOR EV WITH VVC BASED ON INFORMATION SHARING BETWEEN AGGREGATOR AND DSO

This section presents the formulation of the optimization problem concerning the charge/discharge operation for EVs incorporating VVC. As illustrated in Fig. 1, the aggregator, in the scheduling phase, establishes the initial charge/discharge schedules for all EVs, neglecting the active power output restriction imposed by the inverter capacity constraint when injecting reactive power of VVC. This is accomplished by solving the optimization problem. Let $t \in \{1, \ldots, T\}$ denotes a time window of the day-ahead market within a day, where T represents the total number of time windows, and $n \in \mathcal{N}$ indicates the index of a customer who has contracted with the aggregator. The charge/discharge schedule for EVs, denoted as $\boldsymbol{p}^{\mathrm{ev}} = \left(p_{n,t}^{\mathrm{ev}}; n \in \mathcal{N}, t \in \{1, \ldots, T\}\right)$, is optimized to maximize the estimated profit in the day-ahead market. Additionally, we introduce R_t and E_t to represent the revenue and expenditure associated with the purchase and sale of electricity during time window t. The objective function for the optimal operation of EVs can be formulated as a mixed-integer linear programming (MILP) problem:

$$\max_{\boldsymbol{p}^{\mathrm{ev}+}, \boldsymbol{p}^{\mathrm{ev}-}} \sum_{t=1}^{T} \left(R_t - E_t\right). \tag{2}$$

Within this context, the charge/discharge schedule $\boldsymbol{p}^{\mathrm{ev}}$ for EVs is decomposed into two schedules: the charge schedule $\boldsymbol{p}^{\mathrm{ev}+} = (p_{n,t}^{\mathrm{ev}+}; n \in \mathcal{N}, t \in \{1, \ldots, T\})$ and the discharge schedule $\boldsymbol{p}^{\mathrm{ev}-} = (p_{n,t}^{\mathrm{ev}-}; n \in \mathcal{N}, t \in \{1, \ldots, T\})$. This decomposition is undertaken to enhance the optimization convenience.

As there exists a minimum capacity requirement for market participation, the estimated revenue R_t is computed as the summation of two terms, given by:

$$R_t = \hat{u}_t^{\mathrm{m}} \delta_t^{\mathrm{S}} p_t^{\mathrm{s}} \frac{24}{T} + \hat{u}_t^{\mathrm{s}'} \delta_t^{\mathrm{S}'} p_t^{\mathrm{s}'} \frac{24}{T}. \tag{3}$$

Here, p_t^{s} represents the total electricity sold by all customers $\forall n$ to the market, while $p_t^{\mathrm{s}'}$ represent the selling electricity when the total falls below the minimum market capacity P^{m}. The criteria for exceeding the market capacity is determined by binary variables $\delta_{n,t}^{\mathrm{S}}$ and $\delta_{n,t}^{\mathrm{S}'}$. To convert these values from watts to watt-hours, they are multiplied by $24/T$. The variables $\hat{u}_t^{\mathrm{m}}$ and $\hat{u}_t^{\mathrm{s}'}$ denote the forecasted electricity prices in the market and when the total selling electricity is below the minimum market capacity P^{m}, respectively. The symbol $\hat{}$ signifies a forecasted value. It is important to mention that the calculation of p_t^{s}, $p_t^{\mathrm{s}'}$, $\delta_{n,t}^{\mathrm{S}}$ and $\delta_{n,t}^{\mathrm{S}'}$ is elaborated upon in (12)–(17) presented subsequently.

In contrast, we assume that there exists ample demand, ensuring that the total amount of purchased electricity exceeds the minimum capacity required for market participation, denoted as P^{m}. The estimated expenditure E_t can be determined by summing up the electricity purchased from the market by all customers, given by:

$$E_t = \hat{u}_t^{\mathrm{m}} \sum_{n \in N} p_{n,t}^{\mathrm{p}} \frac{24}{T}. \tag{4}$$

Here, $p_{n,t}^{\mathrm{p}}$ represents the electricity purchased from the market, and it is converted from watt values to watt-hour values by multiplying by $24/T$. It is important to note that the variables of electricity sold and purchased may undergo frequent fluctuations considering the charging/discharging capability of EVs. However, for the sake of simplicity, we assume them to remain constant within each time window, denoted by t.

