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Optimal Energy Trading with Demand Responses in Cloud Computing Enabled Virtual Power Plant in Smart Grids

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Abstract—The increasing penetration of renewable energy sources and electric vehicles (EVs) poses a significant challenge for the power grid operator in terms of increasing peak load and power quality reduction. Moreover, there is a growing demand for fast charging services in smart grids. Addressing the growing demand from fast charging services is challenging. To overcome this challenge, in this paper, we propose a new computational architecture combining energy trading and demand responses based on cloud computing for managing virtual power plants (VPPs) in smart grids. In the proposed system, EVs can be charged at high charging rates without affecting the operation of the power grid by purchasing energy through the energy trading platform in the cloud. In addition, users with storage devices can sell energy surplus to the market. On the one hand, the energy trading platform can be regarded as an internal market of the VPP that aims to maximize its revenue. The interest of the EV owners, on the other hand, is to minimize the cost for charging. Therefore, we model the interactions between the EV owners and the VPP as a non-cooperative game. To search for the Nash equilibrium (NE) of the game, we design an algorithm and then analyze its computational complexity and communication overhead. We utilize real data from the California Independent System Operator (CAISO) to evaluate the performance of the proposed algorithm. Our results illustrate that the users with only storage devices can obtain nearly 200% higher revenue on average by participating in the proposed internal market. Moreover, users with only EVs can reduce their charging costs by nearly 50% in average. Users with both EVs and storage devices can reduce the charging costs even further by approximately 120% where the users get profit by utilizing the internal market.

Index Terms—virtual power plant, cloud energy trading, renewable energy, smart grid, electric vehicles.

NOMENCLATURE

A. Sets and Indices

$\mathcal{N}_1$	Set of type-1 users.
$\mathcal{N}_2$	Set of type-2 users.
$\mathcal{N}_3$	Set of type-3 users.
$\mathcal{U}_t$	Set of type-2 and type-3 users in the internal market at time t.
i	Type-1 user index.
l	EV user index.
j	Area index.
$\mathcal{A}_j$	Set of users in area j.

B. Variables

M	Total area number.
N	Total number of users.
$P_{l,t}^{Grid}$	Charging EV l at time t with power from the power grid.
$P_{l,t}^{ET}$	Charging EV l at time t with power from the energy trading platform.
$E_{l,t}^{ST}$	Charging EV l at time t with energy from trading energy in the storage device with the VPP.
$P_{l,t}$	Total power for charging EV l at time t.
w_t	Energy that the VPP purchases to charge storage devices from the external market at time t.
E_t^{total}	Total amount of energy that the VPP purchases from the external market.
$\beta_{i,t}$	Portion of energy that the VPP will buy from user i at time t.

C. Parameters

τ	Duration of a time slot (hour).
T	Number of time slots in the time window.
α_l	Time for user l ($l \in \mathcal{N}_2 \cup \mathcal{N}_3$) participating in the energy trading platform.
$a_{i,t}^{ET}$	Total amount of energy that user i sells to the energy trading platform.
$b_{i,t}^{ET}$	Unit price of user i to sell unit of energy.
$z_{i,t}(z_{l,t})$	Energy level of storage device of user i ($l \in \mathcal{N}_3$) at time t.
z_t^{VPP}	Energy level of storage devices of the VPP at time t.
$a_{l,t}^{EV}$	Desired amount of energy that user $l \in \mathcal{N}_2 \cup \mathcal{N}_3$ with EVs wants to receive from the energy trading platform.
$b_{l,t}^{EV}$	Desired price set by user $l \in \mathcal{N}_2 \cup \mathcal{N}_3$ with EVs to receive unit of energy from the energy trading platform.

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$s_{l,t}^{EV}$	Amount of energy that user $l \in \mathcal{N}_3$ with EVs wants to trade with the VPP.
$e_{l,t}$	Energy level of EV l at time t.
$d_{l,t}$	Energy demand of EV l at time t.
W	Number of time slots with predictable information.
E_t^{base}	Base energy provided by the VPP.
B_t	Base price of unit energy that EV users need to pay to the VPP.
k_t	Electricity price in the external market at time t.
u_t	Price guaranteed by the government to sell energy surplus to the external market.
$r_t(g_{l,t})$	Renewable power generation of the VPP (user $l \in \mathcal{N}_3$) at time t.
$o_{j,t}$	Energy obtained from the type-1 and the type-3 users in area j at time t.
D_l	Surge price of user l.

D. Operators

$\lvert \cdot \rvert$	Cardinality of set.
$\lvert\lvert \cdot \rvert\rvert_2$	Two norm of a vector.
$\mathbb{R}^+$	Positive real number.

Other notations are defined in the text.

1 Introduction

Environmental benefits and economic incentives are two key drivers behind the growing share of renewable energy resources in the distribution grid. However, uncertainties associated with renewable energy production, substantial increase in the capacity of electric vehicles (EVs) in recent years [1], and increasing interest in leveraging energy storage devices introduce new challenges to reliable and stable operations of the power grid, especially during peak hours [2].

To overcome this challenge, several works have discussed the EV charging problem with renewable energy. In [3], EVs were classified with different categories according to their charging behaviors to receive different charging rates in order to address the uncertainty associated with renewable energy generation. In [4], a Markov decision process (MDP) was utilized in smart grids to solve the EV charging problem in a renewable-energy assisted charging framework. The uncertainty associated with renewable energy generation was addressed for both power flow dispatch and charging management problems by the authors in [5]. The charging management problem in a charging station was formulated as a stochastic optimization problem in [6]. The authors in [7] designed an optimal charging strategy using a stochastic game, considering the dynamic behavior of EV owners that can lead to changing of charging parameters, e.g., energy demand or leaving time, during charging, while also incorporating renewable energy resources for charging. Fuzzy theory was utilized to jointly consider the behaviors of EV owners and the behaviors of the charging stations in [8].

The charging rates in [3]–[8] are limited because of the use of alternating current (AC) chargers. The charging rate of AC chargers is comparatively low, and therefore the charging time for EVs is rather long. In the above studies, EV owners were satisfied with the charging time because it was assumed they charge EVs where they stay for a long time during the day, e.g., home or workplace. Slow charging is not practical if EV owners stay in a place for a short time, e.g., rest stop or shopping center. Direct current (DC) chargers, such as CHAdeMO and Tesla supercharger, are designed to provide high charging rates for EV owners. Moreover, the combined charging system (CCS) was developed to extend the charging capability of traditional AC chargers. Such solutions can significantly reduce the charging time. The chargers require a high peak power for a very short duration for fast charging service that poses a technical challenge to the distribution system operator (DSO). The problem of how to offer DC charging services in smart grids without purchasing a very large amount of power from the external energy market has not been addressed in earlier work. In this paper, we propose a cloud-based demand response mechanism for a VPP in smart grids to incorporate such considerations and address the related challenges. That is, the VPP has storage devices and renewable energy production. Subsequently, the VPP can operate an energy trading platform to form an internal market that is deployed in the cloud. Users with storage devices can sell energy surplus to the VPP through the platform. At the same time, EV owners can purchase energy using the platform, and then EVs can be charged with high charging rates by utilizing energy from renewable energy generation and storage devices of the VPP. The price in the trading platform is lower than in the external market, and therefore the consumption of charging EVs with energy from the external market is reduced with internal demand response management.

Previous studies related to demand response mainly use electricity price signals as the main interaction parameter between the power grid operators and the end users [9]–[13]. For instance, in [9], the interactions were modeled as a Stackelberg game to find the best strategies for both the end users and the power grid operators. Strategies for reduciung the peak energy consumption of the data center were proposed in [14]–[16]. The uncertainty related to renewable power generation was considered in [10]. The privacy issues of the end users were incorporated into the demand response management framework in [11], where the authors proposed a reinforcement learning (RL) based solution for scheduling the consumption of appliances in the household and protect the privacy at the same time. Recent breakthroughs in RL were further applied to schedule the consumption of heating, ventilation, and air conditioning (HVAC) system in the household and appliances in the building to implement demand response in [12], [13], respectively. Demand response combined with VPPs to participate in the energy market was considered in [17]–[19]. In [17], the theory of conditional value at risk was introduced to address the uncertainty associated with renewable energy production. A multi-time-scale scheduling strategy proposed in [18] was used to participate in the energy market and implement demand response. A similar problem as [18] was studied in [19]. An iterative algorithm was designed in [19] to solve the formulated problem by separating the original problem into a master problem and a subproblem.

