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An Aggregated Model for Energy Management Considering Crowdsourcing Behaviors of Distributed Energy Resources

BOMIAO LIANG[1], (Member, IEEE), WEIJIA LIU[2], LEI SUN[3], ZHIYUAN HE[1], AND BEIPING HOU[1]

[1]School of Automation and Electrical Engineering, Zhejiang University of Science and Technology, Hangzhou 310023, China
[2]Power Systems Engineering Center, National Renewable Energy Laboratory, Golden, CO 80401, USA
[3]School of Electrical Engineering and Automation, Hefei University of Technology, Hefei 230009, China

Corresponding author: Bomiao Liang (bomiao.liang@gmail.com)

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ABSTRACT Increasing deployment of distributed energy resources (DERs) is re-sculpturing the modern power systems in recent years. Future smart power distribution systems should be competent at accommodating extensive integration of DERs and managing the associated uncertainties at the distribution level. The electricity market has been proved to be an efficient way to employ market signals to direct behaviors of users and DERs with large capacity and homogeneous pattern. However, existing market frameworks cannot effectively handle a large number of small-scale DERs due to their diverse characteristics and arbitrary behavior patterns. In this context, an aggregated model which can represent and manage a diverse collection of DER, load, and storage is proposed. An additional trading platform, namely the energy sharing market, is established to reinforce the coordination and collaboration among various aggregators as well as operators. Energy sharing scheme is applied and a corresponding dynamic dispatch platform is designed to solve the crowdsource problem. The efficiency of the proposed model is validated by the numerical studies, and the market performance and impacts of energy sharing on the power systems are illustrated.

INDEX TERMS Distributed power generation, electricity supply industry deregulation, energy management, energy sharing, crowdsourcing behavior.

I. INTRODUCTION

With the integration of ever-increasing capacities of distributed energy resources (DERs) such as solar photovoltaic, wind, and combined heat and power, the operation and maintenance of power distribution systems are becoming more susceptible to the uncertainties related to various external factors such as weather conditions and the preferences of customers [1], [2]. Together with flexible demand, battery storage, and plugged-in electric vehicles whose rapid growths have been identified around the world, DERs are bringing both challenges and opportunities to system operators [3]. The massive deployment of DERs, especially renewable DERs, has enhanced the value of operational flexibility and is catalyzing the power industry's structural transformation [4].

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Given this background, it is essential to investigate the characteristics and models of various DERs and to construct a supporting market mechanism for the aggregated energy management considering the high penetration of DERs.

Many works have been done on the planning and operation of the DERs in power systems [5], [6]. The improvements mainly lie in the following three aspects: smart electronic devices [7], adapted control methods [8], [9], and emerging breakdown markets such as energy and reserve markets [10], [11]. With more diversified and distributed participants, the economic incentives are essential to the construction of future energy systems. Some pioneer research has been implemented on the price/market-based solutions to this problem [12], [13]. For example, [14] proposed a novel algorithm to economically allocate DERs under specific commitment contracts, taking distribution network investment costs, market influences and individual profits into account. A high

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DER penetration level in the energy systems is facilitated in [15] with an integrated droop-based control framework which ameliorate the conventional frequency droop control with a price-based control mechanism. The concept and framework of a virtual power plant (VPP) are adopted as another solution to accommodate the integration of DERs in [16]. The VPP is formulated as a service-centric aggregator in [17] for the congestion management with integrated DERs, and the VPP's capability to refrain undesirable curtailments is validated with a resort to its rescheduling flexibility. It is widely believed that the variability, uncertainties of renewables and the distributed organization, diverse preferences of DERs will be the prominent features of the future power distribution systems [18]. At the same time, existing work on DER energy management may fall short in terms of coordinating a massive number of entities with various preferences and providing reasonable price incentives to improve the efficiency of resource allocation. To overcome this barrier, the idea of sharing economies such as Uber and Airbnb [19] will be adopted to optimize energy management with high penetration of DERs through distributed energy sharing.

Sharing economy, also known as collaborative consumption, is a business model derived from traditional social activity, with merit put as "access but not ownership" by Brian Chesky [20]. With an increasing number of intermittent renewables participating in the energy paradigm, the importance of operational flexibility is further emphasized. One of the most economical ways is to absorb the uncertainty at the distribution level via collaboration with local flexible supply and demand. Due to the intermittent characteristics of the renewables, it is usually not efficient or practical to obtain sufficient ownership over the required capacity. Instead of accessing them via ownership, a sharing economy platform for dynamic matching can facilitate the transactions between crowdsourced supply and demand providers [21], [22].

In this paper, an aggregator model is proposed to manage a generalized collection of DER, demand, and storage. In light of the sharing economy, a new energy sharing market is established to reinforce the coordination and collaboration among various aggregators and operators. In the energy sharing market, transactions at different time scopes and between different entities are permitted and carried out by the corresponding entities independently. The physical constraints of energy sharing transactions will be checked by a third party (system operators in most cases) to guarantee the feasibility. Under the proposed model, the aggregator can evaluate its hourly decision in different markets according to the approximated profit over the observation interval. In this paper, the optimization model of each aggregator is described as a constrained profit maximization problem, and the total profit is maximized by scheduling the supply/demand behaviors of corresponding DERs in the day-ahead, real-time, and energy sharing markets. The operation behaviors are constrained by the inherent characteristics of its components, the trading rules of different markets, and the energy sharing limitations of the distribution systems concerned. All corresponding revenues are concluded in the objective function to reflect the aggregator's profit, whereas the actual revenue of a transaction may not be fixed at the decision moment due to the uncertainty in price and DER power output. To cope with the uncertainty associated with DERs and market prices, the proposed operation strategy is obtained via a dynamic programming method [23] aiming at maximizing the approximated total profit over the observation intervals.

The remainder of this paper is organized as follows. In Section II, a new energy sharing market mechanism is proposed and detailed. In Section III, the generalized operation model of distributed aggregators is developed. The aggregated model is studied considering distinctive DER characteristics and the system performances under variable DERs. The adaptability and efficiency of the proposed model are verified and demonstrated by numerical results in Section IV, and the market performance and impacts on the power systems are also illustrated. Finally, Section V concludes the paper.

