Adaptive Blockchain-Based Electric Vehicle Participation Scheme in Smart Grid Platform

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ABSTRACT The electric vehicle (EV) charging scheme can reduce the power generation costs and improve the smart grid resilience. However, the huge penetrations of EVs can impact the voltage stability and operating costs. In this paper, a novel EV participation charging scheme is proposed for a decentralized blockchain-enabled smart grid system. Our objectives are to minimize the power fluctuation level in the grid network and the overall charging cost for EV users. We first formulate the power fluctuation level problem of the smart grid system that take into accounts of EV battery capacities, charging rates, and EV users charging behavior. And then, we propose a novel adaptive blockchain-based electric vehicle participation (AdBEV) scheme that uses the Iceberg order execution algorithm to obtain an improved EV charging and discharging schedule. The simulation results show the proposed scheme outperforms the scheme that applying genetic algorithm approach in term of lowering the power fluctuation level and overall charging costs.

INDEX TERMS Electric vehicles, smart grids, blockchain technology, adaptive charging scheme.

I. INTRODUCTION

The emergence of electric vehicle (EV) in the energy market brings the concept of vehicle-to-grid (V2G) and grid-to-vehicle (G2V) that aims to transform the overloaded grid into a beneficial resource. EV can be used as a fast-ramping power backup device for load flattening, peak shaving and frequency regulation with adequate control schemes. The bidirectional power flow of EV charging/discharging in the smart grid system is envisaged to reduce the subsidiary (reserved) power generation cost and increase the grid system robustness [1]. To be more specific, for instance, if a large number of EVs start charging at the same time interval during the power consumption peak-time interval, the large power generators have to start the subsidiary (reserved) generators (with less response time) to supplement the power consumption, where there is delay for the subsidiary generators to start providing power. They usually takes 10 to 15 minutes to start providing power. In [2], a three-party architecture including the power grid, EVs and smart communities renewable energy generations and storage capabilities is proposed to build an energy management framework, which provides an insight for applying feasible optimization methods to achieve effective and intelligent energy management in the power system.

However, the massive load caused by huge penetrations of EVs into the power grid raises concerns about the potential impacts to the operating cost and voltage stability [3].

In the conventional EV charging/discharging scheme, a centralized information center operator which is the aggregator, is used to gather the electricity consumption demand and further command the power transfer in [4]–[6]. With the aid of the aggregator, the control schemes can be applied to control the power flow in the peak hours and off-peak hours respectively. EV is characterized as a diversely distributed power load to the grid system due to the uncontrollability of user behavior. Therefore, the availability for scheduling power exchange, where a deterministic scheduling method may not account for all possible factors that could affect the power system [7]. However, the aggregator compromises the objective of the smart grid where it is designed to decentralize the conventional power grid structure and support the micro-distributed renewable generators [8]. The centralized based system lags the decision making process and undermines the autonomy of the individual grid participants, where participants are incapable of controlling their charging or discharging process. In general, almost all electricity retail consumers are currently making transactions with average price that does

not reflect the actual wholesale price at the time of consumption. This hampers the need to adapt to the fluctuating power demand with respect to the different operation cost [9]. The local distribution markets for energy services can actually be used as a means of efficiently incentivizing and dispatching the distributed energy resources [10].

To improve the efficiency and superiority of grid operations, various control strategies for EV charging and discharging scheme were proposed earlier to control the amount and duration of power transfer. In [11], an automated demand response scheduling algorithm was introduced to accommodate large number of EVs. Alonso *et al.* [5] introduced a smart charging schedule for a low-voltage residential level grid by considering the state-of-charge (SOC) values as the battery capacity and the battery residual that will largely affect the overall grid offload. To consider the dynamic arrival and departure times of EVs, Yao *et al.* [4] used an automated generation control signal to regulate the EV charging or discharging schedule to improve the performance of frequency regulation service. In [12], an aggregated-based optimization model for EV charging strategy was proposed by taking into consideration the stochastic features of the charging procedure and the Genetic Algorithm (GA) was further used to determine the parameters in the system model. However, it was noted that the aforementioned EV charging/discharging schedule algorithms in [5] and [11] presumed the static parameters for the EV available charging time. And the proposed charging scheme in [4] and [12] were based on parameter estimations and theoretical calculations where the flexibility of EVs are not fully considered. Henceforth, the implementation of algorithms in the blockchain platform will not be able to adapt the battery types and user behavior of EVs.