Peer-to-peer (P2P) energy trading has received much attention lately in [20]–[25]. A non-cooperative game was introduced to model the interaction between sellers and buyers for the energy trading platform in [20]. A contract matching theory based approach was utilized in [21] to find the optimal amount of power generation and the corresponding electricity price. A robust algorithm was proposed in [22] to correct the forecast error of renewable energy generation for energy trading. The authors in [23] proposed an optimal bidding strategy by considering discomfort level and possible economic losses. Energy trading with shared storage devices was proposed in [24], where end users can book a part of the capacity of the shared storage system to save the cost of installing storage devices at home. The interactions between the end users, the power grid operator, and the shared storage system were modeled as a Stackelberg game. The authors in [25] developed a two-time scale algorithm to solve the P2P energy trading problem, and blockchain technology was integrated to protect the data from the external observers of the energy market.

In this paper, we propose a computational architecture based on cloud computing for the VPP in smart grids that implements energy trading and provides fast charging services. This computational architecture can further realize demand response. The architecture is similar to the ones in [26], [27] where users bid for computing resources; however, the users in our proposed architecture bid for energy. Specifically, the VPP controls DC chargers [28], [29] to provide the fast charging service. The sources of the chargers can be the combination of power grid, renewable energy, and storage devices so that the power requirement from the external energy market is reduced. Moreover, the VPP operates an energy trading platform in the cloud to form an internal market in which EV owners can purchase energy. The revenue of selling energy in the internal market is higher than in the external market so that users with storage devices are willing to sell energy surplus in the internal market. Since the price in the energy trading platform will be lower than the price in the external market, EV owners will be willing to use the energy from the trading platform. Thus, the VPP needs to purchase less power from the external energy market to offer the DC charging service. The external demand for charging EVs is reduced, and therefore this is the way of implementing demand response in smart grids. Different from [30], [31] that attempted to find the optimal locations for the fast charging service, in this paper, we focus on designing a framework of offering the fast charging service without affecting the operation of the power grid. With the proposed framework, EV owners receive fast charging services from the VPP, and the VPP can mitigate congestion for the DSO by dispatching energy obtained from the energy trading users.

Our main contributions in this work are threefold:

- We propose a novel cloud-based computational architecture for the VPP that operates an internal market for implementing demand response in order to enable users to sell their surplus energy in the internal market, and EVs can receive a high charging rate at the same time.
- We design algorithms to search for the Nash equilibrium (NE) of the non-cooperative game that models the interactions between EV owners and the VPP. Moreover, the computational complexities, the communication overhead, and the performance of the algorithms are analyzed.
- We analyze the performance of our algorithms for real data from California Independent System Operator (CAISO). The results reveal that users with storage devices can obtain significantly higher revenue by participating in the proposed internal market and that users with only EVs can also reduce the charging cost significantly.

The rest of this paper is organized as follows. We begin by introducing the system model in Section 2. Then, the interactions of the users and the VPP are formulated as a non-cooperative game in Section 3. The design of algorithms for finding the NE of the game is provided in Section 4. Next, the real-world dataset to evaluate the proposed method as well as the results of the evaluation are provided in Section 5. Section 6 offers conclusions and suggestions for future work.

2 System Model

In this section, we introduce a novel framework based on cloud computing that the VPP in smart grids uses to provide for energy trading and charging services. We assume a total of N users in the distribution grid that can be separated into type-1, type-2, and type-3 users. The energy trading framework can be regarded as an internal market for users. Let $\mathcal{N}_1$, $\mathcal{N}_2$, and $\mathcal{N}_3$ denote the sets of type-1, type-2, and type-3 users, respectively. In the internal market, the type-1 users sell energy surplus to the energy trading platform. The type-2 and the type-3 users purchase energy from the trading platform, and the type-3 users can further purchase energy by trading energy in their storage devices with the VPP. The distribution grid is separated into M areas. The set of the users in area $j \in \{1, 2, \cdots, M\}$ is denoted by $\mathcal{A}_j$. Moreover, $\mathcal{U}_t$ represents the set of the type-2 and the type-3 users in the internal market at time t. The price of purchasing one unit of energy from the external energy market at time t is denoted by k_t. Considering the government's policy of providing economic incentives to end users to promote renewable energy, u_t is introduced as the unit price from the external market guaranteed by the government for users to sell energy surplus to the external market.

2.1 Type-1 User

In our scenario, each type-1 user only has renewable energy generation, e.g., solar generation and a storage device. At time t, the type-1 users can sell energy surplus in their storage devices through the energy trading platform operated by the VPP. The i-th user in $\mathcal{N}_1$ offers $a_{i,t}^{ET}$ units of energy from own storage device at unit price of $b_{i,t}^{ET}$. The VPP responds with a variable $\beta_{i,t}$ indicating the portion of the energy to purchase from user i. The energy level in the storage devices of user i ($i \in \mathcal{N}_1$) at time t is $z_{i,t}$.

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TABLE 1
Comparisons of the proposed framework with existing literature

	Energy Trading	Demand Response	EV Charging with AC Chargers	EV Charging with DC Chargers	VPP
[3]–[8]	✘	✘	✔	✘	✘
[9], [11]–[16]	✘	✔	✘	✘	✘
[10]	✘	✔	✔	✘	✘
[17]–[19]	✔	✔	✘	✘	✔
[20]–[25]	✔	✘	✘	✘	✘
This paper	✔	✔	✔	✔	✔

2.2 Type-2 and Type-3 Users

The type-2 and the type-3 users have EVs, and they wish to receive charging services from the VPP. The difference between the type-2 and the type-3 users is that the type-3 users also have renewable energy generation and storage devices, while the type-2 users do not. The energy level in the storage device of user l ($l \in \mathcal{N}_3$) at time t is $z_{l,t}$. User l ($l \in \mathcal{N}_2 \cup \mathcal{N}_3$) joins the internal market at time α_l, and time for user l leaving the internal market is f_l. We assign each EV the same index as its user. The energy level of EV l at time t is denoted by $e_{l,t}$. The maximum energy level of EV l is e_l^{max}, and thus the demand of EV l at time t is $d_{l,t} = e_l^{max} - e_{l,t}$. Then, the EV owners set a price, $b_{l,t}^{EV}$, and an amount of energy, $a_{l,t}^{EV}$, to the VPP at time t representing the desired price and the desired amount of energy for user l to use the charging service from the VPP through the energy trading platform in the cloud. In the internal market, the VPP also allows that user $l \in \mathcal{N}_3$ sends $s_{l,t}^{EV}$ to purchase energy by trading energy in the storage device with the VPP. After executing energy trading algorithm, the total power that EV l receives from the VPP at time t is

$$P_{l,t} = P_{l,t}^{Grid} + P_{l,t}^{ET} + E_{l,t}^{ST}/\tau, \tag{1}$$

where $P_{l,t}^{Grid}$ and $P_{l,t}^{ET}$ are the power from the power grid and the energy trading platform, respectively. The energy received for charging EVs by trading energy in the storage devices with the VPP is $E_{l,t}^{ST}$, and τ is the duration of a time slot. Since the type-2 users do not have storage devices at home, $E_{l,t}^{ST}$ is always set to 0 when $l \in \mathcal{N}_2$. The upper bound and the lower bound of $P_{l,t}$ are denoted by P_l^{max} and P_l^{min}, respectively. After receiving power, the energy level of the EV is updated by

$$e_{l,t+1} = e_{l,t} + \eta_l P_{l,t}\tau, \tag{2}$$

where η_l is the charging efficiency of EV l. User $l \in \mathcal{N}_3$ updates the energy level of the storage devices by

$$z_{l,t+1} = z_{l,t} + g_{l,t}\tau - E_{l,t}^{ST}, \tag{3}$$

where $g_{l,t}$ is the renewable power generation of user l at time t.