II. ENERGY SHARING MARKET MECHANISM

Traditional short-term energy markets, including day-ahead, intraday, and real-time markets, are built mainly to serve large utility-scale generators. However, markets constructed in a centralized paradigm are destined to fail in the decentralized scene where a massive number of DERs as well as storage devices (i.e., crowdsourcing supply) become active market participants. In this paper, a new market platform is proposed to facilitate sharing behaviors among different market participants (aggregators).

A. COMPONENT CHARACTERS AND MARKET SETTINGS

Under the sharing market paradigm, every market participant is treated as an independent aggregator, regardless of its property and scale. The aggregators can be the owners of DER, batteries, charging stations, or retailers of traditional electricity consumers, active consumers, prosumers, etc. They can also be a combination of several different participants mentioned above. Meanwhile, the composition and scale of an aggregator still have significant influence over its possible strategy and behavior, e.g., in forms of admittance threshold and product characteristics. The admittance thresholds are distinctive for different components.

Suppose the predicted generation/consumption of a certain aggregator is χ and the prediction deviation is χ_Δ, then the maximum and minimum power bounds are respectively $\chi+\chi_\Delta$ and $\chi-\chi_\Delta$. The DER aggregator can put its uncertain generation capacity on the energy sharing market as potential power supply, whereas the demand should put its uncertain energy consumption capacity as demand. As for the flexible demand and storage, they can tender above their actual capacity considering their consumption characteristics, uncertain behaviors of customers, price fluctuations, and their success in different electricity markets. When a certain type supply is redundant, the corresponding type of demand (bid) is

TABLE 1. Typical components and their characters.

Component	Component characters	
	Composition	Admittance threshold
DER	Photovoltaic, biomass	Operable capacity
Storage	Battery, charging station	Operable capacity
Retailers	Tradition users	Historical consumption[a]
Mixture	Prosumers, smart buildings/blocks	Traceable record
Standalone	External market participants	Security deposit

[a]Historical records are based on the last quarter.

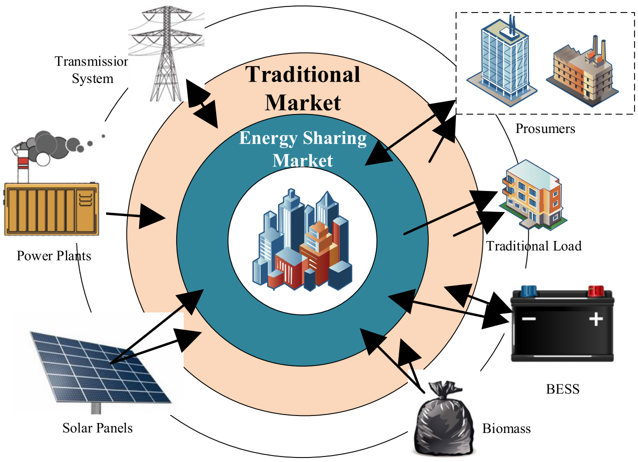

FIGURE 1. Energy sharing market and its participants.

shared among the supply providers proportionally according to their tender quantities over the aggregate demand (which is further referred to as the successful bid percentage in the paper). However, an adjustable supply such as discharging storage unit can only tender for a limited time horizon due to its feasibility range. A brief overview of several typical components in distribution systems and their characters are concluded in Table 1 [24].

Each aggregator can operate in its own way without interfering with the operator or other aggregators. Aggregators can participate in day-ahead, real-time as well as energy sharing market to be introduced in the following context if the admittance threshold and other market rules permit. The energy sharing market structure and its participants are illustrated in Figure 1.

The intrinsic and extrinsic motivations of crowdsourcing have been under debate by many scholars and researches [25], [26]. As the DER penetration and responsive demand increase, the sharing behaviors among the aggregators are expected to increase resource utilization efficiency. Under this circumstance, the energy sharing market is designed to satisfy the transformed energy needs. Two significant characters of the transaction in the energy sharing market are *contract-based* and *capped dynamic pricing*. The *contract-based* character is designed to lower the entry threshold and simplify the approval examination, which is quite meaningful to the crowdsourced supply setting of the energy sharing market. The *capped dynamic pricing* protects the supply and demand from large risks and monetizes the energy appeal with its actual welfare, which is beneficial for rational investment and operation.

B. MARKET CLEARING ALGORITHM

The nature of the energy sharing market platform is an active management problem which requires dynamic type matching. In this paper, all electricity products are assumed to be identical, which means there are only unidirectionally horizontal types from the view of the matching problem.

For any variable z, define $z^+ := max\{z, 0\}$ and $z^- := -min\{z, 0\}$. Superscript t is employed to denote the value of a quantity at time slot t. Let $\bar{z}$ denotes the expectation of the data series $\{z^t\}$ over the observation period T. Denote x_i, $i = 1, 2, \ldots, n$ and y_j, $j = 1, 2, ..m$ as the aggregate amount of type i demand and type j supply, respectively. Denote $\mathbf{x} = [x_1, x_2, ..x_n]$ and $\mathbf{y} = [y_1, y_2, ..y_m]$. Note that according to the crowdsourced setting, each type of demand/supply has a random quantity. The energy sharing market operator decides the optimal matching quantity q_{ij} between demand i and supply j for every pair of (i, j) according to the observed $(\mathbf{x},\mathbf{y})$ and the matching reward r_{ij}. Denote $\mathbf{Q} = [q_{ij}]$ and $\mathbf{R} = [r_{ij}]$, and define operation $*$ as:

$$\boldsymbol{R} * \boldsymbol{Q} = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{m} r_{ij} q_{ij} \tag{1}$$

After the energy sharing is matched, the post matching demand quantity and supply quantity, denoted as u_i and v_i, can be calculated as $u_i = x_i - \sum_{k=1}^{m} q_{ik}$ and $v_i = y_i - \sum_{k=1}^{n} q_{kj}$, respectively. The matrix form can be written as:

$$\boldsymbol{u} = [u_i] = \boldsymbol{x} - \boldsymbol{Q}_{1\times n} \tag{2}$$

$$\boldsymbol{v} = [v_j] = \boldsymbol{y} - \boldsymbol{Q}_{m\times 1} \tag{3}$$

$$\boldsymbol{u} \geq 0, \quad \boldsymbol{v} \geq 0 \tag{4}$$

Meanwhile, the energy matching is constrained by the capacity limit in the distribution systems, as shown in (5).

$$\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{m} q_{ij} \leq C_Q \tag{5}$$

where C_Q represents the maximum energy transaction limit of the area (quantity cap).

