Distributed Model Predictive Control Strategy for Islands Multi-Microgrids Based on Non-Cooperative Game

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***Abstract*—The multi-microgrids system of the island group is geographically dispersed with different ownership. A control strategy based on distributed model predictive control is proposed to optimize the economic scheduling of multi-microgrids on island group. The strategy is designed based on the dynamic non-cooperative game theory to regulate the trading behavior among microgrids belonging to different owners. The mechanism maximizes the economic benefits of the microgrids under the premise of ensuring the closed-loop stability of the single microgrid system. Only a minimum amount of communication information exchange is needed, which avoids the demands of the central controller and can help the microgrid to protect its privacy of operating information. The proposed strategy can maximize the benefits of power trading and significantly reduce the operating cost of the system while ensuring the balance between supply and demand. Simulation results are presented to prove the fairness and validity of the proposed control strategy.**

***Index Terms*—Multi-microgrids, island group, distributed model predictive control, non-cooperative game theory, renewable energy generation**

I. Introduction

The traditional power grid has exposed its shortcomings of vulnerability, uncontrollability and information islands in modern times because of increasingly complex operating conditions [1], [2]. Driven by the trend of decentralization and low carbonization [3], [4], Microgrid (MG) has been widely recognized as the cornerstone of the future smart grid which operates a set of micro-sources and loads as a single, controllable system and provides power to its local area [5], [6].

With the increasing of microgrids, Multi-Microgrids (MMGs) structures interconnected by power and information channels have begun to form among microgrids [7]. It means the Energy Management System (EMS) of each microgrid will take into account the behavior of other individuals in the cluster while controlling its own optimized operation. Therefore, how to realize the connection and collaboration between them has become the focus of the research [8]-[12]. The impact of different topologies of multi-microgrids on communication and coordinated scheduling has been discussed in [8]. A sub-gradient-based cost minimization algorithm was proposed in [9], and the optimal solution of the system operation under limited communication overhead was obtained. A multi-step hierarchical optimization algorithm based on multi-agent system was proposed in [10] considering adjustable power and demand response. In [11], the economic operation of MMGs was described as an optimization problem, which proves that the power sharing among MGs and main grid can reduce the total operating cost. In [12], a three-step internal trading strategy for building microgrid is proposed. The Building Energy Management System (BEMS) and Community Energy Management System (CEMS) is used to deal with the optimization of the building itself and energy coordination between the buildings respectively, and through linkage with external large-scale cooling and heat power equipment to reduce energy shortages and reduce transaction costs with the main grid. However, most of the strategies proposed above are based on the stable operation of the microgrids, and the complex equipment modeling will delay the search of a solution.

Considering the impact of high-penetration renewable energy on the stable operation of microgrids, some studies have focused on uncertain energy management in microgrids [13]-[16]. A scenario-based robust energy management method is proposed in [13] to balance the robustness and economy of microgrid under the worst-case scenario. In [14], the Energy Storage System (ESS) is used to provide spinning reserve services for isolated microgrid, and an optimal scheduling mode by using chance-constrained programming is proposed. In [15], a hierarchical decentralized System of Systems (SoS)

Manuscript received December 18, 2019; revised July 01, 2020, accepted July 20, 2020. Date of publication XXX; date of current version XXX. This work was supported by the National Natural Science Foundation of China 51907031; Department of Education of Guangdong Province: New and Integrated Energy System Theory and Technology Research Group 2016KCXTD022; Operation Fund of Guangdong Key Laboratory of Clean Energy Technology 2017B030314127; Brunel Research Initiative and Enterprise Fund (BRIEF). Paper no. TII-19-5397. (Corresponding authors: Chun Sing Lai and Loi Lei Lai)

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TABLE I
FUNCTION COMPARISON BETWEEN THIS PAPER AND RELATED WORKS (Y: YES; N: NO)