2.3 VPP Model

With the type-1, the type-2, and the type-3 users, the VPP in smart grids can construct and operate an internal market for energy trading based on cloud computing in a time horizon with T equal-length time slots, $[t, t+\tau, t+2\tau, \ldots, t+T\tau]$, as illustrated in Fig. 1. When time t begins, all users receive k_t and u_t from the external market. The type-1 users automatically submit the amount of energy to sell and the corresponding price, $a_{i,t}^{ET}$ and $b_{i,t}^{ET}$, to the energy trading platform deployed in the cloud and then receive the decision, $\beta_{i,t}$, from the cloud. The type-2 and the type-3 users provide the desired amount of energy of charging EVs and the desired price, $a_{l,t}^{EV}$ and $b_{l,t}^{EV}$, to the VPP. Moreover, the type-3 users can send $s_{l,t}^{EV}$ to trade energy in the storage devices for charging. With this information, the VPP executes the algorithm in the cloud, and then EVs receive $P_{l,t}$ from the chargers controlled by the cloud. At the same time, the VPP determines to purchase an amount of energy, w_t, from the external energy market if the power generation from renewable energy resources is not enough or the energy levels in the storage devices are low. Thus, the total amount of the energy purchased from the external market is represented as

$$E_t^{total} = \tau \sum_{l \in \mathcal{U}_t} P_{l,t}^{Grid} + w_t. \tag{4}$$

The power generation of renewable energy resources at time t is r_t, and the energy level of the storage device at time t is z_t^{VPP}. The state of the storage devices is defined as

$$z_{t+1}^{VPP} = z_t^{VPP} + w_t + \tau r_t - \sum_{l \in \mathcal{U}_t} (\tau P_{l,t}^{ET} + E_{l,t}^{ST}). \tag{5}$$

Then, the total energy obtained from the j-th area at time t, $o_{j,t}$, can be defined as in (6)

$$o_{j,t} = \sum_{i \in \mathcal{A}_j \cap \mathcal{N}_1} \beta_{i,t} a_{i,t}^{ET} + \sum_{l \in \mathcal{A}_j \cap \mathcal{N}_3 \cap \mathcal{U}_t} E_{l,t}^{ST}. \tag{6}$$

The VPP can obtain energy from the type-1 and the type-3 users. The type-1 users participate in the energy trading platform by selling energy surplus, and the type-3 users trade energy for charging EVs with the VPP by energy in their storage devices. Therefore, the first sum defines energy obtained from the type-1 users in area j, and the total amount of energy obtained from the type-3 users in area j is represented by the second sum. User $i \in \mathcal{N}_1$ updates the energy level of the storage device by

$$z_{i,t+1} = z_{i,t} - \beta_{i,t} a_{i,t}^{ET}. \tag{7}$$

2.4 Cloud-based Platform

In Fig. 1, the energy trading platform of the VPP is deployed in the cloud, e.g., Microsoft Azure. This is motivated by an Australian energy company, AGL, that also deploys energy services in Microsoft Azure [32]. The cloud service

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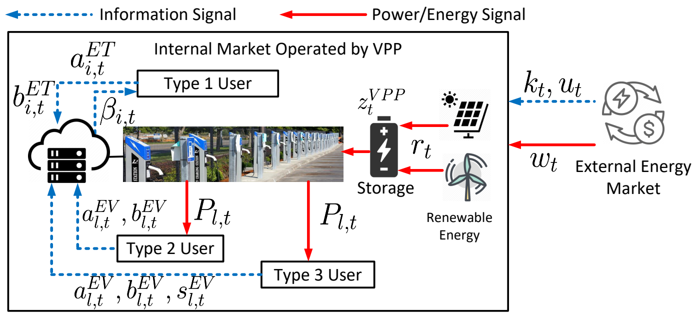

Fig. 1. System model used in this paper.

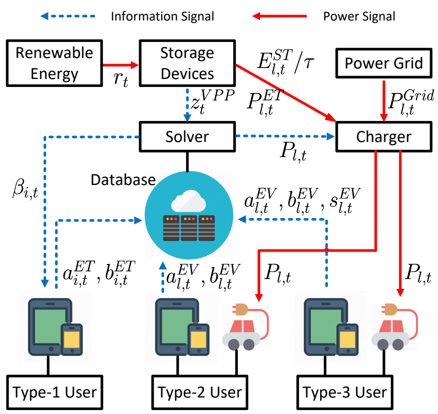

Fig. 2. Structure of energy trading platform deployed in the cloud.

providers can provide stability, scalability, and security of the computing resources so that the VPPs do not need to invest and maintain the infrastructures by themselves. The structure of the platform is introduced in Fig. 2. The VPP has an application in iOS and Android, and the platform can be accessed through the application. Once the users are presented in the platform, they can set the parameters as designed in Sections 2.1 and 2.2. The parameters sent by the users are stored in the database, e.g., MySQL. A solver then uses the parameters in the database to execute the energy trading algorithm that will be designed in Section 4. The outputs of the solver, introduced in Section 2.3, are sent to the chargers and are also stored in the database. The VPP obtains energy from the type-1 users and charges the EVs with $P_{l,t}$ for the type-2 and the type-3 users. During energy trading, the VPP should verify that the type-1 and the type-3 users actually have this amount of energy in the storage devices. Moreover, this verification process needs to take the privacy of the users into account. To this end, some methods based on cryptography can be utilized. Since this part is not the main point of this paper, we refer [33], [34] for more details.

3 Game Formulation

As shown in Fig. 1, the VPP in smart grids builds an energy trading platform to form an internal market in the cloud for the users. The type-1 users sell energy surplus in their storage devices to make profits by participating in the platform. For the type-2 and type-3 users, they wish to receive high charging rates by utilizing energy in the storage devices of the VPP and the renewable energy. The VPP can get profit by operating the energy trading platform and selling energy received from the type-1 and the type-3 users to mitigate the congestion for the grid operator. In this internal market, the VPP wants to maximize its profit; however, EV owners aim to spend less for charging EVs. Therefore, the interactions can be modeled as a non-cooperative stochastic game with the following main components:

- k_t represents the real-time electricity price at time t;
- u_t represents the electricity price guaranteed by the government to sell energy to the external market at time t;
- r_t represents the state of the renewable power generation at time t;
- z_t^{VPP} is the energy level of the storage devices of the VPP at time t;
- $P_{l,t}$ is the action of the VPP to determine how much power should be used to charge EV l;
- $\beta_{i,t}$ is the action of the VPP that determines how much portion of the bid of the type-1 users should be accepted;
- $a_{l,t}^{EV}$ and $b_{l,t}^{EV}$ are the actions of the EV owners representing the desired energy and the corresponding price to receive the service from the VPP;
- the type-2 users, the type-3 users, and the VPP are the players in the game;
- R_t^{ET}, R_t^{BE}, and C_t^{grid} are the payoff functions of the VPP; and
- C_l^{Grid}, C_l^{BE}, C_l^{ET}, and C_l^{Time} are the payoff functions of the type-2 users and the type-3 users.

In the game, the type-1 users are not regarded as the players. This is because the VPP operates the internal market, and therefore the type-1 users cannot obtain the requirement of the type-2 and the type-3 users from the VPP to adjust the amount of energy to sell and the corresponding price. Therefore, the amount of energy to sell and the corresponding price provided by the type-1 users are considered as inputs to the game.

The cost, R_t^{ET}, for the VPP operating the energy trading platform is defined as

$$R_t^{ET} = \sum_{i\in\mathcal{N}_1} \beta_{i,t} a_{i,t}^{ET} b_{i,t}^{ET} - \tau \sum_{l\in\mathcal{U}_t} P_{l,t}^{ET} b_{l,t}^{EV}, \tag{8}$$

where the first sum indicates the cost of purchasing energy from the type-1 users, and the second sum represents the revenue of selling energy to the type-2 and the type-3 users. Then, as mentioned in [35], the VPPs can contribute to mitigating congestion of the distribution grid by dispatching energy obtained from the nearby area. That is, the transmission loss can be reduced if the VPP dispatches energy near the congestion area. Therefore, the VPP wants to receive energy from the storage devices of the type-1 and the type-3 users equally distributed among areas in the distribution grid so that the second payoff function of the VPP is

$$R_t^{BE} = ||\mathbf{x}||_2, \tag{9}$$

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with $\mathbf{x} = [x_1, x_2, \cdots, x_M]$ and

$$x_j = \sum_{i \in \mathcal{A}_j \cap \mathcal{N}_1} \beta_{i,t} a_{i,t}^{ET} + \sum_{l \in \mathcal{A}_j \cap \mathcal{N}_3 \cap \mathcal{U}_t} E_{l,t}^{ST} + \sum_{\hat{t}=1}^{t-1} o_{j,\hat{t}}, \quad (10)$$

where x_j represents the total amount of energy obtained from area j and the third term in (10) indicates the cumulative energy obtained from area j up to time $t-1$. The third payoff function of the VPP is

$$C_t^{Grid} = \sum_{t=t}^{t+T\tau} E_t^{total} k_t, \quad (11)$$

where it represents the procurement cost for purchasing energy from the external energy market in the time window.