The unmatched demand (supply) will be carried over to the next period at a carry-over rate α (β) with a holding cost of c_D (c_S). Denote $\boldsymbol{c_D} = c_D \mathbf{1}_{n\times 1}$ and $\boldsymbol{c_S} = c_S \mathbf{1}_{m\times 1}$, where $\mathbf{1}_{n\times m}$ represents a $n \times m$ matrix with all elements equal 1. When social welfare is maximized, the dynamic matching problem can be expressed by a stochastic dynamic program shown as follows:

$$\begin{aligned} I^t(\boldsymbol{x}, \boldsymbol{y}) = \max_{\boldsymbol{Q}} & [\boldsymbol{R} * \boldsymbol{Q} - c_D \boldsymbol{u} - c_S \boldsymbol{v}^T \\ & + \gamma E I^{t+1}(\alpha \boldsymbol{u} + \boldsymbol{D}, \beta \boldsymbol{v} + \boldsymbol{S}) \\ s.t.\ & (1) - (5) \end{aligned} \tag{6}$$

where $\mathbf{D}$ and $\mathbf{S}$ are the aggregate demand vector and supply vector of the next period $t + 1$, respectively. γ represents the discount factor and satisfies $\gamma < 1$. $I^t(\boldsymbol{x}, \boldsymbol{y})$ denotes the social welfare at time period t. Suppose all unmatched supply and demand incur zero surpluses by the end of the finite-horizon problem (i.e., when $t = T$), the boundary conditions are $I^{T+1}(\boldsymbol{x}, \boldsymbol{y}) = 0$ for all (**x**,**y**).

The existence of the optimal matching policy is guaranteed as proved in [27], but more efforts are still in need to characterize its properties. Specifically, a special energy sharing market case is studied, in which two types of demand (1: uncertain and uncontrollable, 2: responsive) and two types of supply (1: adjustable, 2: intermittent) are employed to characterize the mainstream aggregators in the market. Obviously, the intermittent supply and the responsive demand is a perfect match, so is the adjustable supply and the uncertain demand. The types provided by the aggregator can be easily inferred according to its inherent character. For instance, the DER aggregator tends to provide intermittent supply, whereas the retailer tends to act as a responsive or uncontrollable demand, and the storage aggregator will present as responsive demand and adjustable supply alternatively.

In the energy sharing market, the matching reward r_{ij} between type i demand and type j supply is a nonincreasing function of the distance between the two types. The unit matching reward can be written as $r_{ij} = f(d_{ij})$, where f is a nonincreasing function. The demand and supply imbalance of type i is defined as:

$$\mu = \sum_i \mu_i, \quad \mu_i = x_i - y_i, \; i \in \{1, 2\} \tag{7}$$

where μ_i denotes the imbalance of type i demand and supply.

If $\mu_1\mu_2 \geq 0$, it is obvious that the optimal matching policy is to greedily match between perfect pairs as much as possible. Otherwise, assume $\mu_k > 0$ and $\mu_{k\otimes} < 0$, $k, k^{\otimes} \in \{1, 2\}$. There is one optimal two-step matching procedure discussed as for any fixed arbitrary period t.

STEP1 (Greedy matching of perfect pairs):

Allocate demand and supply of the same type to the maximum acceptable level.

$$q^*_{ii} = min\{x_i, y_i\}, \quad i \in \{1, 2\} \tag{8}$$

where q^*_{ii} denotes the optimal matching level.

STEP2 (Imperfect pair matching by "match down to" policy when $\mu_1\ \mu_2 < 0$) :

Match between the imperfect pair down to the suggested post matching levels u^*_k and $v^*_{k\otimes}$.

$$\begin{aligned} q^*_{k\otimes k} &= 0 && (9)\\ \mu^+ + q^*_{kk\otimes} &= u^*_k && (10)\\ \mu^- + q^*_{kk\otimes} &= v^*_{k\otimes} && (11)\\ q^*_{kk\otimes} &= f^*(t, \mu) = min\{\bar{f}(t, \mu), \mu_k - \mu^+\} && (12) \end{aligned}$$

where $f^*(t, \mu)$ and $\bar{f}(t, \mu)$ are the protection levels to be decided by the market operator according to the imbalance level μ at time period t.

C. DYNAMIC PRICING STRATEGY

Time-based pricing is widely employed by many sharing economy platforms to ensure sufficient supply and resource allocation. The pricing strategy in energy sharing market is designed based on the dynamic utility pricing mechanism to discover the real value of the energy products, together with fixed commission fee, parallel market reference, and cap settings, etc.

The fixed commission fee is calculated based on the maintenance cost instead of a significant proportion of the transaction. Owing to the non-profit nature of the energy sharing market, the commission fee is also greatly reduced, and the market operator maximizes the social welfare as in (6). Therefore, the commission fee for an aggregator participating in energy sharing market possess an insignificant difference than that in other markets and can be neglected when comparing the outcome from different markets.

Energy sharing market is specialized for the matching between uncertain/flexible demand and supply providers at present. Therefore, the real value of the energy products is also evaluated by the parallel markets at the same time, which can act as the base price of the energy sharing market, to account for the general trend of energy produce/consumption in the area. This valuable reference from the parallel market can help guide the pricing strategy of the energy sharing market.

Different from the aforementioned quantity cap, the price cap is decided by all the participating aggregators. A default setting is to set the price cap for type 1 as the weighted parallel market price (denoted as ξ_1) and type 2 as the reserve market price (denoted as ξ_2). The transaction price can be calculated as follows:

$$\begin{aligned} r^t_i &= min\{\omega^t_i(\kappa_{da}\lambda_{da} + \kappa_{rt}\lambda_{rt}), \xi_i\}, \quad i \in \{1, 2\} && (13)\\ \omega^t_1 &= \kappa_1\bar{y}_1/max\{(y^t_1 - \bar{y}_1)^+, \kappa_3\} && (14)\\ \omega^t_2 &= \kappa_2 + \kappa_4(x^t_2 - \bar{x}_2)^+/\bar{x}_2 && (15) \end{aligned}$$

where λ_{da} and λ_{rt} are the energy price in the day-ahead market and the real-time market at time period t, respectively. κ_{da} and κ_{rt} are the corresponding weighting coefficients and $\kappa_{da} + \kappa_{rt} = 1$. ω^t_1 and ω^t_2 are the price coefficients which reflect the fluidity of the energy sharing market. Parameters κ_1, κ_2, κ_3, and κ_4 are derived from the market composition.