In order to adapt the large volumes of EV charging/ discharging demand, the blockchain concept is introduced that allows peer-to-peer transaction platforms that utilizes decentralized storage to record all transaction data [13]. Henceforth, the blockchain technology enables a trustless network to eliminate the operation cost of the intermediary participation, which will realize a quicker, safer and cheaper way in the transactional energy market to reflect fluctuating wholesale prices to the end user. Moreover, blockchain technology has the capability of shifting the high-load household appliances to off-peak hours to not only reduce their electricity costs but also to help to reduce the overloaded peaks [14]. Hence, in [15], a novel mechanism for trading the energy based on the blockchain technology was proposed to adapt the decentralized and competitive environment for the locally produced energy, but the blockchain is solely used as a data storage warehouse to record transactions. Mengelkamp *et al.* [16] further analyzed the economic evaluation of the market mechanism for local energy trading. Furthermore, the smart contract that resides on the blockchain that allows the automation of multi-step processes to self-execute the distributed and heavy workflows is envisaged in the energy industry and the Internet of things [17].

Mnsing *et al.* [18] further demonstrated that the decentralized consensus techniques and blockchains can be used both to coordinate the scheduling of distributed energy resources in a microgrid, and to guarantee a fair payments without requiring a centralized aggregator.

In summary, the uncontrolled EV charging/discharging may lead to instability of the overall grid system operation. Therefore, it is critical to develop effective charging/discharging scheduling algorithms for efficient grid operations. The proposed scheme considers the uncertainty of future events, including the charging profiles of EVs arriving, future load demand in the grid, etc. Besides, the large-scale charging of EVs requires low-complexity control mechanisms to reduce the operating delay and the capital cost of equipment investments. In this regard, this paper presents an adaptive EV charging/discharging scheduling algorithm based on the blockchain platform, named Adaptive Blockchain-based Electric Vehicle Participation (AdBEV) to execute the information posting and decision making process.

To tackle the problem to be formulated, the Iceberg order management algorithm [19] which has been extensively used in the digital financial trading market is adopted to manage the EV charging and discharging demands. The analogy between the energy market and the financial sector is strongly correlated for energy balancing mechanism in the electricity market, where the impact of placing a large order in the market is similar to demanding a large volume of electricity or injecting too much electricity to the grid network. In order to adapt various types and the charging ports of EV in the market, this paper also considers the battery capacity and charging rates. The stochastic EV user behavior of charging in a city district of London are adopted as the problem constraints in the simulation. The primary contribution of the paper can be summarized as follows:

1) We develop a novel EV participation scheme that introduces the concept of decentralized EV charging and discharging on a blockchain enabled smart grid system;
2) For EV charging schedule, we formulate a charging and discharging schedule problem for EVs on blockchain enabled smart grid system;
3) To minimize the power fluctuation level, we propose the AdBEV scheme based on the iceberg order algorithm that execute the best order strategy to match the smart grid electricity charging and discharging demand;
4) We demonstrate that the proposed AdBEV scheme has better power fluctuation level as compared to the benchmark scheme that uses GA. Additionally, we also show the proposed algorithm can achieve lower computation cost as compared to the benchmark scheme in the Ethereum platform.

The rest of the paper is organized as follows. Section II builds the system model based on the matching imbalances of the EV user profile for charging/discharging. Section III presents the problem formulation and the algorithm description. Section IV demonstrates the simulation results and the
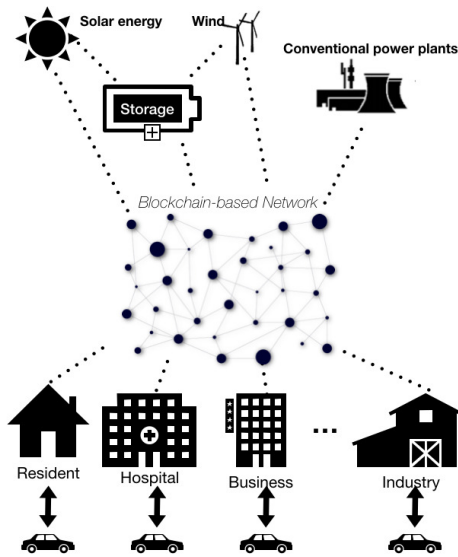
FIGURE 1. The system structure of the smart grid incorporating the public blockchain trading platform where the dotted line indicates the electricity and data/payment exchange.

comparison between the AdBEV and GA. The conclusions are summarized in Section V.

II. SYSTEM MODEL

To extend the previously developed system model from [20], we consider a residential area where the maximum power capacity of a substation transformer is P_{max}. The participants in the grid system include the conventional large power plants, distributed micro renewable generators and storages which compose the electricity provider side. Besides, the consumer power loads, for example the residential area and hospital, are all connected to the public blockchain power exchanging platform, where the electricity supply and demand information are transmitted, encrypted and saved in the blockchain platform. The electrical grid structure incorporating the public blockchain platform for trading electricity is illustrated in Figure 1.