Functions	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[26]	[27]	[28]	[29]	[30]	This study
Optimal economic operation of single MG	Y	Y	Y	Y	Y	Y	N	Y	N	N	Y	Y	Y
Real-time operation	N	N	N	N	N	N	Y	Y	Y	Y	N	N	Y
Multi-time scale operation	N	N	N	N	N	N	N	Y	N	Y	N	N	Y
Feedback correction	N	N	N	N	N	N	N	N	N	N	N	N	Y
Uncertainty modeling	N	Y	N	Y	Y	Y	N	N	N	N	N	N	N
Power exchange among MGs	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	Y	Y
Operating information sharing among MGs	N	Y	N	N	N	N	Y	Y	N	N	Y	N	N
Isolated operation of MMGs	N	N	N	N	Y	N	N	N	N	N	N	N	Y
Game among MGs	N	N	N	N	N	N	N	N	N	Y	Y	Y	Y
Bidding methods in power exchange	N	N	Y	N	N	N	N	N	N	N	N	N	Y
Distributed control without control center	N	N	N	N	N	N	N	N	Y	Y	N	N	Y

architecture for MMGs system is proposed, and the energy management problem is formulated as a bilevel optimization considering the issue of uncertainty of renewable energy. A hierarchical stochastic system is proposed in [16], in which the central entity in the upper-level and the Local Energy Management Systems (LEMSs) in the lower-level reduce the power exchange with the external main grid by solving the optimal power flow. However, with the summary and research on the characteristics of the microgrid, real-time operation strategy shows its advantages compared with day-ahead operation strategy because of its timeliness.

Model Predictive Control (MPC) is a kind of control method that emphasizes the state of predictive models [17], [18]. Due to its flexibility and feedback closed-loop stability, it is gradually applied to the optimal control of microgrids [19]-[22]. In the case of MMGs, MPC was initially applied as a strategy for centralized control [23], [24]. However, as the scale of the microgrid expands, the differentiation between microgrids is obvious, and the introduced control strategy that needs to collect a large amount of information faces enormous challenges.

Therefore, the Distributed Model Predictive Control (DMPC) strategy has become another better solution. An online optimal charging strategy for multiple Electric Vehicle (EV) charging stations in the distribution systems was proposed in [25], which satisfies power flow and bus voltage constraints. A peer-to-peer optimization scheme with DMPC was designed in [26], which treats each MG as a single operating point to improve the optimization of the entire network by pairing each other. However, this strategy needs to traverse the entire system in each round of pairing, which still causes huge calculation burden, and the amount of control used this matching mechanism may not be the global optimal solution. In [27], the utilization rate of renewable energy was maximized to reduce the operating cost of energy management. However, the preferential load shedding in the strategy will have a great impact on the users in the microgrid. Moreover, the proportion of energy transmission in the iteration is fixed, which will cause insufficient flexibility in interaction among microgrids.

Nevertheless, the researches mentioned above based on the coordination and cooperation optimization in MMGs, but in reality, the ownership and operator of the microgrids are often different in MMGs. Global optimal scheduling may not be achieved in order to ensure fairness between individuals. Game theory is a framework for solving this problem. A control structure based on Game Theory Agent (GTA) was proposed in [28], and the proposed non-cooperative coordination control method not only guarantees the control-related benefit of the individual agent, but also focuses on the stability of the frequency and voltage in multi-microgrids system and the single microgrid. A feasible comparison between cooperation and non-cooperative game methods for battery energy storage and capacity in multi-microgrids is proposed [29]. However, the analysis and demonstration of non-cooperative game behavior and control strategies are not sufficient. In [30], a two-level game algorithm was studied, in which the upper layer finds the boundary of non-cooperation and cooperation, and the lower layer carries out the cooperative trading loss cost game. However, the game strategies in the abovementioned research [28]-[30] mainly consider the interaction between the microgrids and the distribution network, and the specific interactions and bidding games among microgrids with different owners are rarely mentioned in these studies, which is very important for MMGs applied on islands.

So far, no research has been done to propose a DMPC control strategy for the multi-microgrids system on islands considering the low calculation burden and flexible energy transmission. Furthermore, the analysis of the energy trading behavior among microgrids under the consideration of coexistence of multiple stakeholders is still open to research.

Motivated by the aforementioned research gap, this paper proposes an operation and interaction mechanism among microgrids of different owners. Compared with existing related research, this paper has some improvements in different aspects. More functions could be taken into account with the method as proposed in the present paper. Table I shows the comparison.