When a certain type of supply is redundant, the corresponding type demand (bid) is shared among the supply provider according to its tender quantity over the aggregate demand. The price is calculated upon the tender quantity as well, though the bid quantity and the actual transaction can be proportional and uncertain. This design of energy sharing market is to provide sufficient incentives for distributed storage to improve the system state. The market design also applies to more horizontally differentiated types of demands and supplies which have heterogeneous flavors of their own to meet more differentiated energy needs.

III. GENATALIZED AGGREGATOR OPERATION MODEL

The aggregator is modeled according to the characteristics discussed in Section II. The aggregator's profit maximization strategies are studied based on its outcome from internal scheduling and operation in different markets. In this section, only the aggregators that incur actual electricity generation or consumption are considered. A generalized operation model that applies to four different types of aggregators, namely DER, storage, retailers, and mixture, as shown in Table 1, is proposed. With the proposed model, the aggregator can adjust its internal schedule and the market tenders to maximize its expected profit considering the uncertainty from intermittent DER prediction and load forecast.

A. INTERNAL SCHEDULING & MARKET OPERATIONS

Denote the estimated maximum generation of the aggregator-owned DER and the estimated maximum consumption of aggregator-served demand at the hour t as w_t and l_t, respectively. Then,

$$w_t = y_1^t + B_t^{'} \tag{16}$$

$$l_t = x_2^t + A_t + B_t^{''} \tag{17}$$

where $B_t = B_t^{'} - B_t^{''}$ denotes the bidding quantity in the other markets, A_t is the responsive demand, C_t is the adjustable supply. Assuming the aggregator divides its remaining bid quantity between the day-ahead and real-time markets equally, and the weighted price is λ_B^t. λ_B^t is employed in the calculation of the transaction price according to (13)-(15), as well as when the revenues from energy sharing market are compared with those from traditional markets. The proportional decision variable for responsive demand part A_t is denoted as θ_t. Then for an aggregator, its actual flexible demand at hour t is $\theta_t A_t$.

As for the storage device with an hourly power of S_B (in kW) or $S_{B\%}$ (the percentage of S_B and the storage capacity), denote its hour flexible demand and adjustable supply proportional decision variable as $\phi_1^t \in [0, 1]$ and $\phi_2^t \in \{0, 1\}$, respectively. Then $\phi_1^t S_B$ and $\phi_2^t S_B$ are the actual flexible demand and adjustable supply at hour t. The state variable of the storage device is ρ_t. The bidding operation and the expected revenue π_t for aggregator at hour t can be expressed as the following.

$$\pi_t = r_2^t(\varphi_2^t y_2^t - \psi_2^t x_2^t) + r_1^t(\varphi_1^t y_1^t - \psi_1^t x_1^t) \tag{18}$$

$$x_1^t = \phi_1^t S_B + \theta_t A_t \tag{19}$$

$$y_2^t = \phi_2^t S_B + C_t \tag{20}$$

$$\rho_{t+1} = \rho_t + min\{max\{\varphi_1^t \phi_1^t M_t - \psi_2^t \phi_2^t M_t^{'}, -S_{B\%}\}, S_{B\%}\} \tag{21}$$

$$0 \le M_t \le S_{B\%}, \quad 0 \le M_t^{'} \le S_{B\%} \tag{22}$$

$$0 \le \rho_t \le 1, \quad t = 1, 2, \ldots, T \tag{23}$$

$$\phi_1^t \phi_2^t = 0, \quad t = 1, 2, \ldots, T \tag{24}$$

$$\varphi_1^t, \varphi_2^t, \psi_1^t, \psi_2^t \in [0, 1] \tag{25}$$

where M_t ($M_t^{'}$) is the actual charge (discharge) percentage over the storage capacity. φ_t^1, φ_t^2, ψ_t^1, and ψ_t^2 are the successful bid percentages over the tender quantity, which are determined by the market composition. Eqn. (24) guarantees the storage device cannot function as flexible demand and adjustable supply at the same time.

As described in Section II-B, the aggregator operates in the operation interval based on the indication from the related outcome over the longer observation interval. To avoid interrupting the charging process for regular batteries and electric vehicles, the observation interval of this kind is usually set as 2 days ($T = 48$) [28], which is also long enough to cover the profit interval as the charging depth should be significantly above this level for a for-profit battery owner. Neglecting the fixed annualized cost of the ownership or usage contract bond over the observation period, the aggregator should maximize the variable profit over the observation interval according to the known information, via the recursive process as described in (26).

$$P_g^t = \pi_t + maxE(P_g^{t+1}) \tag{26}$$

where P_g^t is aggregate variable profit from hour t to the end period T and $E(P_g^t)$ is its expectation. The boundary conditions of the state variable (27) and (28) should hold for consistency.

$$P_g^{T+1} = 0 \tag{27}$$

$$\rho_1, \rho_{T+1} \in [\Gamma_1, \Gamma_2] \tag{28}$$

where Γ_1 and Γ_2 are the tolerable storage level for the continuous operation defined by the aggregator boundaries.

B. PROFIT MAXIMIZATION STRATEGIES

In (26), the uncertainty comes from the prediction error in intermittent DER supply and passive demand. It should be noticed that for adjustable supply provider (or flexible demand), the aggregator can only decide the bidding behavior, with the actual transactions subject to the intermittent generation curve and load curve. Under this circumstance, an approximate dynamic method is designed to practically maximize the aggregator profit. For any given hour t, the operation strategies for profit maximization of the aggregator can be derived in 5 steps:

i. Settle the internal state of DER and load for the hour according to (16), (17), and the known parameters such as energy sharing market price curve, the capacity of responsive demand, storage and adjustable supply, etc.
ii. Count the actual consumption (generation) of passive demand (intermittent supply) during the hours before hour t and calculate the average index $\bar{M}_{t-1}$, $\bar{M}_0 = S_B$.
iii. Evaluate the actual state of the storage device, by applying (21) to the hours before t.
iv. Assume $M_\tau = \bar{M}_{z-1}$, $\tau = t + 1, \ldots, T$, maximize the approximated P_g^t (denote as $A(P_g^t)$) as below with respect