In this model, it is assumed that the EV is capable of publishing and transmitting the charging or discharging order to the smart grid public blockchain trading platform. The charging/discharging process of EV can be realized by a programmable charging installation. This is to enable the instant on/off switching of the power transmission to the EV as instructed by the grid operator (assuming the sophisticated design of switches). The work flow for the transaction to be processed in the blockchain platform is demonstrated in Figure 2. The electricity orders which include buy and sell are initiated by the driver owners, and orders are entered to the blockchain enabled trading platform as soon as the initiator's identity is identified. The orders are then processed using the AdBEV scheme and further to be published to the open order book. The matched orders are transacted and verified by the peers in the network. Orders that are finally confirmed by both parties are saved in a distributed manner.
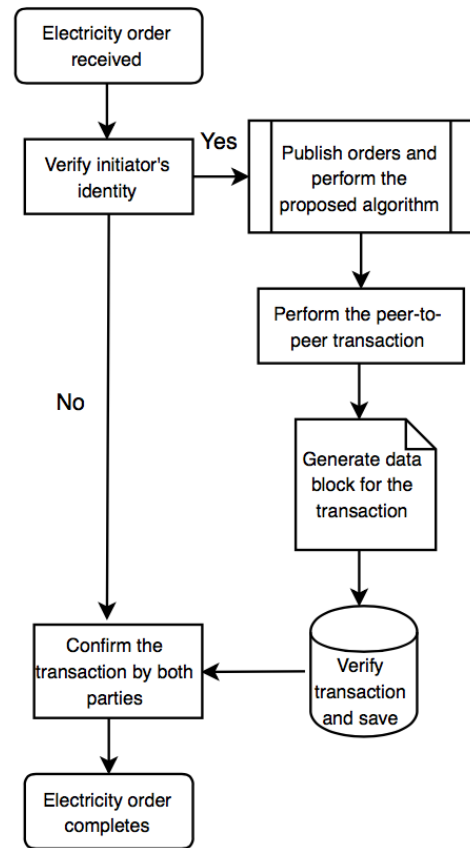

FIGURE 2. The work flow for transaction execution in the blockchain-enabled smart grid system.

We first define the EV status matrix X as:

$$X_{i,t} = \begin{cases} 1, & \text{if } EV_i \text{ is connected at time } t \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The power demand of EV depends on the battery residual (SOC_{ini}) in each EV and the expected SOC (SOC_{exp}) after charging. Hence, it can be formulated as follows:

$$P_{EV}(t) = \sum_{i=1}^{I} \left(X_{i,t} \left(SOC_{exp}(i) \pm SOC_{ini}(i) \right) \right). \quad (2)$$

In the process of scheduling EV charging/discharging, it is important to consider the quantity of the EVs that stay connected to the grid network so that we can infer the maximum time for order waiting. In order to achieve the low power fluctuation level and user satisfaction, this paper combines the charging duration and energy transfer amount to infer the hourly charging demand pattern during a day.

We model the vehicle activity profiles for a typical residential EV charging demand in a day frame referring to [21]. By combining with the charging duration and the amount of energy transfer, we can infer the charging demand pattern during a day. Through examining the characteristic of the EV charging distribution, the amount of power transfer for

EV charging can be modeled as the sum of sines as Equation (3) considering the balance between model accuracy and complexity, and it can be represented by a time segment vector $\eta(t)$ composed the percentage of stay-on-line EV in Equation (4).

$$\kappa_j(t) = \sum_{j=1}^{J} \sum_{t=T_f}^{T_s} \left(a_j sin(b_j t + c_j) \right) + \varepsilon. \tag{3}$$

$$\overrightarrow{\eta(t)} = [\kappa_1(t), \ \kappa_2(t), \ \ldots, \ \kappa_j(t)] \%. \tag{4}$$

The T_f is the first time step and T_s is second time step elapsed, which enables the formation of a particular fitting in jth order of sine series. The j indexes the order for the sum of sine series which is referred from the Matlab curve fitting toolbox, where J determines the model complexity of the sum of sines. The a_j, b_j, and c_j are the parameters in the sum of sine series. As the charging load profile indicates that certain numbers of EVs must stay on-line in the process, the number of EV connecting at the charging point in each time frame Equation (4) can be reformulated as:

$$N_{car}(t) = \Omega \cdot [\kappa_1(t), \ \kappa_2(t), \ldots, \kappa_j(t)], \tag{5}$$

where Ω is the total number of EVs in an area.

After each iteration of order execution, the power demand after one time segment will change accordingly. Hence, we can reformulate the Equation (2) with the amount of power exchange Q_i as follows corresponding to the order category:

$$P_{EV}(t') = \sum_{i=1}^{I'} (X_{i,t'} Q_i) \tag{6}$$

Then, we can define the total residential load as the sum of EV charging/discharging demand and load profile without EV in order to formulate the EV charging problem.

$$P_{total}(t) = P_{home}(t) + P_{EV}(t), \quad t \in T, \tag{7a}$$

$$P_{total}(t) + \varsigma(t) \leqslant P_{sub}, \quad \forall t, \tag{7b}$$

$$V_{min} \leqslant V(t) \leqslant V_{max}, \quad \forall t, \tag{7c}$$

where P_{home} is the power load without EV. The EV charging/discharging scheduling problem can be solved by aggregating the above random process (7a) with the proposed algorithm. To improve the power system operation, the peak transformer substation load demand must not be exceeded after implementing EV charging/discharging energy to the residential electricity demand. In constraint (7b), the error item $\varsigma(t)$ denotes power losses or branch overloaded plus the total power load shall not exceed the substation power capacity P_{sub}. Hence, there is a maximal number of EV max($N_{car}(t)$) that can be adopted in the grid network to avoid exceeding the substation capacity. Furthermore, we constrain the voltage levels in buses are not allowed to fall outside the maximum and minimum limits in constraint (7c).