A. CONSTRAINTS OF OPTIMIZATION PROBLEM

The optimization problem encompasses a set of constraints as depicted in (5)–(20). The operational restrictions pertaining to the charge/discharge of EVs are outlined as follows:

$$0 \le \delta_{n,t}^{\mathrm{ev}+} + \delta_{n,t}^{\mathrm{ev}-} \le 1, \tag{5}$$

$$0 \le p_{n,t}^{\mathrm{ev}+} \le P_{n,t}^{\mathrm{ev}+} \delta_{n,t}^{\mathrm{ev}+}, \tag{6}$$

$$-P_{n,t}^{\mathrm{ev}-} \delta_{n,t}^{\mathrm{ev}-} \le p_{n,t}^{\mathrm{ev}-} \le 0. \tag{7}$$

In (5), the constraint ensures that charging and discharging operations do not occur simultaneously for a given customer n in a time window t. This is achieved by utilizing binary variables, $\delta_{n,t}^{\mathrm{ev}+}$ for charging and $\delta_{n,t}^{\mathrm{ev}-}$ for discharging. Furthermore, the active power outputs for EV charging from the grid, denoted as $p_{n,t}^{\mathrm{ev}+}$, and discharging to the grid, denoted as $p_{n,t}^{\mathrm{ev}-}$, are subject to limitations imposed by the maximum active power output for charging, $P_{n,t}^{\mathrm{ev}+}$, and discharging, $P_{n,t}^{\mathrm{ev}-}$, respectively.

The power flow constraints can be succinctly presented as follows:

$$0 \leq \delta^{\mathrm{p}}_{n,t} + \delta^{\mathrm{pcc}-}_{n,t} \leq 1, \tag{8}$$

$$0 \leq p^{\mathrm{p}}_{n,t} \leq P^{\mathrm{p}}_{n,t}\delta^{\mathrm{p}}_{n,t}, \tag{9}$$

$$-P^{\mathrm{pcc}-}_{n,t}\delta^{\mathrm{pcc}-}_{n,t} \leq p^{\mathrm{pcc}-}_{n,t} \leq 0, \tag{10}$$

$$p^{\mathrm{p}}_{n,t} + p^{\mathrm{pcc}-}_{n,t} = \hat{p}^{\mathrm{net}}_{n,t} + p^{\mathrm{ev}+}_{n,t} + p^{\mathrm{ev}-}_{n,t}. \tag{11}$$

Equation (8) establishes constraints on the unidirectional power flow at the PCC for customer n within the same time window t. This is achieved by utilizing binary variables for forward power flow $\delta^{\mathrm{p}}_{n,t}$ and reverse power flow $\delta^{\mathrm{pcc}-}_{n,t}$. The forward power flow at the PCC, denoted as $p^{\mathrm{p}}_{n,t}$ and corresponding to the purchasing electricity mentioned in (3), is bounded by the maximum forward power flow $P^{\mathrm{p}}_{n,t}$. Similarly, the reverse power flow at the PCC, represented by $p^{\mathrm{pcc}-}_{n,t}$, is limited by the maximum reverse power flow $P^{\mathrm{pcc}-}_{n,t}$ for customer n at time window t. Furthermore, (11) ensures that the sum of the forward and reverse power flows $p^{\mathrm{p}}_{n,t}$ and $p^{\mathrm{pcc}-}_{n,t}$ for customer n at time window t, where either or both must be zero, equals the sum of the active powers for EV charging $p^{\mathrm{ev}+}_{n,t}$, EV discharging $p^{\mathrm{ev}-}_{n,t}$, and the forecasted net power of other electricity consumption and generation for customer n within the specific time window t, denoted as $\hat{p}^{\mathrm{net}}_{n,t}$.

The constraints pertaining to the sale of electricity can be expressed as follows:

$$0 \leq \delta^{\mathrm{S}}_{t} + \delta^{\mathrm{S}'}_{t} \leq 1, \tag{12}$$

$$-M\delta^{\mathrm{S}}_{t} \leq p^{\mathrm{S}}_{t} \leq 0, \tag{13}$$

$$0 \leq p^{\mathrm{S}'}_{t} \leq M\delta^{\mathrm{S}'}_{t}, \tag{14}$$

$$p^{\mathrm{S}}_{t} + p^{\mathrm{S}'}_{t} = P^{\mathrm{m}} + \sum_{n\in N} p^{\mathrm{pcc}-}_{n,t}, \tag{15}$$

$$p^{\mathrm{s}}_{t} = P^{\mathrm{m}} - p^{\mathrm{S}}_{t}, \tag{16}$$

$$p^{\mathrm{s}'}_{t} = P^{\mathrm{m}} - p^{\mathrm{S}'}_{t}. \tag{17}$$

As mentioned above, the sale of electricity comprises two components: one for the market, denoted as p^{s}_{t}, and the other, $p^{\mathrm{s}'}_{t}$, when the total selling electricity is below the market participation capacity, P^{m}. Equation (12) introduces constraints to determine the mode of electricity selling within time window t, using binary variables $\delta^{\mathrm{S}}_{n,t}$ and $\delta^{\mathrm{S}'}_{n,t}$. The upper limit for each selling electricity is set to a sufficiently large value using the Big M method, with $M = 10^6$. The values of p^{s}_{t} and $p^{\mathrm{s}'}_{t}$ are assigned by comparing the sum of the reverse power flow $p^{\mathrm{pcc}-}_{n,t}$, as constrained in (10), with the minimum market participation capacity, P^{m}, as defined by (15)–(17).