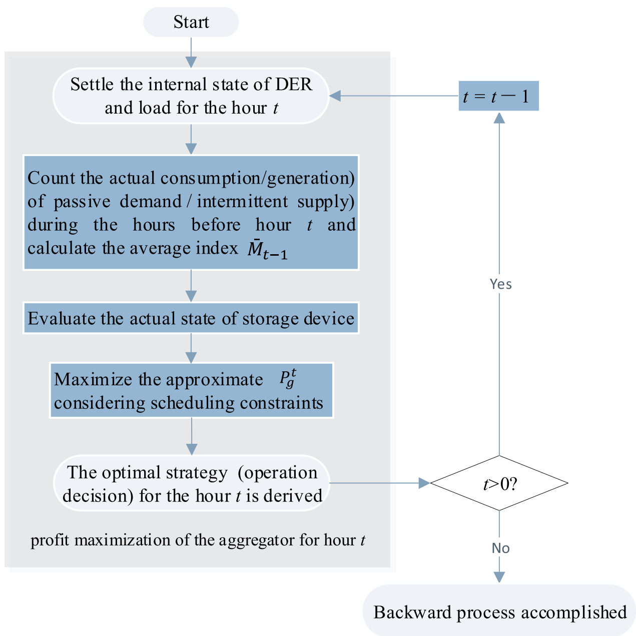

FIGURE 2. Flowchart of the dynamic optimization of aggregator profit maximization.

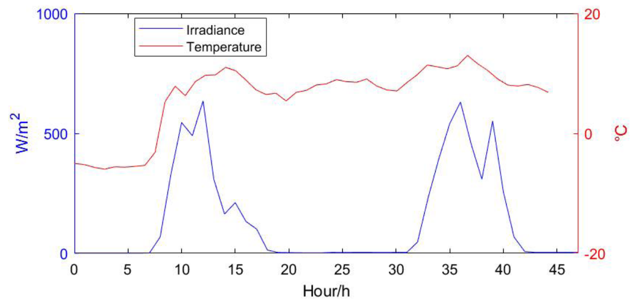

FIGURE 3. Sunlight irradiance and temperature in the typical 48 hours.

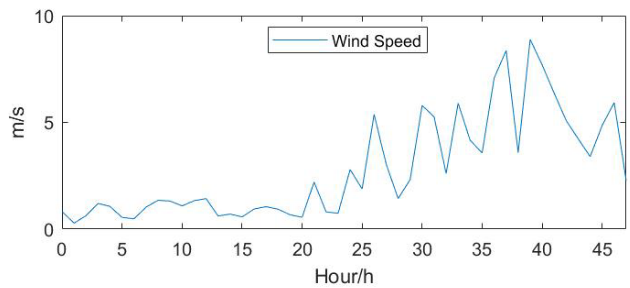

FIGURE 4. Wind speed at BMS (19 ft) in the typical 48 hours.

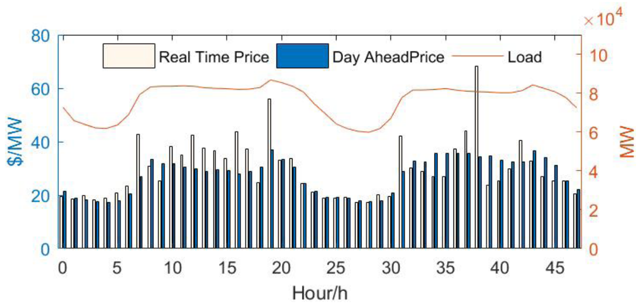

FIGURE 5. Energy price in the day-ahead market, real-time market, and the day-ahead bid quantity in the typical 48 hours.

to constraints in (21)-(28).

$$\max_{\Phi_t^1,\Phi_t^2,\Theta_t} A(P_g^t) = \pi_t + \sum\nolimits_{\tau=t+1}^{T} \pi_\tau \tag{29}$$

where $\Phi_t^1 = [\phi_t^1]_{1\times(T-t+1)}$, $\Phi_t^2 = [\phi_t^2]_{1\times(T-t+1)}$, and $\Theta_t = [\theta_t]_{1\times(T-t+1)}$.

v. The optimal strategy for the hour t is then derived and record in the first elements in Φ_z^1, Φ_z^2, and Θ_z.

The process of the aggregator strategy development can be depicted as the flowchart in Figure 2.

IV. CASE STUDIES

An example energy sharing market comprised of several typical aggregators is employed to illustrate the function of the proposed additional market paradigm. The performance of the typical aggregators using referral model is also evaluated.

A. ENERGY SHARING MARKET SIMULATION

Suppose there exist $N = 50$ aggregators in the energy sharing market presenting the intermittent/adjustable supply and responsive/passive demand. The aggregated controllable generation capacity (gas, diesel, etc.) is 200 kW, whereas the generation capacity (rating) of intermittent renewable energy sources such as photovoltaic and wind is 13 MW. The average aggregated passive demand and the quantity cap over the area are set to 5 MW. The average prediction error of renewable generation and traditional demand are $\pm 10\%$ and $\pm 4\%$, respectively. The total responsive demand capacity and the carry-over rate are 200 kW and of 80%, respectively. The capacities of different aggregators range from 0.2 MW to 1.5 MW, and a series of aggregated storage units are considered. On a typical interval (48h), the important influencing factors including solar radiation, ambient temperature, and wind speed are demonstrated in Figures 3 and 4 based on the data from [29]. The actual solar output from each aggregator can be calculated based on several impact factors such as photovoltaic array area, tilt angel, and conversion efficiency. On the other hand, the outputs of wind turbines and the parameters of heating/cooling appliances are assumed to be identical and only vary in capacity/size. The energy prices in both day-ahead and real-time markets and the day-ahead load bid quantities are demonstrated in [30].

The bid quantities in parallel markets (see Figure 5) and the aggregated demand/supply of a type 1 aggregator over the observation period are illustrated in Figure 6 and 7, respectively.