III. PROBLEM FORMULATION AND ALGORITHM DESCRIPTION

The scheduling of EV charging/discharging demand is adopted to minimize the impact of injecting or consuming excess amount of power to the grid. In this case, the study focuses on an adaptive charging/discharging strategy for various types of EV to flatten the load profile of the transformer substation in the distribution network.

A. PROBLEM FORMULATION

A half-hourly daily power exchange order book profile of a residential network is applied as the input data in the EV scheduling problem, where the decision parameters are the EV charging/discharging demand for each 24 hours. To levelize the fluctuation level of the whole system, it is necessary to develop an adaptive schedule to fill the gaps of the residential load profile. To describe the measurement of fluctuation level in two consecutive time segments of the grid, the overall utility function is as follows:

$$P_{PFL} = \sum_{t=1}^{T} \|P_{total}(t) - P_{total}(t-1)\|, \tag{8}$$

where P_{PFL} is the overall power fluctuation level for a day with half-hourly temporal resolution, $P_{total}(t)$ and $P_{total}(t-1)$ is total power in the transformer at hour t and $t-1$.

The objective of the system is to minimize the power fluctuation level index P_{PFL} of the overall power grid system with the collections of variables to be optimized for corresponding i and its corresponding SOC_{exp}, which can be formulated as follows:

$$\min_{\forall SOC_{exp}(i) \in I} P_{PFL}. \tag{9a}$$

$$\text{S.T. } \sum_{t=1}^{T} \sum_{i=1}^{I} \left(SOC_{exp}(i) \pm \left(SOC_{ini}(i) \right) = \sum_{t=1}^{T} P_{EV}(t), \tag{9b}$$

$$SOC_{ini} \in (0, 1), \quad \forall i, \tag{9c}$$

$$SOC_{exp} \leqslant P_{max}, \quad \forall i, \tag{9d}$$

$$X_{i,t} = \{0, 1\}. \quad \forall i, \ \forall t, \tag{9e}$$

Equation (9b) limits the total charging and discharging power equal to the order demand from EVs with respect to the available EV number i and the achieved $SOC_{exp}(i)$. Equation (9c) sets the initial SOC to be within the interval (0,1). Though in practice, this constraint may result in a less flattened power load profile, this is to ensure the user demands are satisfied in the process. Constraint (9d) are imposed to guarantee that the maximal SOC after charging does not exceed the EV battery capacity P_{max} for each EV i. The constraint in (9e) indicates that one EV can only have two statuses, which are connecting and disconnecting to the grid system.

The formulated problem is a mixed combinatorial non-convex problem due to the binary constraint for EV connection status $X_{i,t}$ in Eq.(8e). In general, there is no systematic

and computational efficient approach to solve this problem optimally. As can be observed, the optimization problem is to designate the optimal number of EVs to execute power transfer,(charging/discharging) thus to minimize the overall power fluctuation level.

B. ADBEV SCHEME

In this section, we propose the AdBEV scheme to solve the above problem by using the electricity exchange book for power trading system. Moreover, the power demand in the next time slot is affected by the previous scheduling results. Hence, it is needed to ensure that the total power charging demand from EV is satisfied while the minimum power fluctuation for the grid system is obtained.

When considering the charging/discharging schedule for EVs, a distributed power exchange system should rely on a price competitive market in order to provide participants the incentive for maximizing their benefits. If participants wish to meet their instant power demand, they have to initiate a high bid price order or a low ask price order. In the mean time, a large order that exceeds the grid network capacity (threshold) should be split into smaller orders according to the order specifications, which in this case the offloading balance can be achieved by tranching the large power demands in a fast responsive manner. In this algorithm, for simplicity we assume the order initiator can only send out one order until it is being executed.

