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Dynamic Pricing for Decentralized Energy Trading in Micro-grids

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Abstract —The fast deployment of distributed energy resources in the electric power system has highlighted the need for an efficient energy trading transactive model, without the need for centralized dispatch. In this field, a particular challenge is the determination of an effective pricing scheme that is able to produce benefits for all participants. In this paper, a novel dynamic pricing methodology is presented, offering a market-oriented means to drive decentralized energy trading and to optimize financial benefits for owners of distributed energy resources. Firstly, a price-responsive model for each type of distributed energy resource is investigated. Particularly, the decoupled State of Charge function is proposed to calculate the value of a single charging/discharging action for energy storage systems. In addition, an adaptable three-tiered framework is designed, including micro-grid balancing, aggregator scheduling, and trading optimization. By launching Tier I, II, and III, the spot prices for participants are iteratively updated and optimized in inner-micro-grid, inner-aggregator, and inter-aggregators level. The framework is able to maximize the financial savings from renewable energy, and meanwhile, provide a dynamic price signal to assist stakeholders in determining response actions and trading strategies. A realistic case is simulated using Java Agent Development framework based multi-agent modeling. The results indicate that the presented methodology enables decentralized energy trading and permits easier marketization of micro-grids with a high share of distributed energy resources.

Keywords— micro-grids, aggregator, dynamic pricing, decentralized energy trading, multi-agent system, JADE

1. Introduction

In an effort to reduce greenhouse gases emissions, distributed renewable energy has developed rapidly in the last few decades. As a result, the power system is now exposed to the unpredictable nature and operational fluctuations of distributed renewable energy. Therefore, the significant challenge is to maintain stability and secure operation of the wider power system. To maintain system stability, renewable generation is often curtailed, leading to a large amount of energy being wasted. To tackle this problem, various strategies have been proposed in the last few years, including demand response, energy storage to facilitate distributed renewable energy consumption. A 'smart distribution grid', involving flexible loads (FL), energy storage systems (ESS) and distribution generators (DG) has gained significant research interest in this regard.

This paper, is focused on energy trading in the 'distribution network market', where there are a number of participants known as aggregators. The aggregators strike contracts with distributed resource owners who have the freedom to choose their own aggregators. In this context, how to control and coordinate various distributed energy resources (DERs) to meet the local energy demand, and how to optimize the energy flow through trading and competition among different aggregators are some of the challenging problems that need to be solved.

Micro-grid management as a promising decentralized solution for coordinating control of distributed generators, local controllable loads and energy storage units at the distribution network has become a hot research area in both academia and industry. It is widely acknowledged that micro-grid is capable of providing a number of benefits, including resiliency improvement [1], security enhancement [2], adaptive DERs scheduling [3], local balance [4], and investment deferral [5]. To solve an optimization problem in a micro-grid, a mathematical programming method is often used. A comprehensive review for micro-grid optimization in terms of optimal power flow is presented in reference [6], which summarizes various objective functions,

Nomenclature

The main nomenclature used throughout the letter are listed below for quick reference.

Acronyms

AGG	aggregator	MAS	Multi-agent system
DER	distributed energy resource	MGC	micro-grid community
DG	distribution generator	PV	photovoltaics
DNO	distribution network operator	SOC	state of charge
ESS	energy storage system	UESS	utility-scale ESS
FL	flexible load	UWT	utility-scale WT
JADE	Java Agent Development framework	WT	wind turbine

Symbols

Δq^{i}	net demand of the *i*-th micro-grid	p_{L0}	initial price of energy demand
$\Delta q_{\mathrm{sum}}^{AGG}$	net demand of the aggregator	p_{spot}	spot price
ε	price elasticity of demand	p_{spot}^{AGG}	the region spot price of the aggregator
f_{DG}	distributed generation distribution	p_{spot}^{i}	the region spot price of the *i*-th micro-grid
F_{DG}	distributed generation default possibility		
k_{pen}	the penalty coefficient	P_{ESS}	profit of ESS regulation
*n*MG*m*	the unit managed by aggregator *n* and located in the micro-grid *m*	P_{L}	profit of load demand response
		q_{DG}	scheduling generation of DG
*n*UWT	the utility-scale WT managed by aggregator *n*	q_{ESS}	optimal regulation quantity of ESS
		q_{for}	forecasted generation of DG
*n*UESS	the utility-scale ESS managed by aggregator *n*	q_{L}	energy demand quantity of FL
		q_{L0}	initial demand quantity of FL
p_{DG}	marginal generation cost of DG	q_{real}	real generation of DG
p_{ex}	price of exporting energy into DNO	q_{SOC}	state of charge quantity
p_{im}	price of importing energy from DNO	q_{SOC}^{+}	optimized State of Charge quantity
p_{sell}^{h}	threshold price of the *h*-th aggregator selling energy	S_{AGG}	the set of aggregators
		S_{M}	the set of micro-grids
p_{buy}^{j}	threshold price of the *j*-th aggregator buying energy	σ	standard deviation of generation difference
p_{L}	marginal value of energy demand		

constraints, and methodologies. As the number of micro-grids increases in the neighboring area, the interactions among them need to be monitored, controlled and managed. Consequently, the concept of micro-grid community (MGC), which interconnects and coordinates a cluster of adjacent micro-grids with a designed topology and control structure, is proposed. Reference [7] addressed the challenge of coordinating micro-grids with energy exchange through a hierarchical energy management system. Reference [8] investigated a dynamic economic dispatch approach for an agent-based MGC. An optimal interconnection strategy using minimal cut-set-based methodology is investigated in reference [9] to enable a MGC with a higher adaptability, and to accommodate operational fluctuations.

In the above literature, all DERs need to be directly controlled and optimized by the micro-grid community, which normally requires global observability and considerable coordination effort. However, DERs in the MGC may be installed by different owners, driven by their own goal of maximizing profits [10]. Therefore, a Nash equilibrium method for solving DERs transactions has been proposed, where DERs execute transactions

independently [11]. In [12], a naïve auction algorithm is used to match DERs, enabling them as both buyers and sellers in the distributed energy market. The Stackelberg game is widely accepted for solving optimal strategies in dynamic trading scenarios [13]. In addition, win-win interaction frameworks are summarized in [14].

Since the DER owners may not have the expertise to participate in energy market transactions, a new entity called ‘aggregators’ emerged [15], where DER owners can select an aggregator as a means to access to the energy market. Based on the state of its signed DERs, aggregators develop the appropriate scheduling plan and trading strategy with each other. A micro-grid is often regarded as an aggregator in MGC. Reference [16] proposed a new energy trading framework based on repeated game theory, enabling aggregators to trade energy sources independently and randomly. Based on historic energy exchange among aggregators, prospect theory and Nash equilibrium were applied to analyze aggregator's trading propensity [17].

Current research on MGC focuses on various types of goal optimization and market equilibrium. There are still many challenging problems to be solved. For example, after the DG model construction, the operating cost of generating units using renewable energy such as wind and photovoltaics (PV) is often neglected [28] or is considered as a small maintenance cost [19], which has led to the highly competitive DGs in the market. However, the inherent fluctuations and uncertainty of both wind & PV generation, and the subsequent impact on power system security, have limited their injection into the electrical grid. Therefore, it is necessary to take such inherent generation uncertainties or risks into account. In [20], the Conditional Value-at-Risk method was used to convert the generation risk into the total cost. Inspired by this idea, a new operational model for DERs is proposed in this paper, where the marginal cost of DG is estimated based on the possibility of power generation defaults and penalties. The proposed marginal cost model can directly deduce the optimal power generation corresponding to the price (here referred to as the optimal price-responsive generation).