It should be mentioned that the supply and demand information in Figure 7 are the estimated expectations. According to Section II, the energy sharing market operator will first greedy match the supply and demand of the

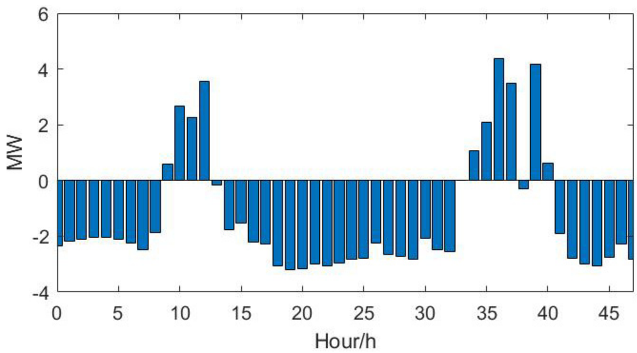

FIGURE 6. Bid in parallel markets of a type 1 aggregator.

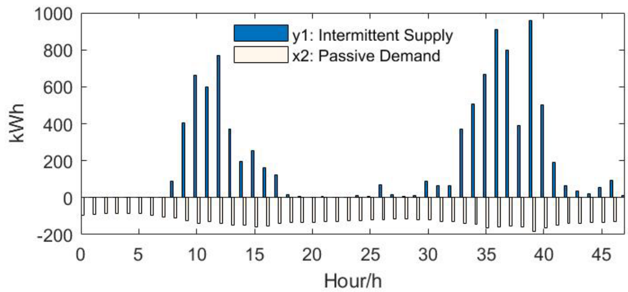

FIGURE 7. Demand and supply of a type 1 aggregator in energy sharing market in the typical 48 hours.

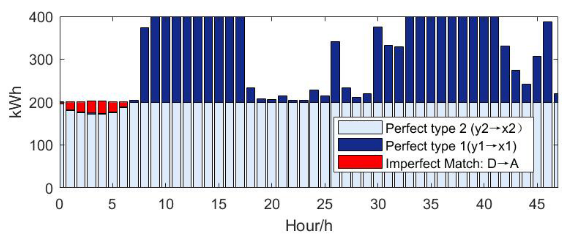

FIGURE 8. Performance of energy sharing market without storage in the typical 48 hours.

same type to obtain the post matching levels, and then match between the imperfect pair to fit the calculated post matching levels. Apparently, the intermittent supply cannot be directly employed for uncertain demand by the market operator, whereas the adjustable supply employment for flexible demand is acceptable (but not economic). When the aggregated storage power is 0, the perfect match quantity for each hour is presented in Figure 8, and the unserved intermittent supply will disappear when no other measures are taken.

As can be seen from Figure 8, the design of energy sharing market can facilitate the DER absorption with local responsive demand, this advantage will be expanded when the coordination and support from storages are brought in. The DER aggregator no longer needs to own responsive demand or storage, which is also the merit of sharing economy. The storage power can be regarded as responsive/flexible demand or adjustable supply according to the system requirement when allocated properly. The aggregated market performance throughout the typical 48 hours under different storage

TABLE 2. Market performance under different storage capacities.

Performance (kW)	Hourly storage power				
	0	0.2MW	0.4MW	0.6MW	0.8MW
Perfect match 1	5106.0	8447.5	10281.2	11679.4	12080.0
Perfect match 2	9456.0	10825.8	9902.2	11254.5	10223.3
Imperfect match	144.0	144.0	144.0	144.0	144.0
Remain y_1	14078.7	10737.1	8903.4	7505.2	7104.7

penetration levels are presented in Table 2. From Table 2, it can be referred that the support from storage devices can facilitate the intermittent renewable energy exploitation in the energy sharing market, reflected in the increase of perfect match 1 and the decrease of abandoned renewable energy (remaining y_1). But the improvement faints as the capacity grows(no significant increase in perfect match 1 for a storage capacity higher than 0.8 MW, and perfect match 2 begins to decrease at a capacity of 0.8 MW), indicating that a reasonable capacity of storage that is compatible with system DER capacity will benefit the market most. At the same time, the impact of storage capacity on the perfect match 2 is ambiguous, as its functions constantly change according to the external environments. Another phenomenon should be considered is that participation in the energy sharing market conflicts with acting as traditional responsive demand, which should be clearly accounted for in the investment decision.

B. AGGREGATOR PROFIT ANALYSIS

As described in Section III, the aggregator can adjust its internal schedule and market bids to maximize its expected profit. Without loss of generality, three typical aggregators are taken as the example

i. DER: 1.5 MW photovoltaic arrays;
ii. Demand: 0.5 MW composite demand, 10% of which is responsive;
iii. Storage: 1 MW storage whose maximum power per hour is 10%.

The bid/tender ratio for responsive demand service is set to be 55%, whereas that for storage is set to 100%. The initial energy level of the storage unit is 50% and the terminal acceptable stored energy level ranges between [45%, 55%]. The transaction prices for different categories can then be derived according to (13)-(15). The parameters and performances of different types of aggregators are different due to the various characteristics of DERs. The transactions in the energy sharing market are obtained from the dynamic programming process in Section III-B and the results are demonstrated in Figures 9, 10, and 11, respectively.

The transaction behaviors of a storage unit are solved iteratively by the means of dynamic programming. In each round of iteration, the decision for the moment is optimized based on (29) with all constraints considered. Clearly, under the circumstance where the bid/tender ratio also applies to storage, the corresponding aggregator should bid tender several times of its hour power like other

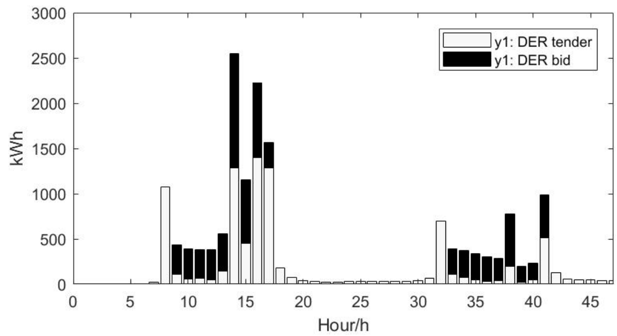

FIGURE 9. Transactions of aggregator (i) in the energy sharing market in the typical 48 hours.