The main contributions of this paper are summarized as follows:

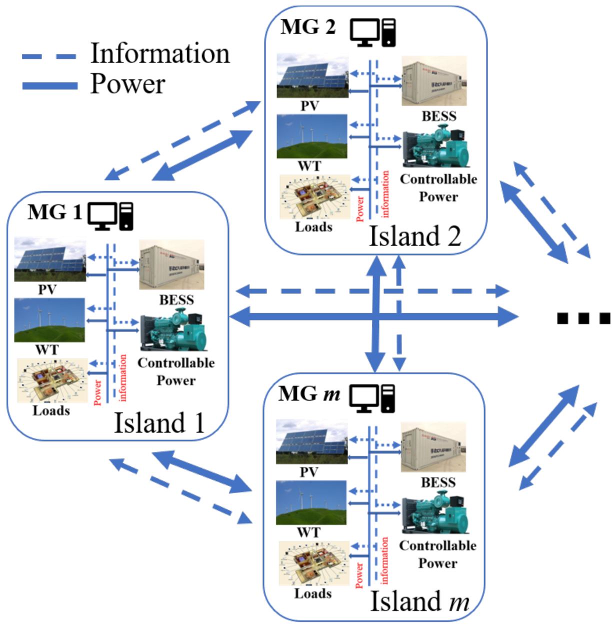

Fig. 1. Multi-microgrids system on islands.

1) By avoiding the complexity of the mathematical model and responding to output uncertainty of renewable energy in small time scale, MPC with closed-loop feedback mechanism is used to model a single microgrid. In order to reduce the pressure on the generators, the reserve power is used as a reference for redistribution in the output correction.

2) In response to the different goals of each microgrid caused by different owners, non-cooperative game is used to ensure the fairness and efficiency of power trading among microgrids. Considering the isolated operation of the islands MMGs system without connecting to the main grid, a method for bidding in the energy trading market based on double auction is provided.

3) Furthermore, based on the non-cooperative game mechanism, as a smaller amount of information sharing can help the microgrid to protect its privacy of operating information, a DMPC strategy is designed to ensure overall optimization and stability of the MMGs system. Simulation results are presented to verify the effectiveness of the proposed strategy.

The remainder of this paper is organized as follows. The system model of MMGs is presented in Section II. Section III shows the DMPC strategy for MMGs based on non-cooperation game. Section IV analyzes the results of the studied cases. Finally, Section V concludes this paper.

II. System Modeling for the Islands MMGs

This section describes the studied MMGs system on islands in this paper, then gives the topology of the single MG, and finally the dynamics of the components are modeled based on the predictive behavior.

A. System Overview

A structure of microgrids for islands is shown in Fig. 1. Each MG corresponds to an island in real life which contains Battery Energy Storage System (BESS), loads, and Distributed Generation (DG) units and has its own sub-microgrid controller. Agents can share information with others. The power can be transmitted via submarine cable. It should be noted that, the number of microgrids can be extended to m or more. In this paper, the MMGs system is not connected to the main grid, which means that the microgrid should consider the self-consumption of regional renewable energy and system balance. It is worth noting that these MGs are likely to belong to different owners or the same owner. We will discuss this further in Section III.

B. Distributed Generation Units

Distributed generation units mainly include uncontrollable and controllable power supplies.

1) *Uncontrollable Power Supply*

Uncontrollable power sources include Photovoltaic generation (PV) and Wind Turbine (WT). Compared to inland, the sea wind is stronger, but it means the volatility is also greater. We represent the renewable energy power as the sum of PV and WT:

$$PR_i(k) = PV_i(k) + PW_i(k) \tag{1}$$

Considering the cleanliness of renewable energy, people want to use it to meet the demand first, and try to maximize energy efficiency.

2) *Controllable Power Supply*

Because of the uncertainty of renewable energy, controllable power supply such as fuel cells, gas turbines, and diesel engines should be considered in practical applications. The dynamic model of these power supplies are as follows:

$$PG_i(k+1) = PG_i(k) + \Delta PG_i(k) \tag{2}$$

where $PG_i(k+1)$ is the output of generator in MG i at period $k+1$ and $\Delta PG_i(k)$ is the controlled variable. These variables also need to meet the following constraints:

$$PG_i^{\min} \le PG_i(k+1) \le PG_i^{\max} \tag{3}$$

$$\left|\Delta PG_i(k)\right| \le \Delta PG_i^{\max} \tag{4}$$

where $PG_i^{\min}$ and $PG_i^{\max}$ indicate the normal operating range of the generator. $\Delta PG_i^{\max}$ indicates the upper limit of the ability to adjust.