Another problem is that in the energy storage model, the profit is usually calculated according to the difference between electricity price for charging and discharging during a full-cycle [21]. When the electricity price in the next period of time is uncertain, it is difficult to realize the global optimization of energy storage bidding strategy. In the energy market, every charge or discharge action of stored energy is to maximize profits. Therefore, the decoupled state of charge (SOC) value is proposed and established in this paper by quantifying the potential value of each charge or discharge action to assess bidding strategy in any interval.

For energy management at MGC, a hierarchical structure is often employed, including micro-grid optimization and coordination [8], aggregator optimization with market transactions [22], aggregator optimization with aggregator transaction [16], DERs transaction with micro-grid transactions [12]. In a MGC market, DERs in a micro-grid may be entrusted to different aggregators while DERs located in different micro-grids may select the same aggregator, as shown in Fig 1. That is, DERs assemble based on the profits rather than the geographical location. Based on this, an iterative three-tiered optimization approach is proposed in this paper to achieve the overall optimal operation of a MGC, Tier I to solve the individual micro-grid optimal operation problem; Tier II to solve the aggregator scheduling or coordination optimization problem; Tier III for aggregator trading optimization problem.

In the existing literature, most applications are based on a uniform global clearing price for the energy market, which results in a DER located in different micro-grid gaining the same benefit. To improve on this limitation, optimal power flow [8] and the coordination of different micro-grids [23] are taken into account. On this basis, in order to ensure the profitability of distributed resource owners, and reflect the competitiveness of aggregators, a novel clearing method corresponding the above hierarchical optimization is proposed, which is able to quantify the contribution of each DER and can be considered as a win-win method.

To summarize, the contributions of this paper are as follows: (1) The marginal cost of distributed generation is deduced by utilizing risk associated with the DER generation, which subsequently determines the optimal

generation response to market price. (2) The single charge or discharge profit of ESS is quantified by decoupling the full-cycle profits based on a value curve and historic data, which can promptly generate a suitable bidding strategy instead of adopting global optimization. (3) A win-win framework is proposed to maximize profit through addressing dynamic guiding prices during a three-tiered optimization within a MGC. (4) An impartial clearing is designed according to the contribution of each response behavior, facilitating a fair sharing platform. (5) The presented scheme is useful to optimize the DERs configuration that higher profit can be obtained in the scarce resources micro-grid.

The rest of this paper is organized as follows. In Section 2, the overall architecture of MGC is detailed in the description of the market participants and their responsibilities. The price-responsive models for DG, ESS, and FL are deduced based on generation risk, decouple SOC value, and the elasticity of demand in Section 3. Section 4 details an iterative three-tiered optimization according to the power market equilibrium of supply and demand., A realistic case study is demonstrated in Section 5 to verify the efficiency and advantages of the presented transactive energy scheme. The conclusion follows in Section 6.

2. Micro-grid Community Architecture

2.1 Basic Description

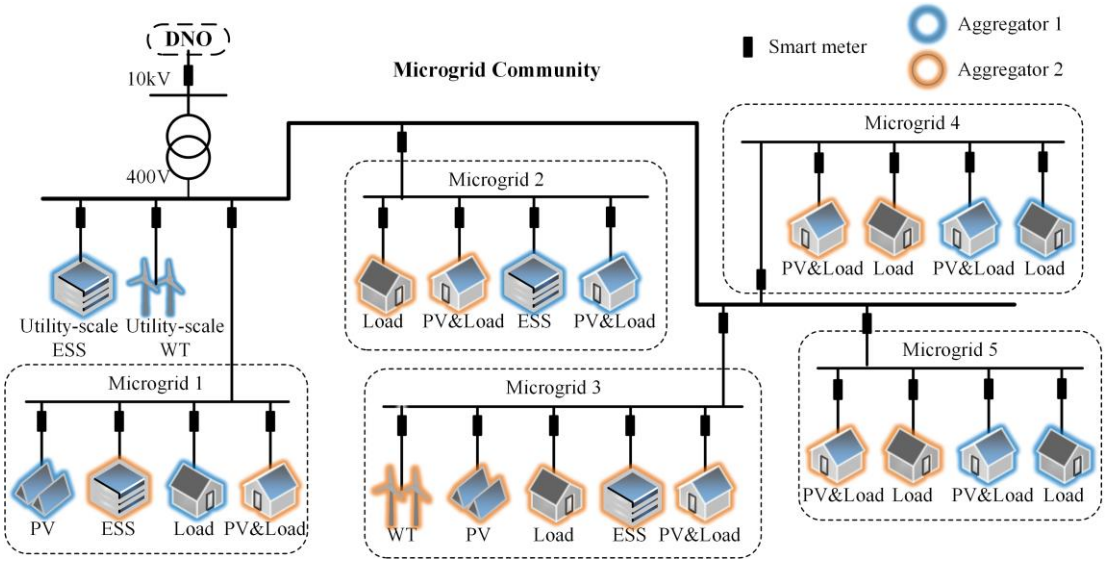

Fig. 1. Micro-grid Community Architecture

A typical distribution network has a series of DERs in different geographical positions, owned by different families or different organizations. Due to the lack of awareness on global operating information, it is difficult for owners to manage and trade energy optimally. However, the owners of DERs can entrust the scheduling of their assets to one of the professional aggregators. In this case, MGC is formed, which has the problems of the influence of geographical location, the management optimization within an aggregator, and the competitive trading between the aggregators. As shown in Fig 1, MGC is composed of a number of micro-grids with DG, ESS, and FL connecting to the widely distributed connection points. The larger scale resources, named as utility-scale devices, might be connected directly to the main feeder. In the studied mechanism, several aggregators are authorized to participate in energy trading in the range of MGC. The net demand of an aggregator monitored from smart meters must equal its pre-scheduled profile. Otherwise, the aggregator will be penalized by the distribution network operator (DNO) according to the quantity of imbalanced electricity. The risk of penalty encourages the aggregators to utilize the local market to balance fluctuations. In addition, a trading platform is established for MGC to facilitate energy trading among aggregators.

Therefore, MGC, as a cluster of neighboring micro-grids connecting to the same feeder, is technically defined as follows:

A. At least two micro-grids equipped with a variety of DERs exist in MGC.

B. Multiple aggregators, as agencies of DERs operators, are allowed to conduct transactive energy business in MGC through short-term energy trading for economic profits pursuit.

C. DERs located in micro-grids might belong to various owners who may select any appropriate aggregator.

D. The target of MGC commercial operation is to enable autonomously optimized coordination of DERs while satisfying the interests of market participants.

2.2 Market Participants and Responsibilities

Multi-agent system (MAS), a widely accepted method of distributed modeling, can simulate the Agents with independent ability of reaction, decision-making, communication and expansion. And the approach is popular in distributed resource scheduling [24], decentralized energy optimization [25], and coordinated control strategy [26]. In addition, some studies adopt MAS to analyze the solution of game theory, offering another way to investigate the competitive and cooperative energy transaction within MGC [27].

In this paper, Java Agent Development Framework (JADE)-based multi-agent system is applied to model the participants in MGC. Due to too much information transmission, transactions of Agents are sorted out into Fig. 2, which shows the starting time, finishing time, relationship, and functions of each Agent.