1) NORMAL ELECTRICITY EXCHANGE ORDER

For a electricity exchange order with a small quantity, the demand is formatted as an input to send to the electricity exchange stand book Std_{in} in the form of a vector which can be denoted as follows:

$$\overrightarrow{O_i} = (\gamma, Id_i, \sigma_i, Q_i), \qquad (10)$$

where the Id_i is the unique identifier for the charging/discharging initiators where they can be EVs or other components, the σ_i is the agreed unit price for the electricity order, the Q_i is the electricity demand quantity of this order, and γ is a matrix indicating whether it is a electricity charging or discharging order:

$$\gamma = \begin{cases} 1, & \text{charging order} \\ 0, & \text{discharging order.} \end{cases} \qquad (11)$$

Then for each inserted order message, the solution should be applied to the current book Std_{in} to generate any matched trades in the order of matching precedence. And all non-error output (each matched trade order) should be directed to the Std_{out}. The trade information format is expressed as follows:

$$\overrightarrow{T_i} = (Id_{sell}, Id_{buy}, \sigma_m, Q_m), \qquad (12)$$

where the Id_{sell} and Id_{buy} are the matched electricity buy and sell order identifier respectively, the σ_m is the matched price in pence and the Q_m is the matched quantity for the order. Following the receipt of an order message, and after receiving

any matches in the book and outputting any generated trade messages, the solutions should display the current full order book in the above format.

2) ICEBERG ELECTRICITY EXCHANGE FORMAT

Assuming that a large participant holds total power demand (ϕ_0) for exchange and it should be liquidated before time T_{max}, then we assign a peak size ϕ_p and a limit $\bar{S}$ to this iceberg exchange demand. For the charging demand side, latter is strictly higher than the initial best bid price S_0 which is denoted as:

$$S_0 < \bar{S}, \qquad (13)$$

such that the first proportion of the order is not immediately executable, and vice versa.

In order to process the iceberg power exchange smoothly and ensure the benefit gained from participants, it is crucial to choose the price for this demand. According to [19], the best charging price S_t can be modeled by a jump-diffusion process. Since we aim to build a power exchange market for EV users, in order to obtain the guide price for each time interval, for $S_t < \bar{S}$, we adopt the widely used geometric Brownian motion for stock price to model the real-time electricity price in one day:

$$dS_t = \mu S_t dt + \sigma S_t dW_t, \quad \text{with } S_0 < \bar{S}, \qquad (14)$$

where the percentage drift μ and the percentage volatility σ can be set to constants, and the W_t is a Wiener process. Thus, for a given highest price value S_0, we can obtain the best iceberg price S_t according to the following equations.

$$S_t = S_0 \exp\left((\mu - \frac{\sigma^2}{2})t + \sigma W_t\right), \qquad (15)$$

$$E(S_t) = S_0 \, e^{\mu t}. \qquad (16)$$

Then, the iceberg format can be formulated as the vector in Equation (16) which integrates the order best price σ_{S_t} and the total demand ϕ_i. And the Q_{pi} is the peak size for one trading period which is never greater than ϕ_i theoretically.

$$\overrightarrow{O_i} = (\gamma, Id_i, \sigma_{S_t}, \phi_i, Q_{pi}), \qquad (17)$$

Both the normal and icerberg electricity exchange should be displayed in the order book according to the priority function as follows:

$$f(P_{1p}(n), P_{2t}(n)) = \alpha Rank(Pr) + \beta Rank(T), \qquad (18)$$

where $Rank(Pr)$ and $Rank(T)$ are defined as the ranking for price and generation time respectively, and $\alpha = 10\beta$ in order to build a price-competitive market.

Table 1 builds the trading system where the proposed algorithm first initialize the electricity charging and discharging demand and identify the normal and iceberg orders. Then we sort all orders with respect to the ranking function $f(P_{1p}(n), P_{2t}(n))$ in order to match those orders for exchange. After executing all orders within each trade frame interval, it gives the respective response for those orders.

TABLE 1. Electricity trading system with order book initialization.

Step 1. Initilization
Initialize the EV electricity exchange order in the Std_{in} and identify the iceberg order whose place order exceeds the market capacity. Set the order peak size $P_{max}(t) = Q_{pi}$.
Step 2. Sort the orders
Sort all orders according to $f(P_{1p}(n), P_{2t}(n))$.
Step 3. For orders n = 1, ... , N-1 at $t \in T$
Match the charging and discharging electricity order according to the adaptive EV charging/discharging algorithm. Send the output orders to the Std_{out} and calculate the $P_{EV}(t)$. **end**
Step 4. Generate full order book
If the order is placed: Generate the receipt for the order message; Otherwise: Update the buy/sell order according to the new order book; Set the order $P_{2t}(n) = P_{2t}(n) + 1$, and go back to step 2.

TABLE 2. Adaptive blockchain-based electric vehicle participation (AdBEV) scheme.