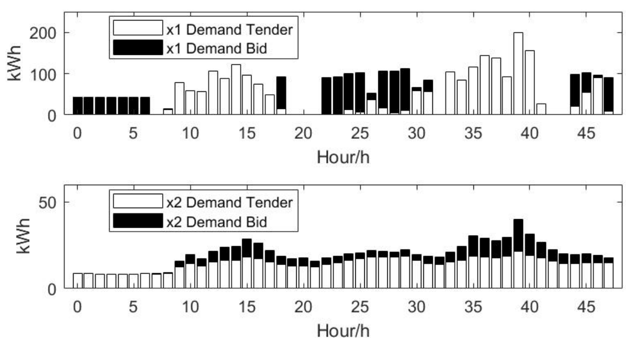

FIGURE 10. Transactions of aggregator (ii) in the energy sharing market in the typical 48 hours.

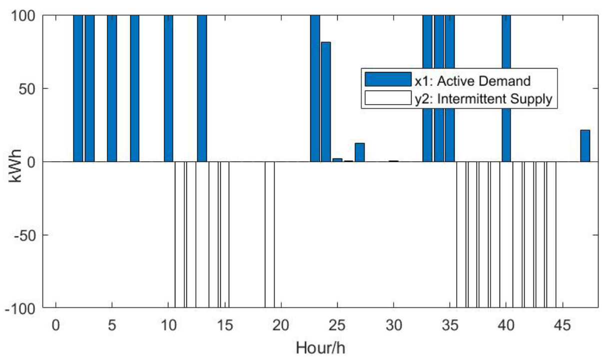

FIGURE 11. Transaction of aggregator (iii) in energy sharing market in the typical 48 hours (neglecting bid/tender ratio for responsive demand).

responsive demands when the storage is charging to ensure its energy level. The storage energy level focusing on decision strategy of the storage is also demonstrated in Figure 12.

C. COMPARISONS

The design of energy sharing market is to facilitate and stimulate the participation of intermittent renewables in the energy paradigm. Without the energy sharing market, the intermittent renewable energy supply cannot be exploited, and the uncertain part of demand has to be met with additional power supply.

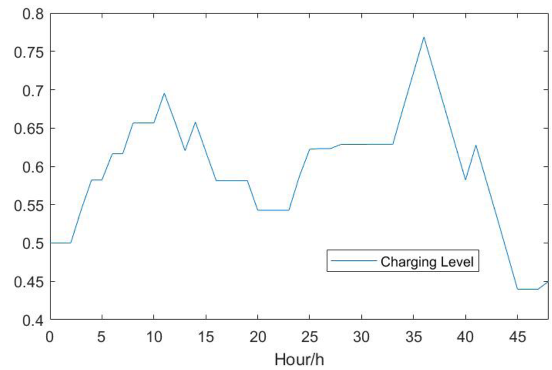

FIGURE 12. Charging level.

TABLE 3. Influences of energy sharing market.

Aggregator	Profit ($)	
	With energy sharing	Without energy sharing
i	480.0	471.0
ii	-311.3	-351.5
iii	22.3	14.4

The profit with and without energy sharing market of the three typical aggregators during the typical 48 hours are compared in Table 3. The total social welfare from energy sharing market from the simulation can also be clearly calculated (i.e., $ 246.55). It can be inferred that the energy sharing market is an economical way to absorb the uncertainty at the distribution level where an extra incentive is given to the storage owners.

V. CONCLUSION

The paper introduces the active management to the energy management paradigm to embrace the massive deployment of DER. A recommended aggregator operation model for new market participants to undergo revenue-based operation according to its inherent characters and risk preferencesi is developed. The proposed energy sharing market can better serve the increasing crowdsourced DER energy supply and monetize the distribution level storage. In the meantime, the revenue analysis can provide the aggregator some insight on investment decision. It should be mentioned that the sharing platform itself applies to crowdsourcing supplies, literally a large number of distinctive aggragtors, which might re-sculpture the energy market paradigm as its share increases. The energy sharing market scale is determined by the amount of market share with flexibility advantages/ appeals, rather than its own design. A finer division of energy products in energy sharing market (vertical or mixed types from the aspect of dynamic matching perspective) will be conducted and studied in the future work to emphasize the differentiation in future energy appeal.

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REFERENCES

[1] (Feb. 2015). *Electric Power Research Institute. The Integrated Grid: A Benefit-Cost Framework*. [Online]. Available: https://www.epri.com/#/pages/product/3002004878/

[2] J. Smith, B. Rogers, J. Talyor, J. Roark, B. Neenan, T. Mimnagh, and E. Takayesu, "Time and location: What matters most when valuing distributed energy resources," *IEEE Power Energy Mag.*, vol. 15, no. 2, pp. 29–39, Mar./Apr. 2017.

[3] S. Acha. (2013). *Modelling Distributed Energy Resources in Energy Service Networks. Raleigh: The Institution of Engineering and Technology*. [Online]. Available: https://ebookcentral-proquest-com.wwwproxy1.library.unsw.edu.au/lib/unsw/detail.action?docID=1204008

[4] Y. Weng, Y. Liao, and R. Rajagopal, "Distributed energy resources topology identification via graphical modeling," *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 2682–2694, Jul. 2017.

[5] C. Yuan, M. S. Illindala, and A. S. Khalsa, "Co-optimization scheme for distributed energy resource planning in community microgrids," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1351–1360, Dec. 2017.

[6] D. Wu, T. Yang, A. A. Stoorvogel, and J. Stoustrup, "Distributed optimal coordination for distributed energy resources in power systems," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 414–424, Apr. 2017.

[7] M. Bayat, K. Sheshyekani, M. Hamzeh, and A. Rezazadeh, "Coordination of distributed energy resources and demand response for voltage and frequency support of MV microgrids," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1506–1516, Mar. 2016.

[8] M. B. Delghavi and A. Yazdani, "Sliding-mode control of AC voltages and currents of dispatchable distributed energy resources in master-slave-organized inverter-based microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 980–991, Jan. 2019.

[9] B. M. Eid, N. A. Rahim, J. Selvaraj, and A. H. El Khateb, "Control methods and objectives for electronically coupled distributed energy resources in microgrids: A review," *IEEE Syst. J.*, vol. 10, no. 2, pp. 446–458, Jun. 2016.

[10] M. Caramanis, E. Ntakou, W. W. Hogan, A. Chakrabortty, and J. Schoene, "Co-optimization of power and reserves in dynamic T&D power markets with nondispatchable renewable generation and distributed energy resources," *Proc. IEEE*, vol. 104, no. 4, pp. 807–836, Apr. 2016.