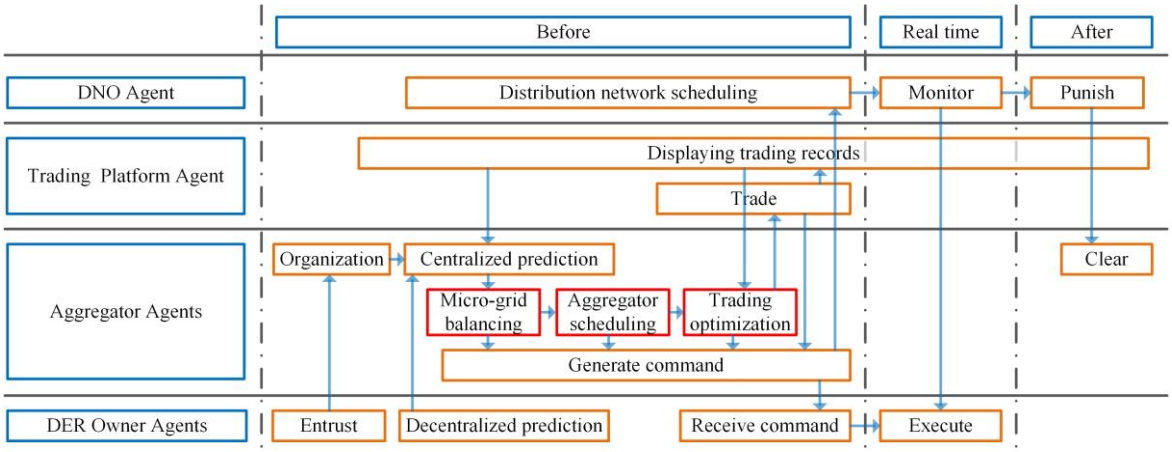

Fig. 2. The Functions of Multi-Agent System in Micro-grid Community

The functions of related agents are further explained as follows:

1) DNO Agent: DNO Agent, as a grid-connected reserve power source, is responsible for calculating the total electrical consumption or injection of MGC, in order to plan the distribution network scheduling. The total net demand of each aggregator Agent is monitored in a specified interval, with the difference between scheduled quantity and actual quantity used to determine whether the penalty function is launched.

2) Trading Platform Agent: Trading Platform Agent is responsible for maintaining trading procedures and displaying transaction records.

3) Aggregator Agents: Aggregator Agent is responsible for organizing its signed DERs, acquiring and sorting prediction data, computing optimal operation, performing energy trading with other aggregators through Trading Platform Agent, and transmitting strategy commands to DER owner Agents.

4) DER Owner Agents: DER Owners Agent needs to select an aggregator Agent independently, report the power prediction to its selected aggregator Agent, and execute the control strategy provided by the Aggregator Agent.

In the following paper, the solution and process of the core algorithm (Red block in Fig. 2) is further studied.

2.3 Java Agent Development Framework

Java Agent Development Framework is a development platform for simulating multi-agent system based on Java language. It has several unique characteristics. (1) The functions, behaviors, algorithms of each Agent can be modeled separately, forming a clear format and architecture. (2) Each Agent is equipped with an inbox and outbox. And JADE library provides numbers of communication samples, like “Request”, “Propose”, “Inform”, “Reply”, “Agree”, “Refuse”, facilitating unobstructed transactive between Agents. (3) The information flow and content can be readily monitored by the provided functions. These characteristics make it clear and systematic to design a Micro-grid Community and its transaction.

3. Proposed Price-responsive models of DERs

The operation scheduling predicted and reported by all DERs according to their own wishes is generally not the optimal operation scheduling. The operation scheduling should be optimized for profit. This section will address two problems: How do DERs respond the spot price? How much profit will be obtained by the response? Thus, the price-responsive models of DG and ESS are deduced, and that of FL are sorted out via existing research.

3.1 Price-responsive model of DG

The operating cost of distributed renewable generation is negligible due to the free resources such as wind and solar. Obviously, more electricity is generated more profits are made. However, renewable generation curtailments frequently occur due to generation uncertainty, leading to significant energy waste. The maximum profit, therefore, can be obtained by finding the equilibrium point between generation benefits and risk cost. First, the risk cost is quantified as follows:

In general, the probability of DG output uncertainty is widely acknowledged as a normal distribution [28].

$$f_{\mathrm{DG}}\left(q_{\mathrm{real}}\right)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left[-\frac{\left(q_{\mathrm{real}}-q_{\mathrm{for}}\right)^{2}}{2\sigma^{2}}\right] \tag{1}$$

where σ is the standard deviation, q_{for} and q_{real} represent the forecasted generation and real output of distributed renewable energy respectively. Assuming optimized output is q_{DG}, if $q_{\mathrm{DG}} > q_{\mathrm{real}}$, it means real output cannot satisfy the scheduling generation required by the aggregator, which is a generation default. $F_{\mathrm{DG}}(q_{\mathrm{DG}})$ which is the q_{DG}-th generation default possibility, can be calculated using the following normal cumulative distribution based on the probability density of the DG output.

$$F_{\mathrm{DG}}\left(q_{\mathrm{DG}}\right)=\int_{0}^{q_{\mathrm{DG}}} f_{\mathrm{DG}}\left(q_{\mathrm{real}}\right)\mathrm{d}\,q_{\mathrm{real}} \tag{2}$$

Therefore, the risk cost of the q_{DG}-th, $p_{\mathrm{DG}}(q_{\mathrm{DG}})$, namely the marginal cost function, can be expressed as default possibility multiplied by default penalty:

$$p_{\mathrm{DG}}\left(q_{\mathrm{DG}}\right)=k_{\mathrm{pen}}\cdot p_{\mathrm{ex}}\cdot F_{\mathrm{DG}}\left(q_{\mathrm{DG}}\right) \tag{3}$$

where p_{ex} is the price of exporting energy to DNO. And $k$pen means the penalty coefficient which is set as 2 in this paper. In this special case, when local generation is redundant, the optimal scheduling is to export forecasting quantity to DNO. If penalty increases, the optimal generation scheduling will be more conservative but helpful to increase system stability. And vice versa, DG always tries to bet the opportunity that real generation is more than forecast generation due to less penalty of default.

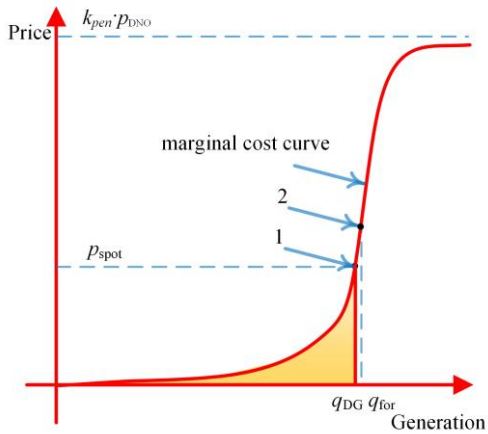

Fig. 3. The proposed generation cost of DG

As shown in Fig.3, rather than simply set the marginal cost of DG as a constant as indicated in the literature [19], we consider its variation is in the range of 0 and $k_{pen} \cdot p_{im}$ in this study. If the spot price is at the point 1 in Fig.3, more (less) generation at point 1 enables the marginal cost higher (lower) than spot price, which requires to reduce (enhance) generation for profit. The equilibrium that the marginal cost equals to the spot price represents the optimal generation which may not be the forecasting generation. And the profit of generation scheduled at point 1 can be calculated as:

$$p_{\text{spot}} = p_{\text{DG}}\left(q_{\text{DG}}\right) \tag{4}$$

Therefore, price-responsive quantity of DG can be expressed as the inverse function of formula (4):

$$q_{\text{DG}}\left(p_{\text{spot}}\right) = p_{\text{DG}}^{-1}\left(p_{\text{spot}}\right) \tag{5}$$

3.2 Price-responsive model of ESS

As an energy service provider, ESS makes profit by charging or discharging at the appropriate time. It is clear that every charge and discharge action is intended to gain profit. Generally speaking, the profit of an ESS is measured based on the price difference between these two actions. However, this method has a problem that it cannot differentiate each individual benefit gained from these actions. To tackle this, a new price function, called decoupled State of Charge function, is proposed to reflect the profit of each charge/discharge action.