For EV owner l, it has four payoff functions

$$\begin{cases} C_l^{Grid} = \tau P_{l,t}^{Grid} k_t, \ C_l^{ET} = \tau P_{l,t}^{ET} b_{l,t}^{EV}, \\ C_l^{BE} = \alpha_{EV} E_{l,t}^{ST}, \quad C_l^{Time} = t - \alpha_l + d_{l,t}/(\tau P_{l,t}), \end{cases} \quad (12)$$

where C_l^{Grid}, C_l^{ET}, and C_l^{Time} represent the cost for using energy from the grid to charge the EV, the cost for purchasing energy from the energy trading platform, and the waiting time cost, respectively. The type-3 users trade energy in the storage device to receive energy for charging EVs from the VPP, and therefore they have less energy to use in the household. Function C_l^{BE} is the cost for this part.

The VPP aims to minimize the operation cost denoted by the following optimization problem.

$$\begin{aligned}
\min_{w_t, \beta_{i,t}, P_{l,t}, o_{j,t}} \quad & R_t^{ET} + R_t^{BE} + C_t^{Grid} && (13a)\\
\text{subject to} \quad & 0 \le z_t^{VPP} \le z^{max}, && (13b)\\
& \max\{z^{dis}, -z_t^{VPP}\} \le z_{t+1}^{VPP} - z_t^{VPP} \le z^{ch}, && (13c)\\
& 0 \le E_t^{total} \le E^{max}, && (13d)\\
& u_t \le b_{i,t}^{ET} \le k_t, \quad \forall i \in \mathcal{N}_1, && (13e)\\
& u_t \le b_{l,t}^{EV} \le k_t, \quad \forall l \in \mathcal{U}_t, && (13f)\\
& 0 \le \beta_{i,t} \le 1, \quad \forall i \in \mathcal{N}_1, && (13g)\\
& \sum_{i \in \mathcal{N}_1} \beta_{i,t} a_{i,t}^{ET} = \sum_{l \in \mathcal{U}_t} \tau P_{l,t}^{ET}, && (13h)\\
& 0 \le \tau P_{l,t}^{ET} \le a_{l,t}^{EV}, \quad \forall l \in \mathcal{U}_t, && (13i)\\
& 0 \le E_{l,t}^{ST} \le s_{l,t}^{EV}, \quad \forall l \in \mathcal{U}_t, && (13j)\\
& 0 \le \tau P_{l,t}^{Grid}, \quad \forall l \in \mathcal{U}_t, && (13k)\\
& \sum_{t=\alpha_l}^{f_l} \tau P_{l,t} = \frac{d_{l,\alpha_l}}{\eta_l}, \quad \forall l \in \mathcal{U}_t. && (13l)
\end{aligned}$$

The energy level of the storage devices of the VPP is bounded by the capacity in (13b). Eq. (13c) is the constraint related to the charging and discharging of the storage devices. The limit of the total amount of energy purchased from the external energy market is stated in (13d). The pricing constraint of the users is provided in (13e) and (13f). Specifically, the type-1 users want to sell energy at a price higher than u_t. Then, the type-2 and the type-3 users should purchase energy with a price higher than u_t to attract the type-1 users to participate in the energy trading platform. Moreover, k_t is the upper price limit. Eq. (13g) is the constraint related to $\beta_{i,t}$. Constraint (13h) ensures that energy purchasing from the type-1 users should be the same as the energy for charging EVs. The maximum and the minimum values of each component of $P_{l,t}$ are presented in (13i)-(13k). The VPP has to fulfill the demand of the EV users when the time slot reaches f_l as mentioned in (13l).

EV owners aim to minimize the total cost related to charging the EVs with different sources and waiting time, and therefore the type-2 and the type-3 users solve the following optimization problem.

$$\begin{aligned}
\min_{P_{l,t}^{Grid}, E_{l,t}^{ST}, P_{l,t}^{ET}} \quad & C_l^{Grid} + C_l^{BE} + C_l^{ET} + C_l^{Time} && (14a)\\
\text{subject to} \quad & P_{l,t} = P_{l,t}^{Grid} + P_{l,t}^{ET} + E_{l,t}^{ST}/\tau, && (14b)\\
& P_l^{min} \le P_{l,t} \le P_l^{max}, && (14c)\\
& P_{l,t}^{Grid} \ge 0, E_{l,t}^{ST} \ge 0, P_{l,t}^{ET} \ge 0, && (14d)\\
& E_{l,t}^{ST} = 0, \quad \forall l \in \mathcal{N}_2, && (14e)\\
& 0 \le e_{l,t} \le e_l^{max}, && (14f)\\
& e_l^{max} \le e_{l,f_l}. && (14g)
\end{aligned}$$

The total power for charging the EV is stated in (14b), which is bounded by P_l^{min} and P_l^{max}, as specified in (14c). In (14d), it ensures that components of $P_{l,t}$ is non-negative. Moreover, the type-2 users do not have storage devices, and therefore $E_{l,t}^{ST}$ is set to 0 for type-2 users in (14e). The energy level of the storage device should be non-negative and cannot exceed the maximum level, as stated in (14f). Constraint (14g) indicates that the demand should be fulfilled when users leave the internal market.

4 Algorithm Design

4.1 Price Determination

The EV owners' interest is to minimize the total cost for charging EVs. According to (13f), the unit price for purchasing energy in the internal market is lower than buying it from the external market. Therefore, EV owners prefer joining the internal market rather than the external market. However, they should decide how to set the optimal value for $b_{l,t}^{EV}$. They have a high chance to receive power if they set the desired price of electricity, $b_{l,t}^{EV}$, close to electricity price in the external market, k_t. This strategy incurs a relatively high charging cost. By contrast, EV users can set the value of $b_{l,t}^{EV}$ close to its minimum value, u_t, indicated by (13f) to reduce the charging cost. This may reduce the chance of receiving power from the VPP. In the following, we discuss how to choose the optimal value for $b_{l,t}^{EV}$.

Consider a price function for EV owners as

$$b_{l,t}^{EV} = D_l (a_{l,t}^{EV} - E_t^{base})^2 + B_t, \quad (15)$$

where D_l is the surge price. The surge price indicates that the user raises the price if the user wishes to receive more energy than E_t^{base}. Quantities E_t^{base} and B_t are the base energy and the base price provided by the VPP, respectively. Considering the time limit, the EV user chooses $a_{l,t}^{EV}$ based on

$$\arg\min_{a_{l,t}^{EV}} b_{l,t}^{EV} + \gamma (d_{l,t} - a_{l,t}^{EV} - s_{l,t}^{EV}), \quad (16)$$

where γ is a tradeoff parameter. Eq. (16) ensures that EV owners receive a penalty if energy received for charging cannot meet the demand when the value of $b_{l,t}^{EV}$ is set

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very low. There is no constraint in (16), and therefore the optimal value of $a_{l,t}^{EV}$ can be obtained by using the first order derivatives of (16) as

$$a_{l,t}^{EV*} = \min\left\{d_{l,t} - s_{l,t}^{EV}, E_t^{base} + \frac{\gamma}{2D_l}\right\}. \tag{17}$$

In (15), the value of D_l should also be determined for which we utilize the relationship between energy for charging and remaining time slots for EV owners. This point is formalized in the following assumption.

Assumption 1. *The required energy amount sent by the EVs, i.e., $a_{l,t}^{EV*}$ and $s_{l,t}^{EV}$, should be greater than the demand equally distributed to the remaining time slots as*

$$a_{l,t}^{EV*} + s_{l,t}^{EV} \geq \frac{d_{l,t}}{f_l - t}. \tag{18}$$

By using (18) and the solution of $a_{l,t}^{EV*}$ obtained from (17), we can get

$$0 \leq D_l \leq \left[\frac{\gamma(f_l - t)}{2d_{l,t} - 2(E_t^{base} + s_{l,t}^{EV})(f_l - t)}\right]_+, \tag{19}$$

where $[a]_+$ indicates $\max\{a, 0\}$. In practice, (19) provides a way for EV owners to set a proper value for D_l to further settle the value of $b_{l,t}^{EV}$. The calculation in this section is listed in Appendix A in detail.