The operation of EV charge/discharge is subject to the constraint imposed by the SoC of the EV's onboard battery, expressed as follows:

$$SoC_{n,t+1} = SoC_{n,t} + \frac{\left(p^{\mathrm{ev}+}_{n,t}\eta - p^{\mathrm{ev}-}_{n,t}\eta^{-1}\right)\frac{24}{T} + E^{\mathrm{ev\_d}}_{n,t}}{E^{\mathrm{ev}}_{n}}, \tag{18}$$

$$\underline{SoC}_{n} < SoC_{n,t} < \overline{SoC}_{n}, \tag{19}$$

$$SoC_{n,1} = SoC_{n,T} = SoC^{\mathrm{ref}}, \tag{20}$$

where $SoC_{n,t}$ represents the SoC of the EV's onboard battery for customer n at time window t. The parameter η denotes the charge/discharge efficiency, $E^{\mathrm{ev\_d}}_{n,t}$ corresponds to the energy consumed for scheduled EV driving activities, such as commuting and shopping, within the time window t for customer n. E^{ev}_{n} represents the energy capacity of the battery in watt-hours. The upper and lower limits of the SoC operation range for customer n are denoted by $\overline{SoC}_{n}$ and $\underline{SoC}_{n}$, respectively. Moreover, at the beginning and end of each day, the SoC values $SoC_{n,1}$ and $SoC_{n,T}$ are set to the reference SoC value, SoC^{ref}, to ensure an adequate energy level for driving.

In the initial schedule, the limitations on the maximum active power output for charging, $P^{\mathrm{ev}+}_{n,t}$, and discharging, $P^{\mathrm{ev}-}_{n,t}$, as stated in (6) and (7), are defined based on the apparent power capacity of each EV, denoted as S^{ev}_{n}:

$$P^{\mathrm{ev}+}_{n,t} := S^{\mathrm{ev}}_{n}, \tag{21}$$

$$P^{\mathrm{ev}-}_{n,t} := S^{\mathrm{ev}}_{n}. \tag{22}$$

These constraints are established to obtain the optimal solution without considering the curtailment of active power resulting from prioritizing the reactive power output of VVC. As discussed in Section II, this study assumes that all EVs employ VVC. Consequently, when the EVs are simultaneously charging or discharging within time window with low or high market electricity prices, a significant voltage drop or rise occurs in the DS, leading to reactive power injection or absorption by VVC. The subsequent subsection addresses the incorporation of updated maximum active power output constraints that consider VVC.

B. EVALUATION OF EV CHARGE/DISCHARGE SCHEDULE FROM DSO'S PERSPECTIVE AND UPDATING OPTIMIZATION CONSTRAINTS

The aggregator conveys the initial schedule, denoted as $\boldsymbol{p}^{\mathrm{ev}}$, which represents the solution to the optimization problem presented in (2)–(22), to the DSO for evaluation. This evaluation does not consider the active power curtailment caused by prioritizing the output of reactive power in VVC. The expected active power curtailment within the initial schedule $\boldsymbol{p}^{\mathrm{ev}}$ results in a missed opportunity to increase profits. Ideally, the constraints related to active power curtailment by VVC would be directly incorporated into the optimization problem to avoid potential missed opportunities. However, this proves challenging from the aggregator's perspective.

The reactive power output of VVC is contingent upon the voltage at the PCC, which is typically ascertained by power flow calculations. Power flow calculations require detailed information about the DS, including network topology, line impedances, control device configurations, and variations in active and reactive power for all customers. While such information is accessible to the DSO, it is not readily available to the aggregator. Consequently, in this study, the DSO performs the power flow calculation based on the shared charge/discharge schedule $\boldsymbol{p}^{\mathrm{ev}}$, along with other pertinent information, to evaluate the potential for active power curtailment by VVC within the shared charge/discharge schedule $\boldsymbol{p}^{\mathrm{ev}}$. Subsequently, the aggregator re-executes the optimization process, incorporating updated active power constraints based on the evaluation conducted by the DSO.