In general, the quantity of ESS transaction is related to the SOC and the spot price [29], the relationship of which can be formulated using $f_{\text{ESS}}(\cdot)$ as follows:

$$q_{\text{ESS}} = f_{\text{ESS}}\left(q_{\text{SOC}}, p_{\text{spot}}\right) \tag{6}$$

where q_{SOC} is the State of Charge, and q_{ESS} is the optimal adjusted quantity. After the adjustment, the State of Charge can be updated as:

$$q_{\text{SOC}}^{+} = q_{\text{SOC}} + q_{\text{ESS}} \tag{7}$$

where q_{SOC}^{+} is the optimized q_{SOC}. It doesn't need to be adjusted any more at q_{SOC}^{+}. Thus, formula (6) can be re-written as:

$$0 = f_{\text{ESS}}\left(q_{\text{SOC}}^{+}, p_{\text{spot}}\right) \tag{8}$$

As a rule of thumb, the higher spot price, the lower optimal State of Charge. The p_{spot} and q_{SOC}^{+} are negatively correlated and one-to-one correspondence. Therefore, the relationship of these two variables can be

mathematically expressed as:

$$q_{\mathrm{SOC}}^{+} = F_{\mathrm{ESS}}\left(p_{\mathrm{spot}}\right) \tag{9}$$

For simplicity, and without the loss of generality to represent the negative correlated and one-to-one correspondent relationship between optimal SOC and spot price, formula (9) can be expressed as follows, which is derived from [29], [31], [32], [33].

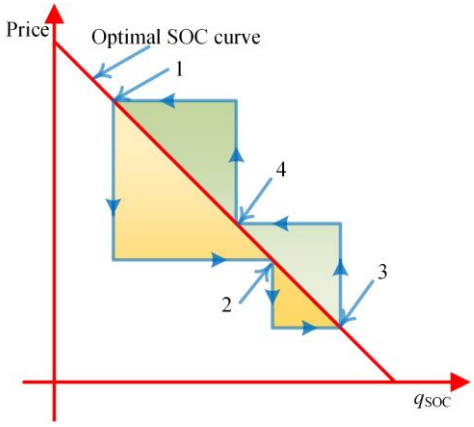

Fig. 4. Expected value of ESS

In Fig. 4, optimal SOC curve expresses the value of the corresponding q_{SOC}. And $p_{\mathrm{spot},n}$ represents spot price at point n. When spot price comes from $p_{\mathrm{spot},1}$ to $p_{\mathrm{spot},2}$, q_{SOC} will adjust q_{ESS} to point 2 (q_{SOC}^{+}) based on formula (9). So the price-responsive model that shows the relationship between p_{spot} and q_{ESS} can be expressed by:

$$q_{\mathrm{ESS}}\left(p_{\mathrm{spot}}\right) = F_{\mathrm{ESS}}\left(p_{\mathrm{spot}}\right) - q_{\mathrm{SOC}} \tag{10}$$

To further illustrate, the expected profit by charging from point 1 to point 2 can be calculated using:

$$P_{\mathrm{ESS}}^{1,2} = \int_{q_{\mathrm{SOC}}}^{q_{\mathrm{SOC}}^{+}} \left[F_{\mathrm{ESS}}^{-1}(q) - p_{\mathrm{spot},2}\right] \mathrm{d}\, q \tag{11}$$

Formula (11) represents the orange area between point 1 and point 2 in Fig 4. Similarly, when the spot price comes to $p_{\mathrm{spot},4}$ from $p_{\mathrm{spot},3}$, the expected profit of charging can be calculated using:

$$P_{\mathrm{ESS}}^{3,4} = \int_{q_{\mathrm{SOC}}}^{q_{\mathrm{SOC}}^{+}} \left[p_{\mathrm{spot},4} - F_{\mathrm{ESS}}^{-1}(q)\right] \mathrm{d}\, q \tag{12}$$

The specific significance of formula (12) is the green area between point 3 and point 4 in Fig. 4.

The calculated results of the above two formulas are decoupled State of Charge value. When q_{SOC} returns to the initial point 1, the sum of decoupled State of Charge value is the shaded areas in the Fig.4. It is equal to the real profit computed by the common method based on the difference the charge and discharge, proving the reasonableness of the proposed method.

3.3 Price-responsive model of FL

Generally, the price elasticity of demand is defined as [30]:

$$\varepsilon = \frac{\mathrm{d}q_L / q_L}{\mathrm{d}p_L / p_L} \tag{13}$$

where q_{L} is the energy demand of FL. The formula (13) can be integrated into a demand response function where p_{L} expresses the value of the corresponding demand, q_{L}:

$$p_{\mathrm{L}} = p_{\mathrm{L0}} \cdot (q_{\mathrm{L}} / q_{\mathrm{L0}})^{-\varepsilon} \tag{14}$$

where q_{L0} and p_{L0} are the initially scheduled demand and price of FL.

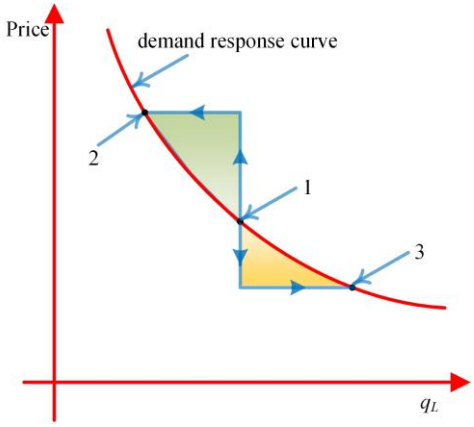

Fig. 5. Demand response profit of FL

As shown in Fig. 5, spot price is p_{L0} at point 1. When the spot price changes, FL will regulate the load quantity to acquire subsidies and pursue higher profits. The subsidy determined by the market is p_{spot}. The maximum profit of regulating is solved on the equilibrium point of the subsidy and the use value. Therefore, the price-responsive model can be deduced when formula (14) is equal to spot price:

$$q_L\left(p_{spot}\right)=(p_{spot}/p_{L0})^{\varepsilon}q_{L0} \tag{15}$$

Further, the total profit of reduction from point 1 to point 2 can be calculated using:

$$P_L^{1,2}=\int_{q_{L0}}^{q_{spot,2}}\left[p_{spot,2}-p_L\left(q_L\right)\right]\mathrm{d}\,q_L \tag{16}$$

The specific significance of formula (16) is the green area between point 1 and point 2 in Fig. 5.