The cost function focuses on the fuel consumption, which is modeled as:

$$J_i^G(k) = [\lambda_i(PG_i(k))^2 + \gamma_i(PG_i(k))]\cdot T \tag{5}$$

where λ and γ are a positive constant determined by the generator. T is the time scale of control strategy.

C. Battery Energy Storage System

As an important backup force for DG, ESS can store excess renewable energy or supplement demand in time to ensure the balance between supply and demand during operation. Considering the economy and reliability of island construction, BESS is a common choice in many projects [31], [32]. The dynamic model of BESS is as follows:

$$SOC_i(k+1) = SOC_i(k) + \eta_i PB_i(k)\cdot T \tag{6}$$

$$\begin{cases} SOC_i^{\min} \le SOC(k) \le SOC_i^{\max} \\ -PB_i^{\max} \le PB_i(k) \le PB_i^{\max} \end{cases} \tag{7}$$

where $SOC_i(k+1)$ is energy stored in BESS at period $k+1$. $SOC_i^{\min}$ and $SOC_i^{\max}$ are the maximum and minimum allowable amount for storage of the BESS. $PB_i(k)$ is the output power of the BESS at period k in MG i. $PB_i^{\max}$ is the maximum output of BESS. And η_i is a charging/discharging efficiency factor:

$$\eta_i = \begin{cases} \eta_i^{ch}, & PB_i(k) \ge 0 \\ 1/\eta_i^{dis}, & PB_i(k) < 0 \end{cases} \tag{8}$$

where $0 < \eta_i^{ch},\ \eta_i^{dis} < 1$.

The battery has limited service life, so the operation goal should minimize the number of BESS working hours. The system should also avoid large current in charging and discharging because the maintenance costs will be paid for this. Therefore, the cost function of BESS is described as:

$$J_i^B(k) = [\frac{C_i^{con}}{2 \cdot Cycles_i \cdot C_i^{cap}} PB_i(k) + C_i^{\deg}(PB_i(k))^2] \cdot T \tag{9}$$

where C_i^{con} is construction cost for BESS. $Cycles_i$ is the number of life cycles for battery. C_i^{cap} represents the capacity of the battery. $C_i^{\deg}$ refers a penalty factor of deep charging and discharging process.

D. Loads

Based on past data, the system's load demand for the whole day can be predicted relatively accurately. The load model during the period k is as follows:

$$PL_i(k) = PLu_i(k) + PLc_i(k) \tag{10}$$

where $PLc_i(k)$ and $PLu_i(k)$ are shedding load and residual load. The cost of the loads comes from compensating the users for dissatisfaction with the part of the load that is cut:

$$J_i^L(k) = C_i^{cut} PLc_i(k) \cdot T \tag{11}$$

where C_i^{cut} is compensation unit price which usually is high. Thus, this cost should be avoided as much as possible during the optimizing process.

E. System Power Balance Constraint

Combining the models in (1), (2), (6), and (10), we can get the power balance constraint in the system as follows:

$$PB_i(k) = PG_i(k+1) + PR_i(k) - PL_i(k) + PLc_i(k) \tag{12}$$

III. Non-Cooperative Game Based Distributed Model Predictive Control Strategy for Islands MMGs

In this section, the MPC strategy for single MG and the DMPC strategy based on dynamic non-cooperative game of the islands MMGs are described.

A. MPC For Single MG

According to the model in the Section II, the cost function can be described as:

$$J_i = \sum_{k \in M} (J_i^G(k) + J_i^B(k) + J_i^L(k)) \tag{13}$$

Therefore, the optimization function for a MG can be described as follows:

$$\begin{cases} Objective: & Min\ J_i \\ Constraints & (3),(4),(7),(12) \end{cases} \tag{14}$$

However, it should be noted that when the optimal control solution is solved, we only input the control amount of length N to the system until the next sampling time $k+N$. The system will then scroll forward over time. N and P are represented as a control layer and a rolling layer, respectively.

The feedback module is aimed at the deviation of smaller time scales. It forms a closed-loop control unique to MPC, which has a significant effect on the stable operation of microgrid system with large disturbance fluctuations, which is mainly divided into two parts.

1) *Predictive correction*

Due to the daily variability of natural resources, the forecast curve of renewable energy power generation is not accurate. The actual output of renewable energy obtained from each data sampling point will be different from the predicted output. Therefore, in smaller time scale, the prediction correction module will analyze the error obtained in the past between the actual and the predicted value. The new prediction data at the feedback layer time scale will be calculated. Finally, in order to adjust the expected dispatch strategy of the microgrid, the newly obtained forecast data will be sent to the output correction module.