The DSO executes power flow calculation to assess the potential for curtailment of active power in the shared charge/discharge schedule $\boldsymbol{p}^{\mathrm{ev}} = \{\boldsymbol{p}_t^{\mathrm{ev}+}, \boldsymbol{p}_t^{\mathrm{ev}-}\}$ provided by the aggregator. The mathematical expression representing the relationship of the PFC can be formulated as:

$$\left\{\boldsymbol{p}_\tau^{\mathrm{ev}+*}, \boldsymbol{p}_\tau^{\mathrm{ev}-*}, \boldsymbol{q}_\tau^{\mathrm{ev}}, \boldsymbol{v}_\tau^{\mathrm{ev}}\right\} = f^{\mathrm{pfc}}\left(\boldsymbol{p}_\tau^{\mathrm{ev}+}, \boldsymbol{p}_\tau^{\mathrm{ev}-}, \hat{\boldsymbol{p}}_\tau^{\mathrm{net}}, \boldsymbol{x}\right). \quad (23)$$

In this context, the time step $\tau \in \{1, \ldots, \mathcal{T}\}$ is utilized for the PFC, which is shorter than the optimization's time window t. This consideration accounts for the time constant associated with voltage control in the DS. As a result, the time step for the initial charge/discharge schedule is converted from t to τ.

Let $m \in \mathcal{M}$ denote the index of all customers in the DS, with $\mathcal{M}$ representing the total number of customers. The voltage at the PCC for EVs $\boldsymbol{v}_\tau^{\mathrm{ev}} = (v_{n,\tau}^{\mathrm{ev}}; n \in \mathcal{N}, \tau \in \{1, \ldots, \mathcal{T}\})$, the reactive power output of EVs' VVC $\boldsymbol{q}_\tau^{\mathrm{ev}} = (q_{n,\tau}^{\mathrm{ev}}; n \in \mathcal{N}, \tau \in \{1, \ldots, \mathcal{T}\})$, and the curtailed charge/discharge schedule due to prioritizing reactive power output by VVC $\boldsymbol{p}_\tau^{\mathrm{ev}+*}, \boldsymbol{p}_\tau^{\mathrm{ev}-*}$ are derived by conducting the power flow calculation using the initial charge/discharge schedule $\boldsymbol{p}_\tau^{\mathrm{ev}+}, \boldsymbol{p}_\tau^{\mathrm{ev}-}$ as input, along with the net active power of all customers in the DS $\hat{\boldsymbol{p}}_\tau^{\mathrm{net}} = (\hat{p}_{m,\tau}^{\mathrm{net}}; m \in \mathcal{M}, \tau \in \{1, \ldots, \mathcal{T}\})$. Here, $m \in \mathcal{M}$ denotes the index of a customer in the DS, encompassing both contracted and non-contracted customers of the aggregator. Additionally, other variables commonly required for the power flow calculation are denoted as $\boldsymbol{x}$.

Note that the reactive power output of EV at time τ in customer n, calculated by the VVC function f^{vvc}, can be expressed as:

$$q_{n,\tau}^{\mathrm{ev}} = S_n^{\mathrm{ev}} \cdot f^{\mathrm{vvc}}\left(v_{n,\tau}^{\mathrm{ev}}\right). \quad (24)$$

Here,

$$f^{\mathrm{vvc}}(v_{n,\tau}^{\mathrm{ev}}) = \begin{cases} Q_1 & \text{if } \dfrac{v_{n,\tau}^{\mathrm{ev}}}{V_{\mathrm{r}}} < V_1 \\ Q_2 & \text{if } \dfrac{v_{n,\tau}^{\mathrm{ev}}}{V_{\mathrm{r}}} > V_2 \\ \beta v_{n,\tau}^{\mathrm{ev}} + \gamma & \text{otherwise,} \end{cases} \quad (25)$$

$$\beta = \frac{Q_2 - Q_1}{V_2 - V_1}, \quad (26)$$

$$\gamma = \frac{Q_2 V_1 - Q_1 V_2}{V_2 - V_1}, \quad (27)$$

where V_1, V_2, Q_1, and Q_2 represent the setting points of the VVC curve shown in Fig. 2, and V_{r} denotes the reference voltage for per-unit (pu) value. Consequently, the realized charge/discharge power, i.e., the charge/discharge power after curtailment resulting from reactive power prioritization, can be determined as:

$$p_{n,\tau}^{\mathrm{ev}+*} = \min\left(p_{n,\tau}^{\mathrm{ev}+}, \sqrt{S_n^{\mathrm{ev}^2} - q_{n,\tau}^{\mathrm{ev}^2}}\right), \quad (28)$$

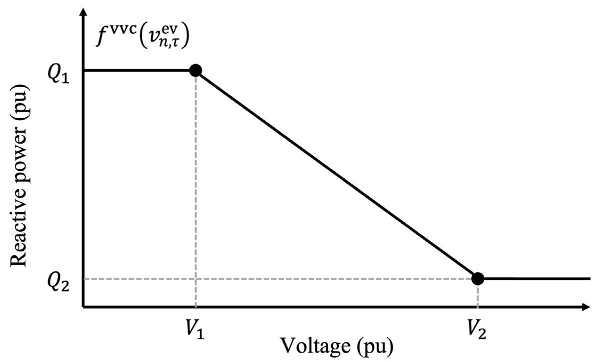


FIGURE 2. Volt-var control (VVC) curve setting.