Similarly, when the spot price decreases, like $p_{spot,3}$, the load quantity will increase. FL also gains profit, which is shown as the orange area in Fig 5. It can be calculated using:

$$P_L^{1,3}=\int_{q_{L0}}^{q_{spot,3}}\left[p_L\left(q_L\right)-p_{spot,3}\right]\mathrm{d}\,q_L \tag{17}$$

4. Dynamic pricing scheme of MGC

In the last section, the price-responsive behaviors of market members are modeled, providing the action criterions to stakeholders while facing price variation. This section will address dynamic spot prices, guiding DERs response to enable the energy balance within a MGC. Besides, a clearing mechanism is designed to quantify the contribution of each response behavior during a three-tier optimization. The schematic framework shown in Fig.6 will be further elaborated in the next segments.

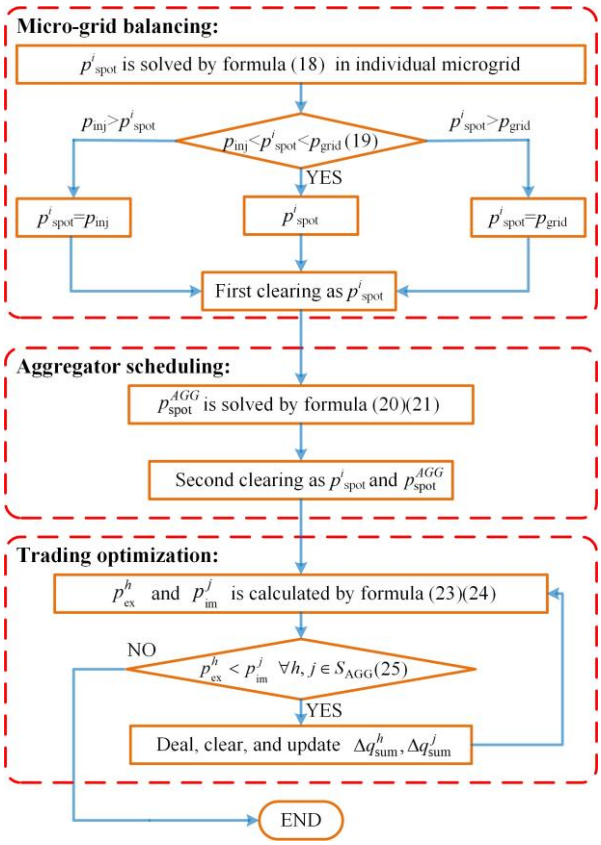

Fig. 6. The process of the three-tiered dynamic pricing scheme

4.1 Tier I: Micro-grid balancing

In Tier I, a micro-grid is motivated by managing its inner DERs to make profits while keeping energy balance of DG, ESS, and FL. And the DERs in a micro-grid determine the operation strategy by optimizing their benefits based on the varying spot price and the proposed price-responsive models (5) (10) (15), forming their optimal supply/demand curves. Therefore, the objective of *i*-th micro-grid in Tier I is to solve the intersection of the supply and demand curves [9]. That is to seeking a spot price of *i*-th micro-grid which makes the its net demand $\Delta q^i(p^i_{spot})$ equals to 0:

$$\Delta q^i\left(p^i_{spot}\right) = q^i_{DG}\left(p^i_{spot}\right) + q^i_{ESS}\left(p^i_{spot}\right) + q_L\left(p^i_{spot}\right) \quad \forall i \in S_M \tag{18}$$

Let p_{ex} and p_{im} denote, respectively, the price of electricity export into and imported from the utility feeders, the spot price motivating the choices of inner DERs in micro-grids needs to follow the constraint:

$$p_{ex} \le p^i_{spot} \le p_{im} \tag{19}$$

As shown in the Fig. 6, if the value of optimized p^i_{spot} solved by equation (18) locates between p_{ex} and p_{im}, the operation of inner DERs is settled and the energy is self-balanced in the *i*-th micro-grid. In the case that p^i_{spot} is lower than p_{ex}, DGs prefer to sell electricity to the utility grid at price p_{ex}. Similarly, FLs is more willing to purchase electricity from the utility grid when p^i_{spot} is higher than p_{im}.

4.2 Tier II: Aggregator scheduling

Energy balance in Tier I is merely related to the resource conditions in one micro-grid, the pricing scheme of which is unable to motivate the globally optimization for a cluster of micro-grids. To address this challenge, the

process of aggregator scheduling is adopted in Tier II to coordinate renewable generation and consumption among the micro-grids and utility-scale DERs. The stakeholders are therefore allowed to utilize their flexible resources to seek higher profit in a wider area.

The spot price p_{spot}^{i} has been derived for each micro-grid in Tier I. But these prices are usually not equal due to the different micro-grid characteristics. A price-driven coordination is needed to avoid underutilization of cost-effective DERs. For example, the DG in the low-spot price micro-grid is likely to seek opportunity to sell its generation to the neighboring micro-grids with more profitable spot price. It is the same case for either ESS or FL. In doing so, the spot prices of micro-grids will be approaching to the optimized spot price of aggregator. Similar to Tier I, the objective in Tier II is solve the global spot price of aggregator which makes the total imbalance electricity of a specific aggregator $\Delta q_{\text{sum}}^{AGG}$ equals to 0:

$$\Delta q_{\text{sum}}^{AGG} = \sum_{i \in S_M} \Delta q^{i}\left(p_{\text{spot}}^{i}\right) + q_{\text{ESS}}^{\text{M}}\left(p_{\text{spot}}^{AGG}\right) + q_{\text{DG}}^{\text{M}}\left(p_{\text{spot}}^{AGG}\right) \tag{20}$$

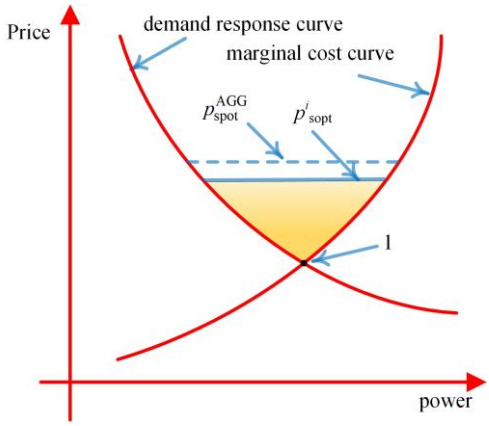

Fig. 7. Illustration of price optimization for a micro-grid at Tier II

As shown in Fig.7, spot price obtained in *i*-th micro-grid moves from point 1 to p_{spot}^{i}. And p_{spot}^{i} is not equal to global spot price of aggregator p_{spot}^{AGG}, due to the fact that an extra fee is charged for compensating delivery cost and regulating energy exchange among the micro-grids. The corrected spot price for the *i*-th micro-grid can be written as:

$$p_{\text{spot}}^{i} = p_{\text{spot}}^{AGG} + k_{\text{cha}} \cdot \Delta q^{i}\left(p_{\text{spot}}^{i}\right) \tag{21}$$

where, k_{cha} is the charge coefficient for energy exchange.

In this operation tier, p_{spot}^{AGG} can be solved through formulas (20) (21) as shown in Fig.6. The micro-grids, whose spot prices still satisfy the constraint (19), are cleared at respective p_{spot}^{i} and the utility-scale DERs are settled on the basis of p_{spot}^{AGG}. Besides, the coordination profit of which can be calculated using the method proposed in section 3, namely the orange area in Fig.7.