Step 1. Initialize the priority setting
For order n = 1, ... , N-1 Assign the $P(n)$ according to $f(P_{1p}(n), P_{2t}(n))$. **end**
Step 2. Best order strategy
If the $P_{EV}(t)$ in the time frame t in T is satisfied: Execute all matching orders; else if $\left(\sum_{i=1}^{I}\overrightarrow{O_i}(S=0)\right) < \left(\sum_{i=1}^{I}\overrightarrow{O_i}(S=1)\right)$: Execute the order according to the priority value $P(n)$, and go to step 3; else: Execute the order according to the priority value $P(n)$, and go to step 4;
Step 3. Aggressive iceberg execution
If the order is a normal buy order: Fill the order from the main grid electricity input; else: if $N_{Q_i} = 1$: Wait for the next cycle until reaching the time limit WT_{max}; else: In single price level, old icerberg retains a higher priority; In multiple price level, a higher price retains a higher priority.
Step 4. Passive iceberg execution
If the order is normal sell order: Push the order into the next order period and remain the priority until being killed; else: Go back to step 1.
Step 5. Repeat
Update the order book in Table 1 and execute.

In Table 2, we propose a best order strategy to match the electricity charging and discharging demand where three cases are considered. If the power demand is satisfied while maintaining a minimized power fluctuation level, then the algorithm executes all matching orders in the order of price ranking. If the total quantity of electricity sell orders is smaller than the buy orders, it first executes the orders with the highest priority values. Then for the unmatched power demand orders, an aggressive iceberg execution strategy is adopted to match the orders in one time frame ($t \in T$). If the number of iceberg orders equals to 1 ($N_{Q_i} = 1$), it waits until the next cycle with the same priority value, otherwise, they will be assigned with new priorities. In the case of more sell

orders occurring, the passive iceberg execution is used where orders are passively waiting for the next cycle execution. For each time frame ($t \in T$), the order book is built and updated.

Since the AdBEV scheme optimizes charging pattern in day-ahead market, if a single day for the whole duration of all the time slots is taken, the proposed scheduling scheme executes only once a day based on the previous EV arrival pattern and residential load profile.

IV. SIMULATION RESULTS
A. EXPERIMENT SETUP
To evaluate the performance of the AdBEV scheme, a residential area substation transformer with $P_{max} = 250$kVA power capacity is used which serves the size of 100 households. We assume that on average each household would have owned one EV. In order to adapt the various types of EV in the market, we choose two types of most popular EV battery capacity of 8.8kWh (Toyota Prius) and 60kWh (Tesla model S) respectively. As for the charging rate, there are different charger connector types for different models from manufacturers, where 3kW (16A) and 43kW (63A) charger compatibility are the typical ones for slow charging and fast charging inlets according to the London local regulations [22]. In the simulation process, the number of EVs for slow and fast charging is set with the ratio of 4:1 according to the availability of the charging ports. Moreover, the EV charge connection status is modeled as two parts, where the first time segment is from 06:00 to 18:00 and the second time segment is from 18:30 to 05:30 (+1). In this model, the initial battery residual (SOC_{ini}) for EVs is randomly generated and the battery level (SOC_{exp}) after charging is set to be 80% for protecting batteries, where the SOC after discharging is set to be 50% for the convenience of EV use.

Considering the distributed trading platform for electricity exchange market, we adopt the Ethereum platform to implement the designed algorithm. The Ethereum platform is a decentralized platform which gives users to run distributed applications in the public blockchain [23]. We use the Solidity language with version 0.4.0 to deploy our smart contract to execute the AdBEV scheme. Henceforth, the gas consumption mechanism from the Ethereum platform provides a direct inspection into the operation complexity in the designed algorithm. In the public blockchain platform, the users have to pay the *gas* cost in Ethereum platform in order to execute the commands in the smart contract [24]. With the increase in the number of peers in the network, the cost for executing a complex algorithm will largely increase the trade price for the electricity [25].

There are two types of orders we set in the simulation: normal orders and iceberg orders according to Equations (5) and (10). The aim of using iceberg orders is to reduce the power load fluctuation triggered by the orders with large trading quantity. In our simulation, the ratio of the conventional orders and the iceberg orders is around 1:1. In addition, the peak size of the trading quantity (Q) in each order is fixed at 4 kW in the simulation. In Table 3, we demonstrate the

TABLE 3. Power exchange order book.

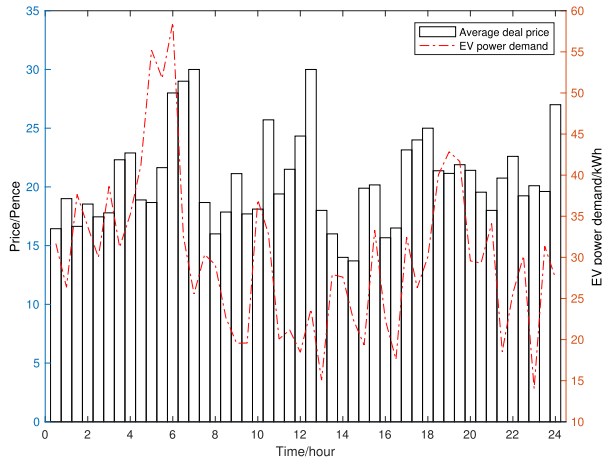| S(Buy/Sell)	Id	Price(pence)	Q(kW)
Buy	12	11	1.07
Buy	*70*	*12*	*4*
Buy	0	13	2.14
...			
Sell	*48*	*14*	*1.80*
Sell	18	15	0.44
Sell	*0*	*17*	*4*