$$p_{n,\tau}^{\mathrm{ev}-*} = \max\left(p_{n,\tau}^{\mathrm{ev}-}, -\sqrt{S_n^{\mathrm{ev}^2} - q_{n,\tau}^{\mathrm{ev}^2}}\right). \quad (29)$$

The differences between realized charge/discharge power and the initial charge/discharge schedule $\left(p_{n,\tau}^{\mathrm{ev}+*} - p_{n,\tau}^{\mathrm{ev}+}\right)$ and $\left(p_{n,\tau}^{\mathrm{ev}-*} - p_{n,\tau}^{\mathrm{ev}-}\right)$ represent the potential opportunity loss of profit. The proposed method updates the constraints on the maximum active power output of EVs as follows:

$$P_{n,t}^{\mathrm{ev}+} := P_{n,t}^{\mathrm{ev}+} - \left(p_{n,t}^{\mathrm{ev}+} - p_{n,t}^{\mathrm{ev}+*}\right), \quad (30)$$

$$P_{n,t}^{\mathrm{ev}-} := P_{n,t}^{\mathrm{ev}-} + \left(p_{n,t}^{\mathrm{ev}-} - p_{n,t}^{\mathrm{ev}-*}\right). \quad (31)$$

It is important to note that the time step of the realized charge/discharge power $p_{n,t}^{\mathrm{ev}+*}$, $p_{n,t}^{\mathrm{ev}-*}$ is converted from τ to t. Then, the optimization problem defined in (2)–(20), (30), and (31) is solved to determine the subsequent EV charge/discharge schedule. During the second optimization, the charge/discharge power is expected to be shifted from the time window in which curtailment would occur to the other time windows within the day. In the control phase, the EVs are regulated in accordance with the finalized charge/discharge schedules.

IV. NUMERICAL SIMULATION

This section performs numerical simulations to validate the efficacy of our proposed optimal charge/discharge operation method for EVs with VVC. The simulation conditions are described in subsection IV-A. Subsequently, subsection IV-B examines three distinct cases involving different EV operations and compares the outcomes in relation to profit, active power profiles of EV charge/discharge, and voltage deviation in the DS.

A. SIMULATION CONDITIONS

The proposed methodology is assessed using a DS model based on authentic data from Japan [32], as depicted in Fig. 3. The model represents a one-feeder configuration comprising a three-phase, three-wire medium-voltage (MV) system with a line-to-line voltage of 6.6 kV, alongside single-phase, three-wire low-voltage (LV) systems with line-to-line voltages of 100/200 V thanks to the center-tapped distribution transformer. Within the model, there exists one OLTC at the distribution substation, 13 MV customers, and 22 distribution transformers serving as LV systems, catering to 265 LV customers. Each LV customer possesses a PV system and an EV. The PV system is rated at 5 kVA and operates at a power factor 0.95. Fig. 4 illustrates a box plot presenting an overview of the PV and load profiles for the 265 LV customers over 36 days.

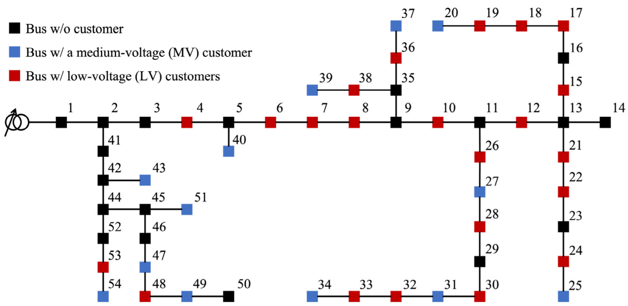
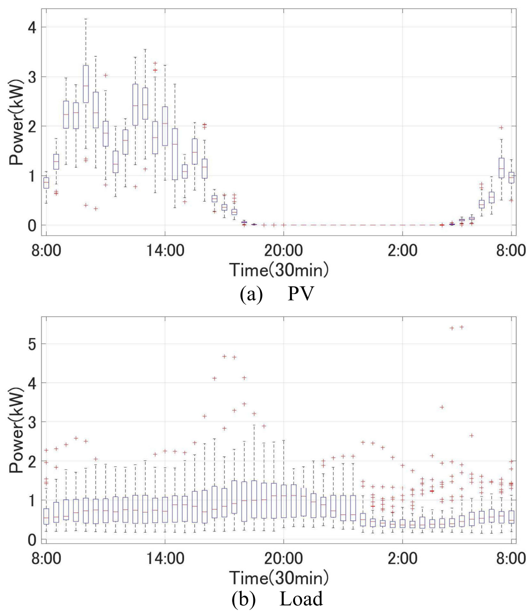


FIGURE 3. Distribution system (DS) model.



(a) PV

(b) Load

FIGURE 4. Boxplot of PV and load for 265 LV customers over 36 days.