4.3 Tier III: Trading optimization

As potential competitors, aggregators are not willing to publish their balance information. That makes the coordination between aggregators more difficult. Therefore, a trading optimization method is used to determine the optimal spot price. According to formula (20), the relationship between aggregator spot price p_{spot}^{AGG} and aggregator imbalance energy $\Delta q_{\text{sum}}^{\text{AGG}}$ can be found, and formulated using $f_{\text{trad}}(\cdot)$ as follows:

$$p_{\text{spot}}^{AGG} = f_{\text{trad}}(\Delta q_{\text{sum}}^{AGG}) \tag{22}$$

Define the unit energy of trading as *x*, for each aggregator, the sell and purchase prices are obtained by using:

$$p_{\text{sell}}^{h} = f_{\text{trad}}(\Delta q_{\text{sum}}^{h} - x) \quad \forall h \in S_{\text{AGG}} \tag{23}$$

$$p_{\text{buy}}^{j} = f_{\text{trad}}(\Delta q_{\text{sum}}^{j} + x) \quad \forall j \in S_{\text{AGG}} \tag{24}$$

where S_{AGG} is the full set of aggregators, and h or j represents an aggregator in the set. Formula (23) means if aggregator h sells x kWh extra electricity to the market (through increasing inner generation or reducing electricity consumption), its spot price will be amended to p_{sell}^{h}. Similarly, formula (24) means if aggregator j purchases another x kWh from market, optimal price of it will be reduced to p_{buy}^{j}. Then, the aggregator h and j report these two optimized sport prices to trading platform. If the following formula is satisfied, the trading between aggregator h and j is achieved.

$$p_{\text{sell}}^{h} < p_{\text{buy}}^{j} \quad \forall h, j \in S_{\text{AGG}} \tag{25}$$

Then, $\Delta q_{\text{sum}}^{h}$, $\Delta q_{\text{sum}}^{j}$, p_{sell}^{h}, and p_{buy}^{j} are updated. The MGC converges to the optimal solution when no more trading is successfully deal with. The optimal solution can be found through various optimization algorithm. In this paper, the simple well-known dichotomous exhaustive search method is adopted.

5. Case Study

5.1 A realistic case of MGC

A realistic case of MGC [8] in Guangxi Province, China, is used to validate the proposed dynamic pricing scheme. As shown in Fig. 1, the studied system consists of five micro-grids, one utility-scale ESS (UESS) and a set of utility-scale wind turbines (UWT). In addition, there are two aggregators working for the trading business in this MGC.

Tab.1. The configurations and parameters of market participants

		Micro-grid 1	Micro-grid 2	Micro-grid 3	Micro-grid 4	Micro-grid 5	UESS	UWT
A1	ESS(kWh)	-	78	-	-	-	100	-
	DG(σ)	0.04	0.04	-	0.04	0.04	-	0.04
	FL (ε)	-0.3	-0.5	-	-0.4	-0.4	-	-
A2	ESS(kWh)	84	-	57	-	-	-	-
	DG(σ)	0.04	0.04	0.04	0.04	0.04	-	-
	FL (ε)	-0.5	-0.4	-0.4	-0.4	-0.4	-	-

A1=Aggregator 1, A2=Aggregator 2

The DERs configurations and parameters of study case are shown in Tab 1. The parameter σ, the standard deviation, is used in formula (1) and the price elasticity of demand ε is defined by formula (13). The DGs generation that directly injects to DNO feeder is paid at price 0.342 CNY/kWh, and per kWh electricity purchased from DNO is charged 0.875 Yuan.

Fig. 8-a and Fig. 8-b shows the day-ahead forecast power of generation and consumption for Aggregator 1 and 2 respectively. Specifically, the color strips above the horizontal axis represent the forecasted consumption of corresponding participants. The total consumption prediction for MGC can be obtained by adding the data of these trips. Similarly, the part below the horizontal axis denotes the power of forecasted generation for one day. To clarify the relation of physical access and contract operation, a special nomenclature is used in this section. For example, the symbol 1MG2 means the unit of DERs signed with Aggregator 1 and equipped in the micro-grid 2. Namely, the first number refers to the aggregator number and the last number represents the micro-grid the DERs belong to. Besides, MG and is the abbreviation of micro-grid.

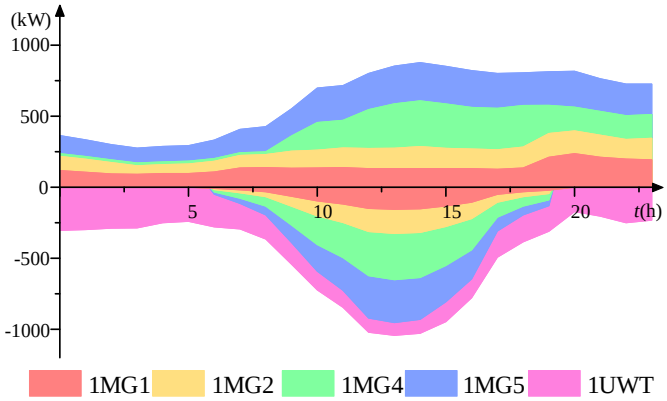

Fig. 8-a. Day-ahead forecasting power of Aggregator 1

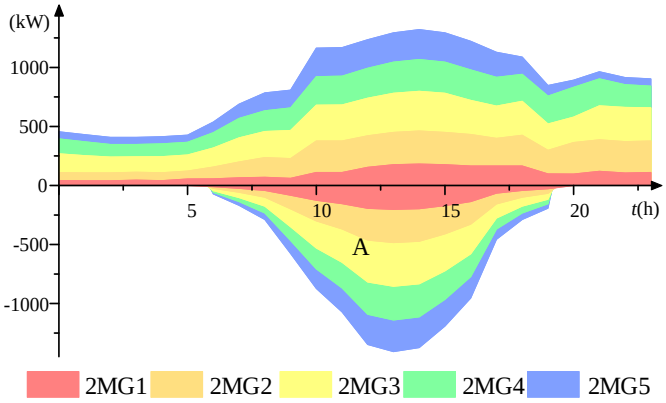

Fig. 8-b. Day-ahead forecasting power of Aggregator 2

5.2 Results and Discussion

1) Overall results of electricity scheduling

The presented methodology is performed to the studied case. And the results at 12:00 p.m. for market shareholders based on the tiered dynamic pricing scheme are shown in Fig.7.