FIGURE 3. Average generated trading price in a day.

partial order book in our simulation. The data structure is determined by the system model (see Section II). The Buy side orders are ranked in ascending order according to the price where it is in descending order in the sell side, which resembles the stock exchange market with price competitive features. Note that for the iceberg orders, we highlight them with bold figures in the quantity (Q) column. Then the system simulates the exchange process with the order input to calculate the overall price fluctuation with respect to the real-time price.

The price of electricity exchange market is variated according to the iceberg order execution algorithm where the drift of the best bid price has been assumed to be a constant. To keep the setup tractable for exposition, we assume a simplified scenario: the best bid price exhibits a zero drift $\mu = 0$ prior to the submission of the iceberg order. The original price fluctuation interval is set to be $\sigma_i \in (10, 30)$ subject to the local area, henceforth, the order price σ_t is modified for certain hours during the day to simulate the retail electricity prices in distribution networks, which are displayed in Figure 3. The price in each hour is calculated from the average price of all the deal orders in each time frame from the order book. As we can see from the figure, the electricity price is higher during 6:00 to 8:00, 11:00 to 13:00 and 17:00 to 19:00, which conforms to the higher power demand P_{EV} for EV charging period as depicted in Figure 3.

B. POWER FLUCTUATION LEVEL MINIMIZATION
The simulation result shows the effect of the algorithm to the power load fluctuation is depicted in Figure 4. It compares
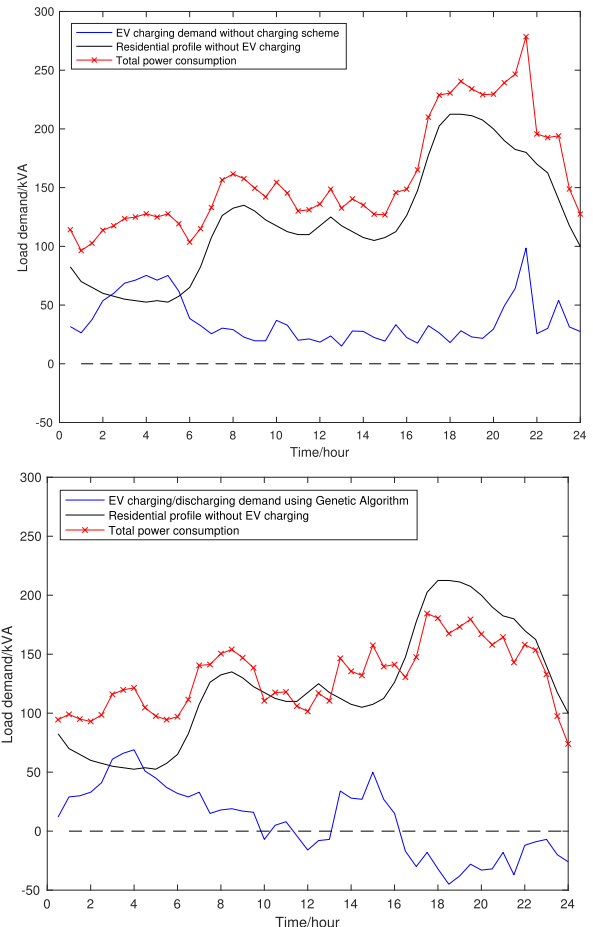

FIGURE 4. Comparisons of the domestic half-hourly load profile. Top panel: Load profile without charging strategy. Bottom panel: Load profile using charging/discharging algorithm.

the daily half-hourly resolution of load profile in a residential area without any EV charging scheduling optimization (top panel) and with the scheduling strategy using GA (bottom panel). In the simulation, we use the domestic residential daily profile from the Elexon report [26]. The red dashed line represents the sum of EV charging demand and residential load in each time frame. The total electricity consumption exceeds the power capacity at 20:30 due to large volume charging needs during this period in this case, with $P_{PFL} = 1.15$ through Equation (7). As in line with [20], after utilizing the scheduling algorithm using GA, the EV charging load is shifted to the off-peak time and the discharging features are considered. It can been seen the GA scheduling algorithm mitigates the peak time electricity consumption with a lower power fluctuation level at $P_{PFL} = 0.85$. Compare with the P_{PFL} index without any scheduling algorithm, the index decreases by 26.1% and the load at substation transformer during the peak period is mitigated.