Algorithm 1: Online VPP Operation Algorithm

Input: $a_{i,t}^{ET}$, $b_{i,t}^{ET}$, r_t, $s_{l,t}^{EV}$
Output: $P_{l,t}^{Grid}$, $E_{l,t}^{ST}$, $P_{l,t}^{ET}$, w_t

1 VPP calculates B_t and E_t^{base} with Algorithm 2
2 EV owners choose D_l based on (19)
3 EV owners submit $a_{l,t}^{EV}$ with (17) and $b_{l,t}^{EV}$ with (15)
4 VPP solves problem $\mathcal{P}_1$
5 $P_{l,t}^{Grid}$ is obtained from (22)
6 VPP executes Algorithm 3 to solve $\mathcal{P}_2$ and get w_t
7 VPP updates z_t^{VPP} with (5), type-1 users update $z_{i,t}$ with (7), and type-3 users update $z_{l,t}$ with (3)

4.2 Searching for Nash Equilibrium

In this section, we design Algorithm 1 to search for the NE of the game. When time slot t begins, the type-1 users deliver the amount of energy to sell and the corresponding price, $a_{i,t}^{ET}$ and $b_{i,t}^{ET}$, to the VPP. At the same time, EV owners submit the desired amount of energy for charging EVs and the desired price, $a_{l,t}^{EV}$ and $b_{l,t}^{EV}$, to the VPP. The type-3 users further provide $s_{l,t}^{EV}$ to the VPP. Moreover, the type-3 users prefer receiving the energy for charging through trading energy in the storage devices than through the energy trading platform. This is because the value of the unit price for trading energy with the VPP, α_{EV}, is assumed to be very small, and therefore the cost of purchasing energy by trading energy in the storage devices with the VPP in the internal market for the type-3 users is much less than the cost of purchasing energy from the external market, C_l^{Grid}, and the cost of purchasing energy from the internal market, C_l^{ET}. This is further clarified in Appendix B.

After receiving all parameters from the users, the VPP first accepts the bids from the type-3 users. That is because the VPP can receive a subsidy from the government by promoting the installation of renewable generation and storage devices to end users.

Next, the VPP calculates the base price of unit energy and the amount of available energy, B_t and E_t^{base}, as shown in line 1 in Algorithm 1. The steps of calculating B_t and E_t^{base} are summarized in Algorithm 2. Specifically, we sort the price determined by the type-1 users, $b_{i,t}^{ET}$, in increasing order in line 1 in Algorithm 2. From line 2 to line 3 in Algorithm 2, E_t^{base} is determined by the remaining energy, a_{remain}, equally distributed to the users in the internal market after accepting the bids from the type-3 users. Next, we examine the sorted list and select the amount of energy equal to the remaining energy and calculate the accumulative cost, c_{accu} from line 5 to line 9 in Algorithm 2. The base price of unit energy, B_t, is then the average of the accumulative cost as described in line 10 in Algorithm 2.

Algorithm 2: Algorithm for Obtaining E_t^{base} and B_t

Input: $a_{i,t}^{ET}$, $b_{i,t}^{ET}$, r_t
Output: E_t^{base}, B_t

1 Sort type-1 users based on their $b_{i,t}^{ET}$ with increasing order as $e_1, e_2, \ldots, e_{|\mathcal{N}_1|}$
2 $a_{\text{remain}} = r_t\tau + \min\{z_t^{VPP}, z^{dis}\} - \sum_{l\in\mathcal{N}_3\cap\mathcal{U}_t} s_{l,t}^{EV}$
3 $E_t^{base} = \frac{a_{\text{remain}}}{|\mathcal{U}_t|}$
4 $c_{\text{accu}} = 0$, $k = 1$
5 **while** $a_{remain} > 0 \cap k \leq |\mathcal{N}_1|$ **do**
6 $\quad \Delta = \min\{a_{\text{remain}}, a_{e_k,t}^{ET}\}$
7 $\quad a_{\text{remain}} = a_{\text{remain}} - \Delta$
8 $\quad c_{\text{accu}} = c_{\text{accu}} + \Delta * b_{e_k,t}^{ET}$
9 $\quad i \leftarrow i + 1$
10 $B_t = \frac{c_{\text{accu}}}{|\mathcal{U}_t|}$

From line 2 to line 3 in Algorithm 1, the values of $a_{l,t}^{EV}$ and $b_{l,t}^{EV}$ are determined using (17) and (15), respectively, after getting E_t^{base} and B_t from the VPP. The calculation of $b_{l,t}^{EV}$ may exceed k_t that violates (13f). Therefore, the value of $b_{l,t}^{EV}$ should be corrected after utilizing (15) as

$$b_{l,t}^{EV} = \begin{cases} b_{l,t}^{EV}, & b_{l,t}^{EV} \leq k_t, \\ k_t, & b_{l,t}^{EV} > k_t. \end{cases} \tag{20}$$

With the information from all users, the VPP attempts to solve (13). However, the original formulation, (13), contains two different time scales that make it hard to solve directly. To address this issue, the original problem, (13), is separated into two subproblems, $\mathcal{P}_1$ and $\mathcal{P}_2$, according to the time scale. Problem $\mathcal{P}_1$, formulated as (21), minimizes the operation cost for operating the internal market in a time slot with $w_t = 0$ and $P_{l,t}^{Grid} = 0$.

$$\mathcal{P}_1 : \quad \min_{\beta_{i,t}, P_{l,t}^{ET}, o_{j,t}} \quad R_t^{ET} + R_t^{BE} \tag{21a}$$

$$\text{subject to} \qquad (13b), (13c), (13g) - (13j). \tag{21b}$$

Here, the upper bound of $b_{l,t}^{EV}$ is limited to the electricity price of the external market, k_t, by using (20). Furthermore, the lower bound of $b_{l,t}^{EV}$ is the base price of unit energy provided by the VPP, B_t, that is larger than u_t. Therefore, the constraint in (13f) is followed. In line 4 in Algorithm 1, Problem $\mathcal{P}_1$ is solved by using the interior-point method [36].

After solving $\mathcal{P}_1$, the value of $P_{l,t}^{Grid}$ is to be determined by checking value of $P_{l,t}^{ET}$ and $E_{l,t}^{ST}$ and the constraint in (14c). If $P_{l,t}^{ET} = 0$ and $E_{l,t}^{ST} = 0$, the VPP will provide a basic level of the power for charging EVs, $P_{l,t}^{Grid} = P_l^{min}$. Otherwise, $P_{l,t}^{Grid}$ is set to 0. This relation can be expressed as

$$P_{l,t}^{Grid} = \begin{cases} P_l^{min}, & E_{l,t}^{ST} + \tau P_{l,t}^{ET} = 0, l \in \mathcal{U}_t, \\ 0, & E_{l,t}^{ST} + \tau P_{l,t}^{ET} > 0, l \in \mathcal{U}_t, \end{cases} \tag{22}$$

where it is mentioned in line 5 in Algorithm 1.

The objective function of Problem $\mathcal{P}_2$ is to minimize the procurement cost for T time slots. We formulate $\mathcal{P}_2$ as

$$\mathcal{P}_2 : \quad \min_{w_t} \quad C_t^{Grid} \tag{23a}$$

$$\text{subject to} \quad (13b) - (13d), (13l). \tag{23b}$$

Minimizing the objective function of $\mathcal{P}_2$ needs all the information of k_t for the T time slots. However, the VPP can only obtain limited information about the k_t in the future because of the policy of the external energy market. Problem $\mathcal{P}_2$ can therefore not be solved directly. We then design Algorithm 3 to find the solution to $\mathcal{P}_2$ and discuss it in more detail in Section 4.3. Algorithm 3 contains a forward step and a backward step. The forward step initializes the future w_t at the beginning of the algorithm, and then the backward step updates the current w_t based on the future cost. After executing Algorithm 3 in line 6 in Algorithm 1, the VPP charges EV l with $P_{l,t}$. In addition, the VPP purchases w_t unit energy from the external market. The type-1, the type-3, and the VPP update their states of the storage devices in line 7 in Algorithm 1. The VPP starts the procedure again when another time slot begins. We prove that the solution solved by the proposed algorithm is the NE of the game in Appendix C.