[11] N. Neyestani, M. Y. Damavandi, M. Shafie-khah, A. G. Bakirtzis, and J. P. S. Catalão, "Plug-in electric vehicles parking lot equilibria with energy and reserve markets," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 2001–2016, May 2017.

[12] B. Gharesifard, T. Başar, and A. D. Domínguez-García, "Price-based coordinated aggregation of networked distributed energy resources," *IEEE Trans. Autom. Control*, vol. 61, no. 10, pp. 2936–2946, Oct. 2016.

[13] F. Rassaei, W. Soh, and K. Chua, "Distributed scalable autonomous market-based demand response via residential plug-in electric vehicles in smart grids," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3281–3290, Jul. 2018.

[14] H. A. Hejazi, A. R. Araghi, B. Vahidi, S. H. Hosseinian, M. Abedi, and H. Mohsenian-Rad, "Independent distributed generation planning to profit both utility and DG investors," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1170–1178, May 2013.

[15] C. Y. Tee and J. B. Cardell, "Market integration of distributed resources through coordinated frequency and price droop," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1556–1565, Jul. 2014.

[16] D. Lew, M. Asano, J. Bormer, C. Ching, U. Focken, R. Hydzik, M. Lange, and A. Motley, "The power of small: The effects of distributed energy resources on system reliability," *IEEE Power Energy Mag.*, vol. 15, no. 6, pp. 50–60, Nov./Dec. 2017.

[17] D. Koraki and K. Strunz, "Wind and solar power integration in electricity markets and distribution networks through service-centric virtual power plants," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 473–485, Jan. 2018.

[18] S. P. Burger, J. D. Jenkins, S. C. Huntington, and I. J. Perez-Arriaga, "Why distributed? A critical review of the tradeoffs between centralized and decentralized resources," *IEEE Power Energy Mag.*, vol. 17, no. 2, pp. 16–24, Mar./Apr. 2019.

[19] P. Muñoz and B. Cohen, "Mapping out the sharing economy: A configurational approach to sharing business modeling," *Technol. Forecasting Social Change*, vol. 125, pp. 21–37, Dec. 2017.

[20] C. Koopman, M. Mitchell, and A. Thierer. (May 2015). *The sharing economy: Issues facing platforms, participants, and regulators*. [Online]. Available: http://ssrn.com/abstract=2610875

[21] M. Palacios, A. Martinez-Corral, A. Nisar, and M. Grijalvo, "Crowdsourcing and organizational forms: Emerging trends and research implications," *J. Bus. Res.*, vol. 69, no. 5, pp. 1834–1839, May 2016.

[22] S. Cui, Y.-W. Wang, and J.-W. Xiao, "Peer-to-peer energy sharing among smart energy buildings by distributed transaction," *IEEE Trans. Smart Grid*, to be published. doi: 10.1109/TSG.2019.2906059.

[23] R. E. Bellman. *Dynamic Programming*. Princeton, NJ, USA: Princeton Univ. Press, 1957.

[24] P. C. Loh, L. Zhang, and F. Gao, "Compact integrated energy systems for distributed generation," *IEEE Trans. Ind. Electron.*, vol. 60, no. 4, pp. 1492–1502, Apr. 2013.

[25] A. Taeihagh, "Crowdsourcing, sharing economies and development," *J. Developing Societies*, vol. 33, no. 2, pp. 191–222, Jun. 2017.

[26] B. Guo, Y. Liu, Y. Ouyang, V. W. Zheng, D. Zhang, and Z. Yu, "Harnessing the power of the general public for crowdsourced business intelligence: A survey," *IEEE Access*, vol. 7, pp. 26606–26630, 2019.

[27] M. Hu and Y. Zhou. (Jul. 2016). *Dynamic Type Matching, Rotman School of Management Working Paper*. [Online]. Available: http://ssrn.com/abstract=2592622

[28] N. Z. Xu and C. Y. Chung, "Uncertainties of EV charging and effects on well-being analysis of generating systems," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2547–2557, Sep. 2015.

[29] A. Andreas and T. Stoffel, "NREL solar radiation research laboratory (SRRL)," Baseline Meas. Syst., Golden, CO, USA, Tech. Rep. DA-5500-56488, 1981.

[30] (2018). *Leading Through the Transition*. [Online]. Available: https://www.pjm.com

BOMIAO LIANG (M'19) received the B.S. and Ph.D. degrees in electrical engineering from Zhejiang University, China, in 2012 and 2017, respectively.

She was on Practicum Exchange with the UNSW Business School, University of New South Wales, from 2015 to 2016. She is currently a Lecturer with the School of Automation and Electrical Engineering, Zhejiang University of Science and Technology. Her research interests include power system restoration, integrated energy systems, and smart grid.

WEIJIA LIU received the B.Eng. and Ph.D. degrees in electrical engineering from Zhejiang University, Hangzhou, China, in 2011 and 2016, respectively.

He was a Postdoctoral Fellow with the University of Saskatchewan, Saskatoon, SK, Canada, from 2017 to 2019. He is currently a Researcher with the National Renewable Energy Laboratory (NREL), Golden, CO, USA. His research interests include smart grid, integrated energy systems, and transactive energy.

Dr. Liu is an Associate Editor for IET Smart Grid.

LEI SUN received the B.Eng. degree from the East China University of Science and Technology, Shanghai, China, in 2012, and the Ph.D. degree from Zhejiang University, Hangzhou, China, in 2017, both in electrical engineering.

He is currently a Lecturer with the School of Electrical Engineering and Automation, Hefei University of Technology, Hefei, China. His research interests include power system restoration, reliability, and integrated energy systems.

ZHIYUAN HE received the B.S. and MA.Sc. degrees in electrical automation from Zhejiang University, Hangzhou, China, in 1983 and 2000, respectively.

He was a Visiting Scholar with the Technical University of Munich, in 1997, and with the Technical University of Berlin, Germany, from 2003 to 2004. He is currently a Professor with the School of Automation and Electrical Engineering, Zhejiang University of Science and Technology. His research interests include power supply and distribution engineering.

Prof. He is the Vice President of the Zhejiang Provincial Power Society, China.

BEIPING HOU received the Ph.D. degree in control science and engineering from Zhejiang University, in 2005.

He is currently a Professor with the School of Automation and Electrical Engineering, Zhejiang University of Science and Technology, Hangzhou, China. His current research interests include machine vision and pattern recognition, texture analysis, and automatic control.