The aggregator assumes responsibility for orchestrating the charge/discharge operation for all EVs under the following conditions. Each EV possesses a battery capacity denoted as E_n^{ev}, which amounts to 40 kWh. The charging and discharging operations are facilitated through a residential bi-directional EVSE characterized by a rated capacity S_n^{ev} of 6 kVA. Moreover, the charge/discharge efficiency, represented by η, stands at 95%. To enable voltage control within the DS, the EVSEs incorporate VVC mechanisms employing the parameter values of $(V_1, V_2, Q_1, Q_2) = (0.86\ \text{pu}, 1.06\ \text{pu}, 0.8\ \text{pu}, -0.8\ \text{pu})$. These values were meticulously chosen from many candidates to ensure precise voltage control and prevent oscillations with OLTC. Maintaining the SoC of the EVs within a predefined range, denoted as $\underline{SoC}_n = 0.1$ to $\overline{SoC}_n = 1$, is an essential aspect of the management process. At the commencement and conclusion of the daily simulation, the SoC is initialized and finalized at $SoC^{\mathrm{ref}} = 0.8$, ensuring an adequate energy reserve for daily driving purposes.

The daily usage patterns of EVs are assumed to be divided into weekdays and weekends. During weekdays, EVs serve as transportation for commuting purposes, remain parked at workplaces during the daytime, and are subsequently parked at home for the remainder of the day. The schedules for commuting are generated based on the questionnaire survey on transportation in the Kanto District Transport Bureau Area in Japan [33]. The energy consumption for a one-way commute is determined to be 1.43 kWh, calculated considering a driving distance of 10 km and an efficiency of 7 km/kWh. On weekends, EVs remain parked at home throughout the entire day. It is assumed that the EVs are continuously connected to EVSEs and readily accessible for energy management when parked at home. Conversely, when EVs are utilized for commuting or parked at workplaces, they are unavailable for energy management.

The day-ahead (spot) market was considered based on the Japanese mechanism. Essentially, this market facilitates the trading of electricity to be delivered the following day. Trading is conducted for 48 time slots, with the day divided into 30-minute intervals. The execution method is a sealed single-price auction. However, in the simulation, the auction procedure was simplified with the following assumptions: first, it was assumed that the desired bid is always successful and that no imbalances occur. The historical spot price was employed as the basis for the final contract price, while the predicted value of that spot price was utilized in the optimization of the EV charging and discharging schedule.

As the aggregator gains advantages through day-ahead market arbitrage, multiple fluctuations in spot prices are considered to assess the efficacy of the proposed method. Fig. 5 displays a boxplot representing the 36-day daily spot prices employed in the evaluation. These prices are derived from the daily spot price profiles from February to October 2021. The daily profiles are categorized into three groups based on increasing standard deviation, and 12 profiles are chosen from each group. Consequently, the 36 profiles encompass 25 weekdays and 11 weekends. The electricity price, $u_t^{s'}$, is set to zero when the total amount of electricity sold falls below the minimum market capacity P^{m}. Therefore, its forecasted value $\hat{u}_t^{s'}$ is also zero. The minimum market capacity P^{m} is set to 0.1 MW per 30 minutes.

In the proposed methodology, the scheduling of EV charge/discharge is carried out using day-ahead forecasted data for PV generation, load demand, and spot prices. While PV generation and load demand are presumed free from forecasting errors, the spot prices are predicted using a

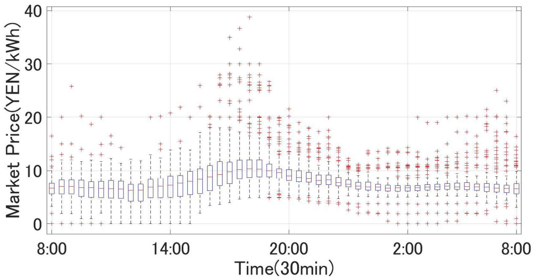


FIGURE 5. Boxplot of day-ahead market prices for 36 days.

sparse regression model based on the least absolute shrinkage and selection operator (LASSO) [34]. For the optimization process, YALMIP serves as the computational tool for formulating the problem, while CPLEX is employed as the optimization solver. The power flow calculations are executed using OpenDSS to facilitate the power flow control.

B. SIMULATION RESULT

To substantiate the efficacy of the proposed approach, we examine three distinct case studies as follows:

- Case 1: The base case where EV charge/discharge operations are not carried out. Each household consumes the PV generation, and any surplus is sold to the market. The remaining electricity consumption is procured from the market.
- Case 2: The aggregator optimizes EV charge/discharge schedules independently, without sharing information with the DSO, using the methodology described in subsection III-A.
- Case 3: The aggregator optimizes EV charge/discharge schedules in coordination with the DSO, by sharing information based on the approach outlined in subsections III-A and III-B (i.e., the proposed method).