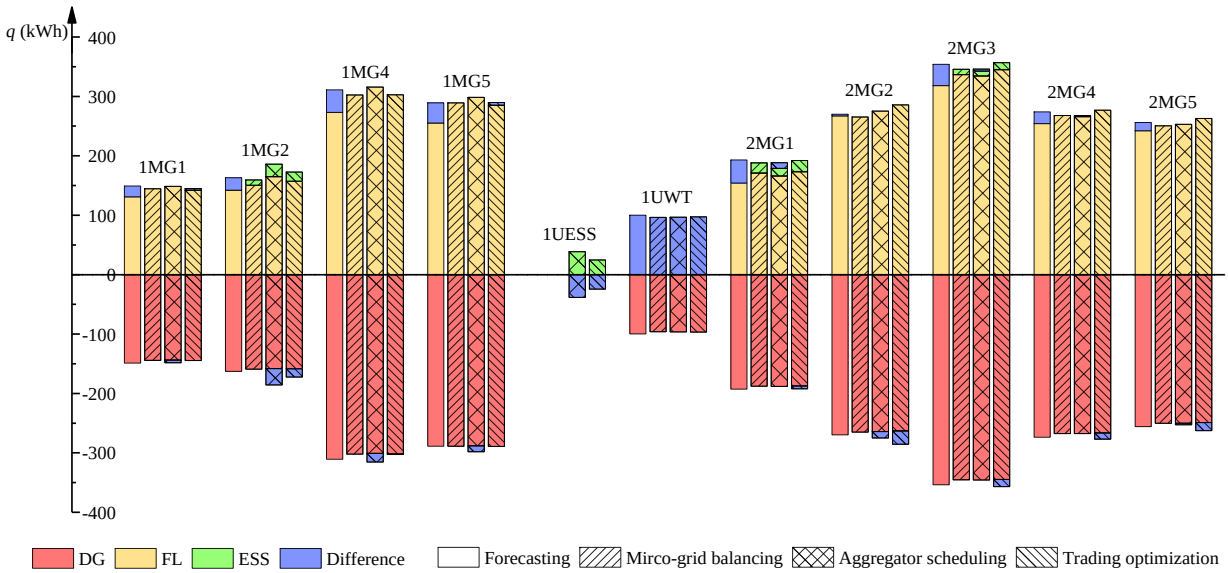

Fig. 9-a. Scheduling of individual micro-grids and utility-scale DERs

Each grouped stakeholder, 1MG1 for instance, has four bars in Fig.9-a. The first bar includes the initially

forecasted DG generation and load demand. The following three bars denote the updated scheduling after executing Tier I, II, and III processes. Different color means different DERs. It is noted that the blue area represents the electricity quantity difference between generation and load demand. Specifically, the total forecasted demand (adding the value of yellow part of each first bar together) is 2036 kWh, which is 323 kWh less than the forecasted generation. The decentralized self-balance of this global energy difference can be driven through the proposed dynamic pricing.

First of all, by launching the routines in Tier I, micro-grids reduce the imbalance energy between generation and demand side by utilizing the response capability of inner DERs. Therefore, compared with the first bar of each participant, the second bar has much smaller or even none of the blue block. The inner self-balance of electrical energy is enabled. Apparently, the utility-scale energy resources operated by DNO, 1UESS and 1UWT, did not run energy interaction in this stage. Specifically, the scheduling of 1UESS keeps unchanged. Whereas, according to formula (5), 1UWT plans to sell 96.256kWh to utility grid at price 0.342 CNY/kWh.

In Tier II stage, aggregators optimize the operation scheduling of the contracted DERs to enlarge the demand of cost-effective renewable energy. Considering the fact that 1UWT sell its generation with relatively low price in Tier I, Aggregator 1 coordinates the contracted DERs to make response to this situation. As a result, the electrical demand increases 92.688 kWh and the other high-cost generation scheduled by Aggregator 1 reduces 3.933 kWh. That is to balance the 96.621 kWh of 1UWT generation which little increases from 96.256kWh as Tier I plan. Besides, the final supply-demand balance is accomplished at 987.556 kWh for the given interval. Similarly, aiming at maximizing the profit, Aggregator 2 re-schedules the energy balance by reallocating 14.055 kWh to 2MG2 and 2MG5, while reducing the equivalent amount in 2MG1, 2MG3, and 2MG4. The growth and decline of the third bars in Fig. 9-a and transfer manner in Fig. 9-b reflect this dynamic scheduling process.

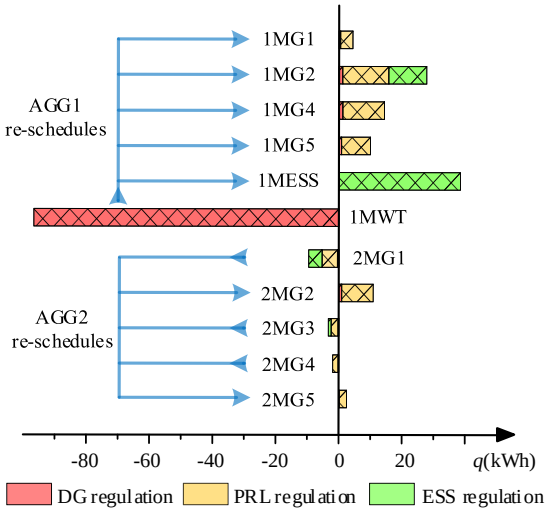

Fig. 9-b. The details of the Tier II

At the end of Tier II, Aggregator 1 obtains the lower spot price than Aggregator 2. The presented framework allows them to make more global energy trading based on their redundant resources. If parameter x in formulas (23) and (24) is set as 0.5 kWh, the trading process is as follows: Aggregator iterates back to Tier II to generate its bidding strategy. That is to calculate the expect price of re-schedule when net demand of Aggregator declines or increase 0.5kWh. The result showing that the expect price of Aggregator 1 still lower than that of Aggregator 2. Hence, Aggregator 1 enhances generation, decreases consumption and augments discharge to selling electricity to Aggregator 2. Through 128 times iteration, 64kWh electricity is traded from Aggregator 1 to 2, as Fig. 9-b shown.

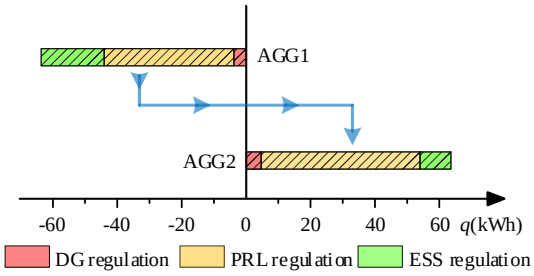

Fig. 9-c. The details of the Tier III

2) The prices and profits analysis

The spot price and total profits of all shareholders are shown in Tab.2. After Tier I calculation, the spot price generated by a micro-grid varies in the range from 0.428 CNY/kWh to 0.598 CNY/kWh. These prices reflect the supply-demand balance of each individual micro-grid. For example, the DERs belonging to 1MG1 has relatively higher DG generation but lowest flexible load. Therefore, they have the lowest spot price due to the large supply abundance. On the contrary, due to the lack of DG, the DERs in the group 2MG2 encounters the highest price because of the shortage of self-balance capability. In Tier II, the micro-grids spot prices for aggregator 1 and aggregator 2 come to around 0.384 CNY/kWh and 0.526 CNY/kWh. It is noted that even the micro-grids or DERs operated by the same aggregator encounter the different prices. That is because the extra regulation fee determined by formula (21) is charged. This price difference also indicates that there exists supply-demand complementarity among the different aggregators. If the energy trading is accomplished in Tier III, the aggregators' profits will increase since energy is more reasonably utilized. Accordingly, the spot prices of aggregators will dynamically change. The prices for participants after trading nearly converge to 0.455 CNY/kWh.