For uncertain data, gray theory is an effective forecasting method to reduce the randomness of data under small samples [33]. Therefore, in this paper, the grey forecasting model is used to correct the prediction curve in the ultra-short-term in the future based on the sampling information known in the past.

2) *Output correction*

After obtaining the output from the prediction module, the microgrid system needs to adjust its own scheduling plan. If no measures are taken, all deviations will be automatically undertaken by the controllable power supply, which is very dangerous. Considering the stability of system in small time scale, the principle of redistribution is described as the minimal pressure on remaining power capacity. The goal can be described as:

$$Min\ \Delta P_i = \frac{|\Delta PG_i'|}{(PG_i^{\max} - PG_i(k+1))} + \frac{|\Delta PB_i'|}{(PB_i^{\max} - |PB_i(k)|)} \tag{15}$$

$$s.t. \begin{cases} PG_i^{\min} \le PG_i(k+1) + \Delta PG_i' \le PG_i^{\max} \\ -\Delta PG_i^{\min} \le \Delta PG_i' \le \Delta PG_i^{\max} \\ -PB_i^{\max} \le PB_i(k) + \Delta PB_i' \le PB_i^{\max} \\ SOC_i^{\min} \le SOC(k+1)' \le SOC_i^{\max} \\ PB_i(k) + \Delta PB_i' = PG_i(k+1) \\ \qquad + \Delta PG_i' + PR_i(k)' - PL_i(k) + PLc_i(k) \end{cases} \tag{16}$$

where $\Delta PG_i'$ and $\Delta PB_i'$ represent the values redistributed to the DG and BESS, respectively.

By solving the optimal problem, the microgrid will obtain a new operation schedule and it will be executed in the next feedback module period. Before the next sampling time of the

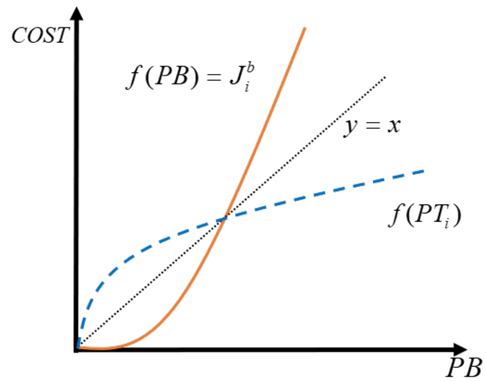

Fig. 2. The principle of seller bidding.

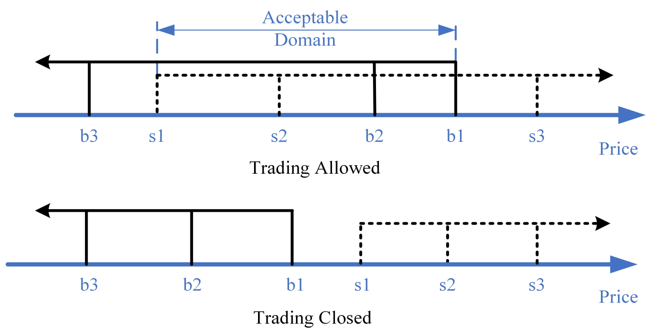

Fig. 3. Conditions for opening the trading market.

rolling layer arrives, the feedback module will be continuously looped on the time scale of the feedback layer.

B. Non-Cooperative Game Strategy

For MGs with power shortages, the use of controllable power supplies and fuel transportation will increase operating costs. For MGs with surplus power, the extra energy stored in the BESS also requires operation and maintenance costs, and the initial construction cost will increase with more demand for battery capacity. Therefore, in the condition of convenient communication and power transmission, owners will actively participate in power transactions within the MMGs in order to obtain more benefits. From the perspective of green and economic operation of the microgrids in island environments, only renewable energy is considered as the transaction content among MGs. The net power in a MG can be defined as follows:

$$PT_i(k) = PR_i(k) - PL_i(k) \tag{17}$$

If $PT_i(k) > 0$, it indicates that the MG has excess power at this time, and we call these MGs as sellers. If $PT_i(k) < 0$, we call them as buyers. Buyers try to seek a lower price among the sellers, and the sellers want to obtain the highest selling price.