With the proposed AdBEV scheduling scheme, EV can generate charging or discharging orders to the market with respect to their connection statuses, battery capacity and charging/discharging constraints. This enables the reduction
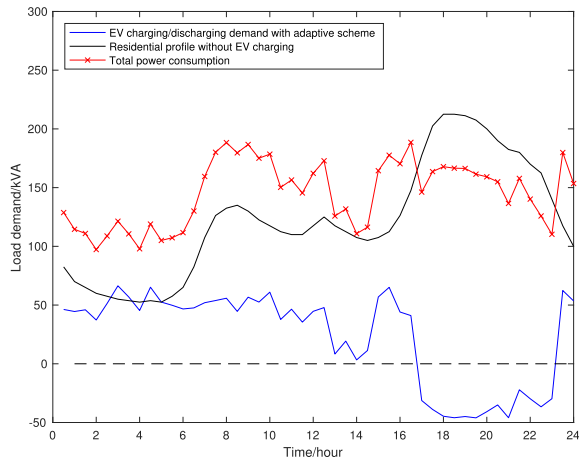
FIGURE 5. Domestic half-hourly load profile using the proposed adaptive EV charging/discharging demand matching algorithm.

FIGURE 6. Computation cost comparison between the EV scheduling scheme using GA and the AdBEV.

of the overall power demand fluctuation level where the optimized result P^*_{PFL} with the proposed algorithm is 0.63, calculated by the Equation (7) which is reduced by 25.9 comparing to the P_{PFL} using the GA scheduling algorithm. Using the optimized EV charging scheme in [20] as the bench mark, the index P^*_{PFL} is proved to be capable of better flattening the consumption loads which is depicted in Figure 5. Furthermore, when we try to increase the number of EVs in the network the $P_{EV}(t)$ will increase linearly as we assume the SOC to be normally distributed [12]. Refer to the overall utility function Eq. (8), we can see the power fluctuation level P_{PFL} is aggregated with the absolute value of the power consumption difference in two consecutive hours, where with the increase of $P_{EV}(t)$ the ability of minimizing the power fluctuation level is linearly increased.

C. COMPUTATION COST ANALYSIS

The computation complexity should be noted as the computation cost is related to the exchange efficiency and cost. The calculation of the *gas* corresponds to the low level operation in the Ethereum Virtual Machine, where each opcode has a *gas* related to it. For example, according to [27], the operators *add* uses 3 *gas* as while multiplication two integers uses 5 *gas*. Also, it is important to note that all transactions cost 21000 *gas* as a base even not interacting with a contract, where the total *gas* is the 21000 *gas* plus any *gas* associated with running the contract if you are interacting with a contract.

In Ethereum, we model the theoretical computation cost with respect to the number of peers in each network as in Figure 6. Note that the actual cost for *gas* of a transaction cannot be determined before the transaction is completed as the transaction in the same block may alter the result. However, in most scenarios, providing the estimate is sufficient to refer the algorithm complexity. We can infer that the benchmark scheduling scheme using GA costs more *gas* than the proposed AdBEV scheme. With the increase in the peer
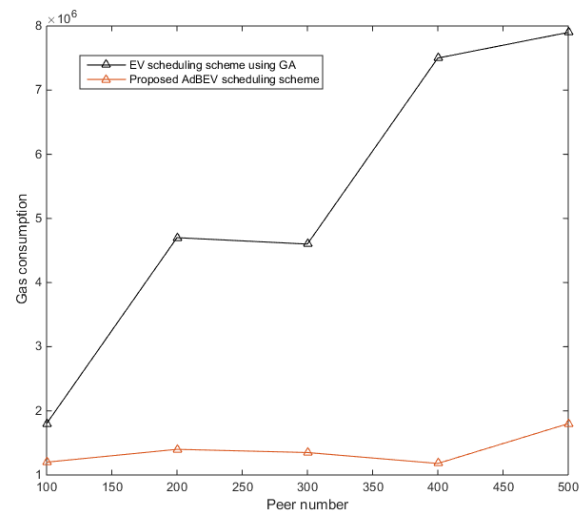
quantity in the network, the total cost for the transaction will undermine the overall power exchange performance.

V. CONCLUSIONS

In this paper, we proposed an AdBEV scheduling scheme to minimize the power fluctuation level which enables an autonomous and secure trading platform for the energy industry. We modeled the EV stay-on-line model to control the availability of charging/discharging amount. The iceberg order execution algorithm is adopted to process the large demand for scheduling. Simulation results are satisfied and such results further implies the capability of the proposed algorithm in substantially decreasing the power fluctuation level, as well as maximizes the EV driver benefits.

We adapt the most trendy EV battery types and charging rate to control the charging and discharging process dynamically. The AdBEV scheme provides insight into the structure for buildings in the transactional energy market into the blockchain technology to further decentralize the smart grid system. The proposed algorithm has a lower *gas* consumption in the execution process and thus maximizes the order trading efficiency. Hence, in the future, it is required to find the balance between the on and off chain complexity, while still leveraging the decentralized capabilities of the blockchain.

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