Initially, we confirm that the proposed methodology generates greater profits than scenarios where information exchange is absent. Fig. 6 illustrates the revenue, expenditure, and profit balance for all cases. These values represent the averages over 36 days and across 265 LV customers. In Case 1, where EVs are not employed for energy management, electricity is purchased at market price to fulfill the demand not met by PV generation. In contrast, surplus PV generation is sold at market price. Consequently, Case 1 exhibits negative profit, whereas Cases 2 and 3 show positive profit. A comparison between Cases 1 and 2 demonstrates that arbitrage based on optimized EV charge/discharge operation contributes to a profit increase of 37.7 JPY. Furthermore, the profit increase from Case 1 to Case 3 amounts to 60.2 JPY. This outcome suggests that the introduction of information sharing further enhances profit. In essence, it can be confirmed that the proposed method, coupled with information sharing, yields a profit 1.6 times higher than the method without information sharing. On average, this translates to an increase of 22 JPY per customer per day. Should this trend persist over a month, it could result in a substantial reduction in monthly electricity costs for a typical household, potentially by several tens of percent.

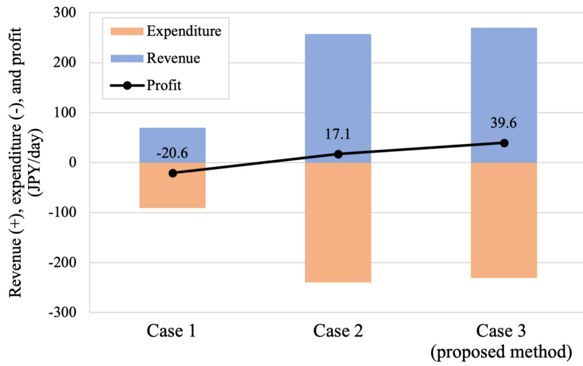


FIGURE 6. Active power profiles on EV charge/discharge in a single weekday day for a customer.

In the proposed method, the incorporation of information sharing enables the updating of active power constraints and the adjustment of the EV charge/discharge time window, thus effectively contributing to profit increase. Fig. 7 presents the active power profiles for EV charge/discharge on a weekday, illustrating a customer's experience in Cases 2 and 3. Positive values on the vertical axis indicate charging, while negative values indicate discharging. The blue lines represent the charge/discharge plans derived through optimization, while the purple lines portray the actual charge/discharge profiles after the control phase. The red lines depict the power discharged for driving purposes. On this day, the EV departs from the residence for the office at 8:00 and returns home at 15:30. During the EV's absence from the residence, it remains unconnected to the grid and only discharges the power needed for its travel.

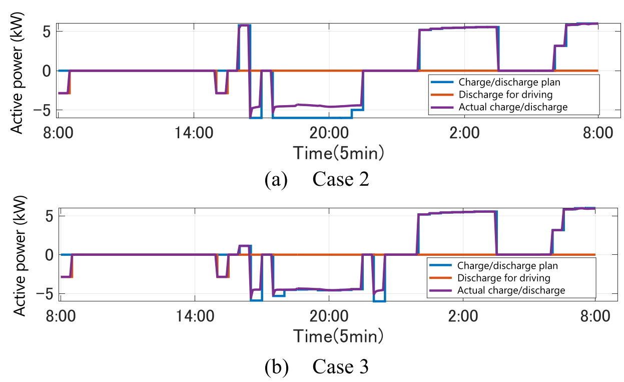


FIGURE 7. Active power profiles on EV charge/discharge on a weekday for a customer.

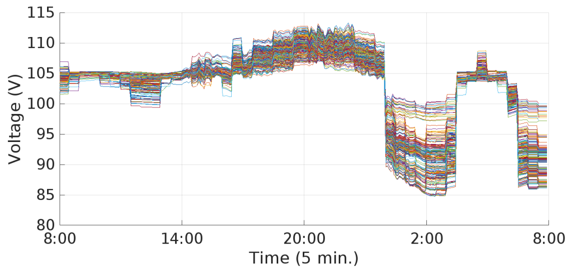
In Fig. 7(a), Case 2 reveals a strategy of utilizing the full 6 kVA rated capacity to maximize charge/discharge during low/high market prices. However, due to significant discharges in active power within the DS, resulting in voltage drops, reactive power is injected through VVC

TABLE 1. Average active power curtailment for 265 LV customers and 36 Days.