First, M_b and M_s are defined as the number of buyers and sellers in MMGs with m MGs. Then the conditions for the existence of the transaction are:

$$M_t = M_b \cdot M_s \neq 0 \tag{18}$$

The general non-cooperative game model G is defined as follows:

$$G = \langle \Gamma; S; U \rangle$$

where Γ represents the participants including buyers and sellers. S represents the strategy. If the buyer bid from MG i

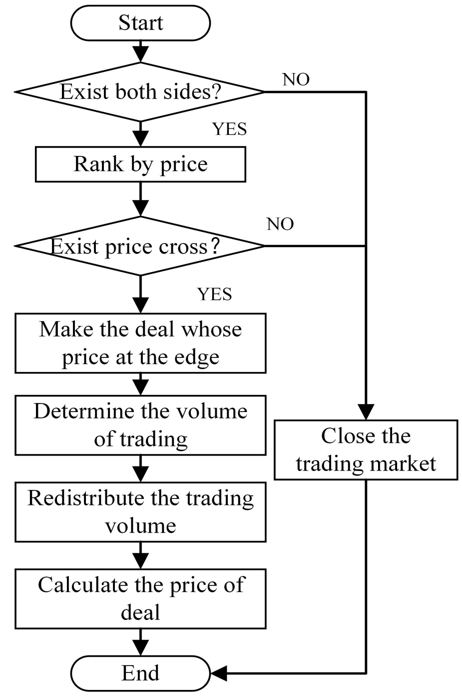

Fig. 4. The flowchart of the trading market.

is b_i and the seller is s_i, the strategy set is $[0, b_i^{\max}]$ and $[s_i^{\min}, +\infty]$. U represents the gain. The gain is the cost of operating for the buyer. The gain for the seller is the profit of the sale.

For buyer, the cost of powering for net power is described as follows:

$$J_{i,k}^{lack}(PT_i(k)) = \alpha_i (PT_i(k))^2 + \beta_i \left| PT_i(k) \right| + \varepsilon_i \tag{19}$$

where α_i, β_i and ε_i are determined by power supply method. According to the definition of marginal cost, the bidding rule is defined as

$$b_i \le \frac{\partial J_{i,k}^{lack}(PT_i(k))}{\partial PT_i(k)} = 2\alpha_i PT_i(k) + \beta_i \tag{20}$$

For seller, the higher net power means the more management costs, which increases the seller's sales expectations, that is, accepts lower prices. According to (9), the charging cost of the BESS is a quadratic curve shown as the solid line in Fig. 2. If we take the curve which is symmetrical about $y = x$, the function of this curve is expressed as follows:

$$\begin{cases} f(PT_i(k)) = \left(\dfrac{2PT_i(k) + C_i}{2C_i^{\deg}}\right)^{\frac{1}{2}} - \dfrac{C_i}{2C_i^{\deg}} \\ C_i = \dfrac{C_i^{con}}{Cycles_i \cdot C_i^{cap}} \end{cases} \tag{21}$$

The marginal function of this curve will respond well to our assumptions. Thus, the bidding strategy of seller is

$$s_i \ge \frac{\partial f(PT_i(k))}{\partial PT_i(k)} = \frac{1}{2C_i^{\deg}} \cdot \left(\frac{2PT_i(k) + C_i}{2C_i^{\deg}}\right)^{-\frac{1}{2}} \tag{22}$$

In the transaction process, the principle of two-way auction is adopted. After the bidding, the price from sellers is sorted from small to large, and the buyers is reversed. As shown in Fig. 3, if there is a cross of two sets on the price axis, the