It is observed that the major profit of each stakeholder is determined in Tier I through the inner self-balance scheme. The total profit, as illustrated in Tab.2, has been 1298.59 CNY after executing Tier I process. It increases only a slight amount in Tier II and III, reaching to 1311.17 CNY and 1316.26 CNY respectively. This fact demonstrates that the presented pricing methodology is able to significantly motivate local energy balance within a micro-grid and efficiently reveal the requirement of supply-demand balance via price signal. Additionally, the scheme provides a novel business and technique platform, allowing the flexible energy resources to satisfy the globally optimized energy balance in a win-win manner. For example, The DGs in 1MG2 plan to sell high-cost generation 159.385 kWh in Tier I. Although their generation decreases to in Tier II 158.227 kWh, the profit enhances because of sharing the benefit of cost-effective generation replacement. It is observed that all of the DERs increase their profit during the Tier I, II, and III processes.

Tab. 2. The pricing information of market participants in Tier I, II, and III

		1MG1	1MG2	1MG4	1MG5	1MSS	1UWT	2MG1	2MG2	2MG3	2MG4	2MG5	Total
Tier I	spot price (CNY/kWh)	0.428	0.529	0.457	0.431	0.576	0.342	0.479	0.598	0.512	0.517	0.540	0.494
	Total profit (CNY)	82.58	91.29	172.90	164.66	0.000	32.24	106.77	152.08	198.28	153.78	143.97	1298.59
Tier II	spot price (CNY/kWh)	0.390	0.438	0.411	0.399	0.384	0.384	0.508	0.547	0.520	0.526	0.529	0.475
	Total profit (CNY)	82.70	94.06	173.64	165.02	3.700	36.22	107.09	152.59	198.31	153.79	144.00	1311.17
Tier III	spot price (CNY /kWh)	0.452	0.48	0.456	0.447	0.456	0.456	0.466	0.498	0.481	0.476	0.480	0.471
	Total profit (CNY)	82.96	94.38	173.97	165.51	4.201	36.23	107.72	153.35	199.06	154.32	144.52	1316.26

3) Impact analysis for aggregator assignment

In the presented framework, the DERs can be assigned to any aggregator according to their decisions. In this section, the impact of aggregator assignment is investigated. Here, we take the utility-scale wind generators, 1UWT, as an example. As a generation unit, 1UWT obtains the higher profit when its output can be more easily consumed.

In the initial case, the spot prices for Aggregator 1 and 2 are 0.456 CNY/kWh and 0.532 CNY/kWh. Apparently, Aggregator 2 has less supply adequacy in self-balance process, which results in the higher spot price. In this comparison, 1UWT is assigned to Aggregator 1 and 2 respectively. And then, two independent simulations are executed, results of which are recorded in Tab. 3-a. In general, both aggregator 1 and 2 are able to increase the income by means of including 1UWT in their operation processes. This is because that enhancing utilization of economical DGs in an optimal manner can assist in decreasing generation cost, accordingly enlarging the energy consumption. Specifically, the results show that if 1UWT selects Aggregator 2 as operator, 1UWT can have more profits, i.e. 3.707 CNY. Compared with Aggregator 1, Aggregator 2 has higher spot price which actually makes the output from 1UWT more valuable. On the other hand, the inclusion of 1UWT enlarges supply adequacy of Aggregator 2, leading to the larger spot price reduction. As a result, more demand response is motivated to increase energy usage due to the lower cost. Therefore, more profits are achieved when 1UWT is assigned to Aggregator 2.

On the contrary, for the micro-grid characterized by positive net load, 2MG2 for instance, it is more appropriate to contract with the aggregators with more inclusion of DG asset. In this case, the higher profits of stakeholders will be created. Tab. 3-b shows the results of the studied cases.

In summary, the presented methodology is capable of creating an accurate price signal to reflect characteristics of all the participants, facilitating the optimal operation of the MGC.

Tab. 3-a. The profit of 1UWT selects different aggregators

	aggregator 1 profit (CNY)	aggregator 2 profit (CNY)	1UWT profit (CNY)	Total profit (CNY)
1UWT managed by aggregator 1	521.038	758.992	36.238	1316.268
1UWT managed by aggregator 2	513.799	763.021	39.945	1316.765

Tab. 3-b. The profit of 2MG2 selects different aggregators

	aggregator 1 profit (CNY)	aggregator 2 profit (CNY)	2MG2 profit (CNY)	Total profit (CNY)
2MG2 managed by aggregator 1	556.278	604.868	155.584	1316.730
2MG2 managed by aggregator 2	557.276	605.639	153.353	1316.268

4) Validation of decoupled SOC value model

Based on the decoupled SOC function proposed in Section 3.2, the relation between price and charging/discharging amount is modeled. Additionally, the expected profit for a single action of ESS can be calculated without requiring the information of complete operation cycle. As shown in Tab.4, regardless charging or discharging, ESS is allowed to obtain profit through the optimized strategy. This indicates that the presented tiered framework enables the self-benefit action decision of ESS in the decentralized energy interaction.

In this test, the spot prices at eight and seventeen o'clock have the same value, 0.875 CNY/kWh. That means q_{SOC} at seventeen o'clock has recovered to its initial state and ESS complete an operation cycle. During these times, the total expected profit as well as the total actual profit of ESS is equal to 43.291 CNY/kWh. This test can validate the feasibility of the decoupled SOC value function as well as price-responsive model of the engaged ESS in dynamic pricing scheme.

Tab. 4. Utility-scale ESS profit during 9-17 o'clock

time (h)	8	9	10	11	12	13	14	15	16	17

Tier II	spot price (CNY/kWh)	0.875	0.573	0.539	0.435	0.384	0.410	0.437	0.467	0.613	0.875
	Expected profit (CNY)	0.000	7.684	4.964	9.959	3.700	0.214	0.113	0.170	0.056	1.184
Tier III	spot price (CNY/kWh)	0.875	0.762	0.751	0.576	0.456	0.471	0.508	0.590	0.766	0.875
	Expected profit (CNY)	0.000	3.589	4.456	1.986	0.501	0.367	0.506	1.514	2.333	0.000

6. CONCLUSION

To enable the commercially flexible operation of a micro-grid community, a novel dynamic pricing scheme with full consideration of multiple stakeholders' economic pursuit was studied to facilitate decentralized energy trading. Based on the models of distributed energy resources with price response behaviors, a three-tiered architecture including micro-grid balancing, aggregator scheduling, and trading optimization was presented to discover the spot price that motivates the efficient utilization of distributed energy resources regardless of their location or property ownership. The methodology facilitates micro-grids with high-shares of renewable energy, improves the utilization of renewable energy consumption, and mitigates against the unavailability of traditional centralized dispatching. By means of multi-agent simulation, the results of a realistic case study show that the scheme is able to realize a win-win framework to reliably optimize the operation of micro-grids and distributed energy resources. In addition, it can also guide owners and aggregators to act appropriately according to an iteratively updated price signal, avoiding the underutilization of distributed energy resources. It is observed that the presented methodology provides sufficient business flexibility and can be readily expanded to apply to more markets. Although acquiring win-win results by simulating realistic cases, there are several aspects limiting the scale applications. From the algorithm perspective, some parameters might be difficult to obtain in real applications, such as the price elasticity of the demand, and the uncertainty of generation. Moreover, if the renewable energy proportion in the micro-grid community is small, the profit of local transactions may be outweighed by the cost for establishing the distributed trading platform and communication facilities. With further research and development, distributed renewable energy combined with local transactive framework represent a possible solution for future microgrid operation.

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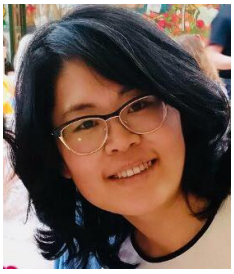

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