4.3 Procurement Decision

In Section 4.2, we separated the original optimization problem for the VPP, i.e., (13), into two subproblems, $\mathcal{P}_1$ and $\mathcal{P}_2$. The objective function of $\mathcal{P}_1$ spans only one time slot, and therefore it can be solved directly. However, the solution for $\mathcal{P}_2$ needs to take the future cost into account. We then design an online algorithm considering the future cost to solve $\mathcal{P}_2$.

For the design, we first transfer the original objective function of a time slot to the form:

$$f_t(w_t, \delta_t) = w_t k_t + \delta_t(y_t - w_t) - \frac{\Gamma \delta_t^2}{2}, \tag{24}$$

where y_t is obtained from

$$y_t = \sum_{l \in \mathcal{U}_t} \left(\frac{d_{l,t}}{f_l - t} - \tau P_{l,t} \right). \tag{25}$$

In (24), the first term indicates the electricity cost, and the second term represents the penalty function if energy in the storage devices cannot meet the remaining demand of EV owners. Quantity δ_t can be regarded as a Lagrangian multiplier, and Γ is used to limit the value of δ_t in the third term in (24). Then, an auxiliary function is added to $f_t(w_t, \delta_t)$ to form the following function

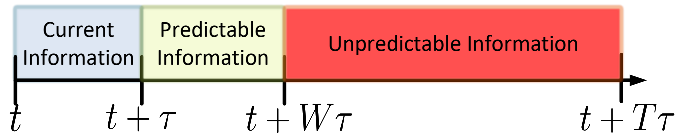

Fig. 3. Time window with the description of each time slot.

$$\mathcal{F}_t(w_t, \delta_t) = f_t(w_t, \delta_t) + \frac{\rho}{2} ||w_t - w_{t-1}||_2^2, \tag{26}$$

where the second term indicates the penalty for the huge variation for w_t between two consecutive time slots. The total cost can be denoted by $\mathcal{F}^T = \sum_{t=t}^{t+T\tau} \mathcal{F}_t(w_t, \delta_t)$. To obtain the minimum value of $\mathcal{F}^T$, online gradient can be utilized. The first-order derivative of $\mathcal{F}^T$ can be obtained from

$$\nabla_{w_t} \mathcal{F}^T = \nabla_{w_t} f_t(w_t, \delta_t) + \rho(2w_t - w_{t-1} - w_{t+1}). \tag{27}$$

Moreover, the online update with Nesterov's accelerated gradient is applied as

$$\begin{aligned} w_t &= w_{t-1} - \eta \nabla_{w_t} \mathcal{F}^T(y_{t-1}, \delta_{t-1}), \\ y_t &= (1+\xi) w_t - \xi w_{t-1}, \\ \delta_t &= \delta_{t-1} + \mu \nabla_{\delta_t} \mathcal{F}^T(w_{t-1}, \delta_{t-1}). \end{aligned} \tag{28}$$

Here, the value of ξ is defined by $\frac{1-\sqrt{\varsigma\eta}}{1+\sqrt{\varsigma\eta}}$.

We assume that W-long look-ahead window of information is available as shown in Fig. 3. Here, the information is k_t. This assumption is reasonable because the VPP can access the price of future W time slots in the external energy market. Thus, the algorithm can exploit this information to reach better results. Specifically, an algorithm containing forward and backward steps can be designed. The update method is summarized in Algorithm 3.

At the beginning of Algorithm 3, the feasible set of w_t is constructed, denoted by $\mathcal{W}_t$. In Algorithm 3, w_t^m denotes the value of w_t during the m-th iteration. Then, the forward steps begin. That is, w_{t+W} is initialized in line 3 of Algorithm 3. After the forward steps, the backward steps start from w_{t+W-1} to w_t. Specifically, the decision at time slot $t+1$ is utilized to update the decision at time slot t. The steps of backward updates are provided from line 5 to line 8 in Algorithm 3. The symbol $\Pi_{\mathcal{W}_t}$ in Algorithm 3 represents the projection of outcome to the set $\mathcal{W}_t$. We provide the proof of convergence of the algorithm in Appendix D.

4.4 Computational Complexity Analysis

In this section, we analyze the computational complexities of the proposed algorithms. Algorithm 1 contains the steps of utilizing Algorithms 2 and 3. Hence, the complexities of using Algorithms 2 and 3 are analyzed first.

For Algorithm 2, the VPP calculates B_t and E_t^{base} and then broadcasts them to EVs. In Line 2, the algorithm requires sorting, and therefore the computational complexity is $\mathcal{O}(|\mathcal{N}_1| \log |\mathcal{N}_1|)$. The computational complexity from line 2 to line 4 is $\mathcal{O}(1)$ since it is not related to the number of users. Line 10 has also the computational complexity of

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Algorithm 3: Online Cost Minimization Algorithm

Input: η, μ, Γ, ρ,W$\in \mathbb{R}^+$, ξ
Output: w_t

Build the feasible set of w_t, $\mathcal{W}_t$, based on (13b)-(13d)
Foward Initialization
$m = 1$
$w_{t+W}^m = \Pi_{\mathcal{W}_t}\left(w_{t+W-1}^m - \eta \nabla_{w_t} f_{t+W-1}(w_{t+W-1}^m, \delta_{t+W-1}^m)\right)$
$\delta_{t+W}^m = \Pi_{\mathbb{R}^+}\left(\delta_{t+W-1}^m - \mu \nabla_{\delta_t} f_{t+W-1}(w_{t+W-1}^m, \delta_{t+W-1}^m)\right)$
$y_{t+W}^m = w_{t+W}^m$
Backward Update
for *t* = *t+W-1* **to** *t* **do**
  $m \leftarrow m + 1$
  $w_t^m = \Pi_{\mathcal{W}_t}\left(y_t^{m-1} - \eta \nabla_{y_t} \mathcal{F}^T(y_t^{m-1}, \delta_t^{m-1})\right)$
  $y_t^m = (1+\xi) w_t^m - \xi w_t^{m-1}$
  $\delta_t^m = \Pi_{\mathbb{R}^+}\left(\delta_t^{m-1} - \mu \nabla_{\delta_t} \mathcal{F}^T(w_t^{m-1}, \delta_t^{m-1})\right)$
$w_t = w_t^m$

$\mathcal{O}(1)$. The computational complexity is $\mathcal{O}(|\mathcal{N}_1|)$ from line 5 to line 9. In summary, the total computational complexity is $\mathcal{O}(|\mathcal{N}_1| + |\mathcal{N}_1| \log |\mathcal{N}_1|)$.

Algorithm 3 decides to purchase w_t amount of energy from the external market. The computational complexity of Algorithm 3 is $\mathcal{O}(W)$, which is determined by the length of the look-ahead window, without considering the computational complexity of the projection. Then, the feasible set of w_t is a box, and therefore the projection of w_t to the feasible set does not incur a significant computation overhead. Thus, the computational complexity of Algorithm 3 is still $\mathcal{O}(W)$.

In Algorithm 1, the computational complexities in line 1 and line 6 come from the execution of Algorithm 2 and 3, respectively. The computational complexities of the two algorithms are analyzed above. The computational complexity from line 2 to line 3 is $\mathcal{O}(|\mathcal{U}_t|)$. Moreover, the computational complexity of line 5 is $\mathcal{O}(|\mathcal{U}_t|)$. Solving Problem $\mathcal{P}_1$ therefore results in a computational complexity of $\mathcal{O}(n^3)$ [36], where n is $|\mathcal{N}_1| + |\mathcal{U}_t|$.

4.5 Communication Overhead Analysis

Communication overhead is also important to consider when utilizing cloud computing. Here, the communication overhead of Algorithm 1 is analyzed.