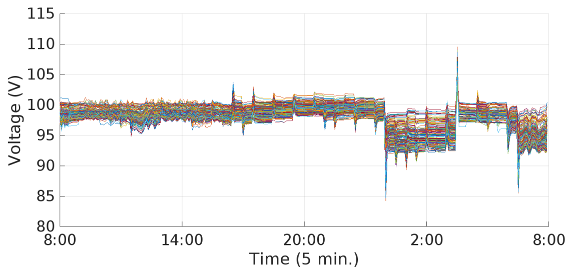
	Charging	Discharging	Total
Case 2 (w/o information sharing)	4.2 kWh	5.3 kWh	9.5 kWh
Case 3 (w/ information sharing; proposed method)	2.4 kWh	0.9 kWh	3.3 kWh

TABLE 2. Average accumulated voltage deviation for 265 LV customers and 36 Days.

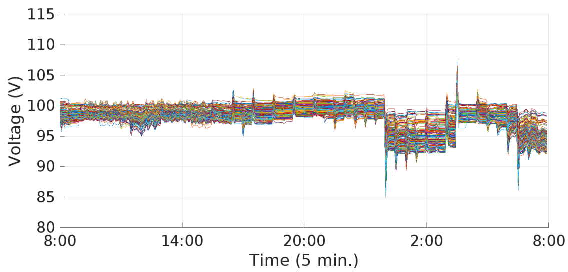
	Upper voltage	Lower voltage	Total
Case 2 (w/o information sharing)	0.9 V	56.7 V	57.6 V
Case 3 (w/information sharing; proposed method)	0.7 V	54.3 V	55.0 V



(a) Result of operating the EV charge/discharge schedule by the first optimization without volt-volt control (VVC).



(b) Case 2



(c) Case 3

FIGURE 8. Daily voltage profiles at all LV customers at PCC.

to maintain the voltage. Consequently, the active power output for EV discharge is curtailed during such time windows, leading to realized profit after the control phase being lower than the expected profit during the scheduling phase. On the other hand, as depicted in Fig. 7(b), the proposed method employs a discharge shift schedule by reducing the discharging amount between 16:30–21:30, while reducing the charging amount between 16:00–16:30, and increasing the discharging amount between 22:00–22:30. This period corresponds to the period with the highest market price when no curtailment is expected. The efficacy of this charge/discharge shift, based on information sharing, can be observed by comparing the curtailed active power amounts displayed in Table 1. The proposed method reduces the overall charge/discharge curtailment, thereby reducing the opportunity loss that hinders profit increase by 65% compared to Case 2. Further reduction in curtailment can be achieved by increasing the frequency of information sharing.

Furthermore, the suggested approach does not hinder the voltage regulation performed by VVC. As depicted in Fig. 8, the voltage profiles of all LV consumers at the PCC on the specified day for Case 2 and Case 3 display similar patterns of voltage fluctuations. Each instance successfully mitigates voltage fluctuations more effectively than without VVC, demonstrating that VVC proficiently governs the voltage profiles even during the charging and discharging of EVs. The extent of voltage variation, as indicated in Table 2, suggests that the application of the proposed methodology does not magnify the magnitude of deviation; thus, it does not disturb the voltage control within the DS.

V. CONCLUSION

A methodology is introduced for the operation of EV charge/discharge, which involves information sharing between the aggregator and the DSO. The aim is to enhance profitability in the day-ahead market by minimizing active power curtailment due to VVC. Integrating the constraint on active power curtailment by VVC into the optimization process of EV charge/discharge operation poses challenges, primarily due to the limited availability of power flow calculation data for the aggregator. In the proposed approach, the aggregator initially shares the optimized schedule with the DSO to assess potential active power curtailment within the DS. Subsequently, the aggregator updates the active power constraint to prevent curtailment and conducts a second optimization for EV charge/discharge operation.

The effectiveness of the proposed methodology is validated through numerical simulations utilizing a DS model grounded on real-world Japanese data. The simulations ascertain that the proposed method successfully enhances profitability in the day-ahead market while maintaining the voltage quality of the DS. This effect remains valid even in the presence of inaccuracies in the predicted market price. It is confirmed that by adjusting the timings of EV charge/discharge based on the shared information regarding potential active power curtailment from the DSO, the proposed method leads to increased profit.

Future endeavors could encompass investigating the ramifications of PV and load forecast errors, considering the associated costs of imbalances, and exploring electricity consignment fees as potential avenues for research. It would also be beneficial to verify the implementation of VVC in PV system, PV and EV hybrid systems, as well as in standalone EVs.

In the proposed methodology, we postulate a scenario wherein the DSO is endowed with all requisite data for PFC, including a DS model. However, the necessary information may not be readily available for PFC. In such instances, a data-driven approach to voltage estimation, devoid of the requirement for a DS model, could prove advantageous. This approach could harness data gleaned from the advanced metering infrastructure (AMI), which has witnessed a surge in popularity in recent years. Moreover, such an approach would facilitate voltage estimation by the aggregator itself, thereby further simplifying the optimization framework elucidated in this paper. The exploration of these data-driven voltage estimation methodologies in future research endeavors is indispensable.

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