In line 1 of Algorithm 1, the type-1 users submit the amount of energy to sell and the corresponding price, $a_{i,t}^{ET}$ and $b_{i,t}^{ET}$, to the VPP and therefore the communication overhead is $\mathcal{O}(2|\mathcal{N}_1|)$. The VPP broadcasts the base price of unit energy and the base amount of available energy, B_t and E_t^{base}, to the type-2 and the type-3 users in the internal market at time t; the communication overhead is then $\mathcal{O}(2|\mathcal{U}_t|)$. The communication overhead when the type-2 and the type-3 users submit the desired amount of energy of charging EVs and the desired price, $a_{l,t}^{EV}$ and $b_{l,t}^{EV}$, to the VPP is $\mathcal{O}(2|\mathcal{U}_t|)$. With the information from all users, the VPP solves Problem $\mathcal{P}_1$. After solving Problem $\mathcal{P}_1$, the VPP sends $\beta_{i,t}$ to the type-1 users. The VPP also sends the power of charging EVs from different resources, $P_{l,t}^{Grid}$, $P_{l,t}^{ET}$, and $E_{l,t}^{ST}/\tau$, to the chargers. The communication overhead after solving Problem $\mathcal{P}_1$ is $\mathcal{O}(|\mathcal{N}_1|+3|\mathcal{U}_t|)$. There is no communication for line 5 in Algorithm 1. In line 6, Algorithm 3 should be applied, and the VPP needs to obtain the electricity price information of future W time slots from the external market. The communication overhead of obtaining the electricity prices from the external market is $\mathcal{O}(W)$. In summary, the overall communication overhead is $\mathcal{O}(3|\mathcal{N}_1| + 7|\mathcal{U}_t| + W)$.

5 Numerical Results

We consider a total of N users in the distribution grid. Here, three scenarios, $N = 50$, $N = 100$, $N = 200$, are studied, and the distribution grid is separated into 3 areas, $M = 3$. Then, according to the data in [37], it is reasonable to consider that 50% of the users have EVs. Three different capacities, 30 kWh (short range), 60 kWh (medium range), and 80 kWh (long range), are randomly assigned to EVs. Moreover, 40% of users with EVs also have storage devices. The capacity of the storage device of the users is set to 15 kWh according to the parameters of Sonnen Eco 9.53. This storage device can support the power generation capacity of solar panels up to 7 kW. Therefore, the capacity of renewable energy generation is randomly generated from $[3, 6]$ kW for the users with storage devices. The value of α_{EV} is set to 0.001. The capacity of storage devices and the capacity of renewable energy for the VPP is provided in Table 2. The value of E^{max} is set to 40 kWh. The price guaranteed by the government from the external market, u_t, is set to 10 cents USD per kWh.

The time horizon is divided into 96 time slots with a length of 15 minutes to represent a 24-hour period. The time for starting to participate in the internal market is generated randomly between $12:00$ and $20:00$. Moreover, the corresponding energy level in EVs is randomly and uniformly generated from the interval $[0, e_l^{max}]$. The maximum charging rate for EVs, P_l^{max}, is set to 100 kW, and 1 kW is assigned to P_l^{min}. The charging efficiency of EV l, η_l, is set to 0.95. The length of the look-ahead window, W, is set to 4. The value of γ is set to 6 for (16). For Algorithm 3, η, μ, ρ, Γ are set to 0.5, 0.2, 0.3, and 2.5, respectively.

The real-time electricity price and the real renewable energy production profile are obtained from California Independent System Operator (CAISO) [38]. Moreover, the data on $07/20/2020$ are applied to the simulations. According to the renewable energy (solar and wind) generation capacity and the corresponding generation profile in California, we further created the generation profile of renewable energy used in the simulation. The simulations for computation time are conducted with MATLAB running on Intel i5-8500B computer with 3.0 GHz CPU and 16 GB RAM.

The proposed method is compared with a scenario that consists of only type-1 and type-2 users. Then, the algorithms in [21] and [39] are used to compare with the proposed method. Specifically, the algorithm in [21] is designed for solving the P2P energy trading problem by applying the contract-matching theory. Then, the VPP is only used to manage the charging tasks of EV owners in [39].

5.1 Analysis: Pricing Output

Here, we compare the output of four different scenarios for our proposed pricing scheme described in Section 4.1. The

TABLE 2
The parameter setting for different number of EVs

N	50	100	200
$\lvert\mathcal{N}_1\rvert$	25	50	100
$\lvert\mathcal{N}_2\rvert$	15	30	60
$\lvert\mathcal{N}_3\rvert$	10	20	40
z^{max} (kWh)	300	600	1200
z^{dis}, z^{ch} (kWh)	15	30	60
Wind Capacity (kW)	40	80	160
Solar Capacity (kW)	30	60	120

TABLE 3
The price submitted from user under different cases and time

	t				
	$14:00$	$15:00$	$15:15$	$15:30$	$15:45$
Case 1-1	15.00	15.00	15.00	15.00	60.00
Case 1-2	15.00	45.00	60.00	60.00	60.00
Case 1-3	15.00	15.00	15.00	15.00	27.00
Case 1-4	15.00	30.00	40.71	60.00	60.00

price from the external market, k_t, is set to 60 cents USD per kWh, and the value of B_t from the VPP is 15 cents USD. The leaving time of user l, f_l, is $16:00$.

Case 1-1: The user is a type-2 user. The value of E_t^{base} is set to 50 kWh, and the demand of the user is 20 kWh.
Case 1-2: The user is a type-2 user. The value of E_t^{base} is set to 10 kWh, and the demand of the user is 20 kWh.
Case 1-3: The user is a type-3 user. The value of E_t^{base} is set to 50 kWh, and the demand of the user is 20 kWh. The user sets $s_{l,t}^{EV}$ to be 5 kWh.
Case 1-4: The user is a type-3 user. The value of E_t^{base} is set to 10 kWh, and the demand of the user is 20 kWh. The user sets $s_{l,t}^{EV}$ to be 5 kWh.

The results are shown in Table 3. The difference between **Case 1-1** and **Case 1-3** is the type-2 user in **Case 1-1** and the type-3 user in **Case 1-3**. It is the same for **Case 1-2** and **Case 1-4**. The proposed method accepts type-3 users to receive energy for charging by trading energy in their storage devices. Therefore, the pricing outcome of type-2 and type-3 users is compared.

According to the results, the type-2 user in **Case 1-1** sets a higher price on $b_{l,t}^{EV}$ than the type-2 user in **Case 1-2**. This is because the VPP offers energy, E_t^{base}, higher than the demand with price B_t; the demand of the user can be fulfilled, and in order to minimize the cost, the user will not set a higher value on $b_{l,t}^{EV}$. Moreover, the user sets a higher price when E_t^{base} is not enough for the demand, which is at time $15:45$. The situation is opposite for the type-2 user in **Case 1-2**; the user sets a high price from $15:00$. The same trend can be observed for the type-3 users in **Case 1-3** and **Case 1-4**. Furthermore, one can notice that the type-3 user in **Case 1-3** sets 55% lower value on $b_{l,t}^{EV}$ than the type-2 user in **Case 1-1** at time $15:45$. This is because the type-3 user can receive energy by trading energy in the storage devices.

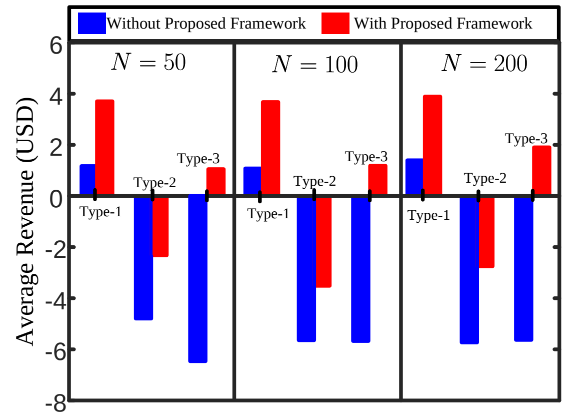

Fig. 4. Revenue of users in different scenarios.

5.2 Analysis: User Revenue

After comparing the pricing determined by the users, we, next, compare revenue for the users. For the type-1 users, the revenue is separated into two parts, (i) revenue from selling energy to the external market with the price guaranteed by the government, and (ii) participating in the internal market if applicable. A negative sign is put to the charging cost of type-2 and type-3 users so that the value becomes the revenue. Type-3 users may have energy surplus in the storage devices, and therefore they can also sell energy to the internal market if applicable or to the external market. The average revenue of users is presented in Fig. 4.

According to the results, the type-1 users get average 210% higher revenue than only selling energy to the external market. This is because the price in the internal market is higher than the external market according to (13e). Moreover, EV owners are willing to pay more if they are about to leave the internal market but the demand is not fulfilled as discussed in Section 5.1. Therefore, the type-1 users get more benefits by participating in the internal market. The type-2 users can also reduce around 47% of the charging cost by participating in the internal market for the same reason that the price in the internal market is lower than in the external market. The type-3 users can further reduce the charging cost by nearly 140% where type-3 users can get profit. This is because the type-3 users do not need to pay for trading energy with the VPP, and they can sell energy surplus to the external market.

After analyzing the revenue of users, the charging rate and the charging time of the type-2 and the type-3 users are compared. Here, the charging time indicates the time difference between α_l and the time when the energy level of the battery reaches e_l^{max}. The average charging power for EVs is denoted by $\bar{P}_{l,t}$. The statistics are summarized in Table 4. According to the results, the type-3 users can obtain slightly lower charging times, i.e., 7%, than the type-2 users. Moreover, the type-3 users receive around 52% higher average charging rate and around 32% higher charging rate in a time slot than the type-2 users. This is because the type-3 users benefit from receiving energy for charging with high priority by trading energy in their storage devices with the VPP. According to Fig. 4 and Table 4, the type-3 users can

TABLE 4
Average Charging Rate and Charging Time of Users

N	Type	$\bar{P_{l,t}}$ (kW)	$\max P_{l,t}$ (kW)	Charging Time (h)
50	2	5.96	16.33	1.80
	3	11.21	23.92	1.70
100	2	5.86	21.61	1.76
	3	7.48	29.78	1.54
200	2	8.12	25.00	1.59
	3	11.52	37.14	1.49

TABLE 5
Profit and power obtained by the VPP

	N		
	50	100	200
Profit ($)	18.22	33.84	122.43
Area 1 (kWh)	162.48	327.62	478.27
Area 2 (kWh)	240.52	346.95	551.56
Area 3 (kWh)	153.64	317.49	531.18

spend less on purchasing energy and obtain higher charging rates for charging EVs. Therefore, the proposed framework can incentivize more users to install renewable energy and storage devices at home.

5.3 Analysis: VPP Revenue

The revenue of the VPP and the energy it obtains are summarized in Table 5. According to the results, one can notice that the profit of the VPP is not significant. This is because the calculation in Algorithm 2 provides the basic price for purchasing energy in the internal market. Specifically, the VPP offers the minimum price to obtain an amount of E_t^{base} energy from the internal market without getting any profit. Then, users set higher prices according to (15) if they want to receive more energy. The VPP can obtain the power equally from each area because of the 2-norm in (9). With energy obtained from the users, the VPP can sell energy back to the external energy market and further mitigate congestion for the DSO to further make profits.

The value of W can influence the revenue of the VPP. Specifically, the VPP can purchase more power in the current time slot if it knows that the electricity price in the future will be higher than in the current time slot, and the energy level in the storage device is not enough in the current time slot. Increasing the value of W may, however, cause the additional computation cost. Thus, the revenue of the VPP and the computation time are evaluated together and are summarized in Table 6. The revenue increases by 11.67% when W changes from 4 to 16. This can clearly indicate that the length of predictable information can influence the decision of the VPP. The revenue cannot further improve if W is further set to 20. According to the results, we can say that the suitable value of W is 16 under $N = 100$. Increasing the value of W can also raise the computation time as more interations are required. Although the computation time rises 57.03% when W is changed from 4 to 20, the value of computation time is still relatively low. This is because

TABLE 6
Profit Comparison with Different W under $N = 100$

	W				
	4	8	12	16	20
Profit ($)	32.47	34.69	35.43	36.37	36.26
Time (10^{-4}s)	1.35	1.52	1.61	1.85	2.12

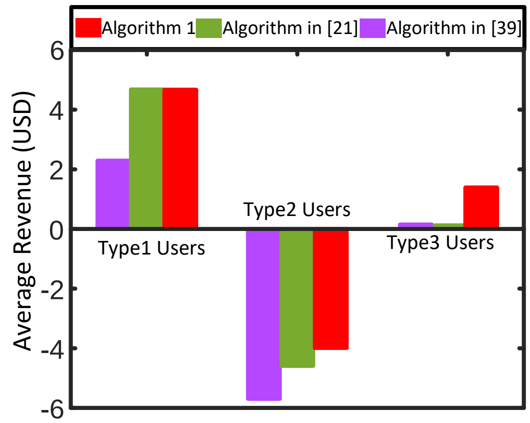

Fig. 5. Revenue of users in different scenarios.

only linear computation is required, and the projection is not complex in Algorithm 3.

5.4 Analysis: Performance Comparison

The revenue of using the proposed method compared with the algorithms in [39] and [21] is provided in Fig. 5. In [39] and [21], the type-3 users are not presented, and therefore the revenue of the type-3 users is set to 0. The energy trading is considered in this paper and in [21], and the revenue of selling energy in the energy trading platform is higher than selling energy to the external market. Therefore, the revenue of the type-1 users in [39] is around 51% less than for the type-1 users in the proposed algorithm and in [21]. Then, the type-1 users set the same price in the simulations so that the type-1 users have the similar revenue in the proposed method and in [21]. In [39], the type-2 users obtain the highest charging cost that is nearly 43% higher than for the proposed method. This is because EV owners pay the same electricity price as the external market to utilize energy from the external market and energy from the storage devices of the VPP to charge EVs. The electricity cost can be reduced by participating in the internal market for the type-1 users. Then, the proposed method causes less electricity cost because the type-2 users in [21] require more energy from the external market. Therefore, the type-2 users in [21] still spend about 15% more than the proposed method. If the EV owners have renewable energy generation and storage devices, the electricity cost can be further reduced as shown by the type-3 users.

The statistics of the VPP are summarized in Table 7. The total amount of energy purchased from the external market is calculated by $\sum_t(\sum_l P_{l,t}^{Grid}\tau + w_t)$. The algorithm in [39] has all the future information, e.g., electricity price,

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TABLE 7
Profit and energy obtained from the external market by the VPP

	Profit ($)	$\sum_t(\sum_l P_{l,t}^{Grid}\tau + w_t)$ (kWh)
Algorithm 1	33.70	20.63
Algorithm in [21]	48.49	37.11
Algorithm in [39]	-8.19	19.48

renewable energy production, and base load profile, so that it can determine the optimal amount of energy to be purchased from the external market. The proposed method only obtains the electricity price of future W time slots that results in purchasing about 6% higher amount of energy than [39]. However, the VPP in [39] obtains the minimum profit because it does not operate an internal market to make profit, and it requires to purchase energy from the external market to charge their storage devices. The algorithm in [21] purchases around 90% higher amount of energy from the external market compared to the proposed method and [39]. This energy is used to provide EVs with the defined minimum energy, $P_l^{min}\tau$, to charge EVs.

6 Conclusion

In this paper, we proposed a novel framework of an internal market based on cloud computing operated by the VPP in smart grids with three groups of users such that the users can sell energy surplus in their storage devices to the market, while users with EVs can purchase energy to charge their EVs. We modeled the interactions between the VPP and the users as a non-cooperative game and designed an algorithm to find the Nash equilibrium of the game. We also analyzed the performance of the proposed algorithm. We utilized data from California Independent System Operator (CAISO) to validate our proposed algorithm and evaluated its performance in terms of the revenue of the VPP and the revenues of the users. The results revealed that users can get nearly 200% higher revenue compared to only selling energy to the external market. At the same time, users with EVs can significantly reduce their charging costs with higher charging rates without degrading the operation of the power grid. Therefore, with the proposed framework, a win-win strategy was designed for both users and the VPP in smart grids.

In the proposed framework, the decisions of the users to sell energy surplus to the internal market are based on the present information, which is the states of the storage devices and the renewable energy production. If the users obtain favorable forecasting and learning abilities, they can potentially have higher revenue. Specifically, machine learning methods can be employed to forecast weather conditions and determine the best bidding strategies for the users. For the energy trading, the VPP must verify that the users selling energy surplus to the internal market should obtain this amount of energy in the storage devices. However, the VPP cannot directly access the storage devices of the users due to the privacy issues. To this end, zero-knowledge proofs from cryptography can be employed.

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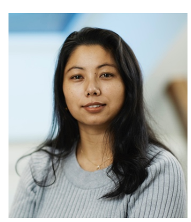

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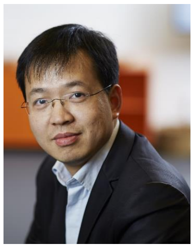

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