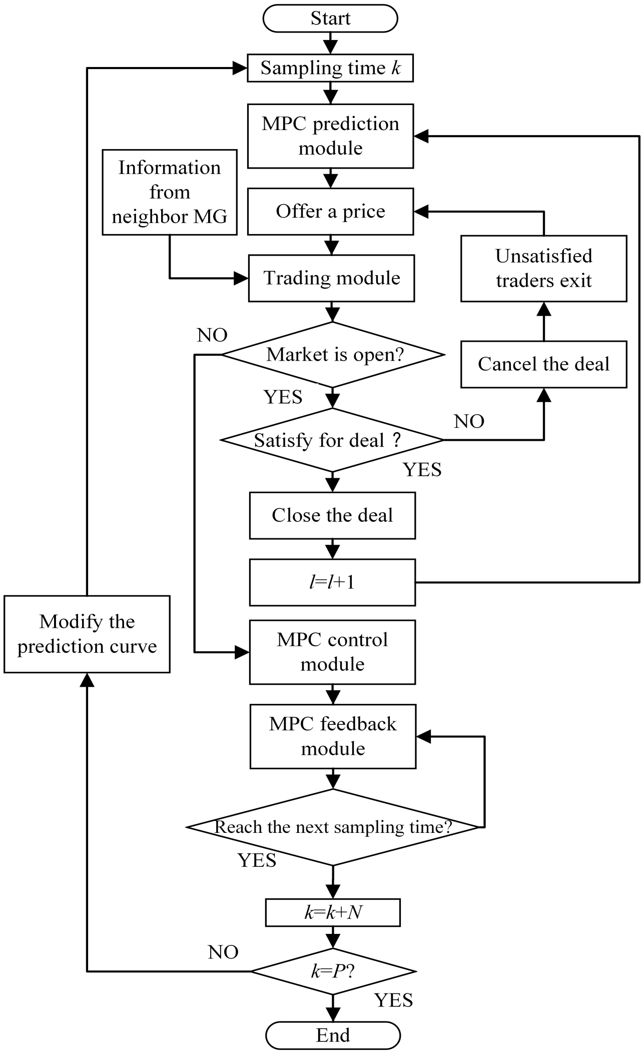

Fig. 5. The flowchart of DMPC strategy for islands MMGs.

transaction can proceed. If the quotation of any MG exceeds this range, it is considered that no one accepts the transactions and this MG will quit the trade. In pursuit of maximizing benefits, two individuals whose price is on the edge of this cross will close the deal. On the other hand, if the crossover does not appear, it means that the transaction cannot satisfy the interests of anyone, and the trading market will be closed. The flowchart of the trading market is shown in Fig. 4.

However, the transaction is not one-off. According to (20) and (22), the smaller the value of net power, the more favorable price for both parties can get, and both are willing to see. The total power shortage of the system is defined as

$$PS(k) = \sum_{i \in buyer} PT_i(k) \tag{23}$$

It represents the sum of the power shortages of all buyers in the system. Then the trading volume is

$$PE_i(k) = \sigma \cdot \omega \cdot P_{tra} \tag{24}$$

where $P_{tra} = \max[PT^{sell}(k), PT^{buy}(k)]$. $PT^{sell}(k)$ and $PT^{buy}(k)$ represent the total net power of sellers and buyers of trading that close the deal, respectively.

If $PT^{buy}(k) = PS(k)$, it means there is only one buyer in the system, and $\omega \in [0,1]$. If $PT^{buy}(k) < PS(k)$, it means there are other buyers in the system waiting to purchase, and $\omega = PT^{buy}(k) / PS(k)$. σ indicates transaction status. $\sigma = 1$ and $\sigma = -1$ is for buyers and sellers, respectively.

If there are multiple sellers or buyers bid the same price, they may close the deal together. In this situation, they are firstly treated as a whole to calculate the trading volume, and then the power will be distributed according to the ratio of their net power.

C. DMPC Strategy for Islands MMGs

As mentioned in Section II-A, the microgrids in MMGs system may have different owners. The ownership can be divided into two situations in an MMGs system on islands, that is, single owner and the coexistence of multiple owners.

Due to construction costs are high and other reasons, most of the microgrid projects of the island group in real life are of the latter case. Therefore, we should make it clear that the operation information and construction of a MG are related to the security and privacy of a company, that cannot be shared, and it is difficult for the third-party or public control centers to join because of geographical factor.

It is assumed that a MMGs system has multiple owners. The microgrids belonging to the same company are regarded as a whole entity.

Thus, only a small amount of information can be shared between the microgrids. θ_k^i is defined as the state of MG i at time k, and it is shown as

$$\theta_k^i = (i, |PT(k)|, price, tr) \tag{25}$$

where $price$ represents the bidding price. $tr = [V_s, V_b]$, where V_s and V_b represent the identity of the seller and buyer, which are logical variables, respectively. Therefore, the collection of the shared information sent from a MG to others can be expressed as

$$MG_i = [\theta_1^i, \theta_2^i, \ldots, \theta_M^i]^T \tag{26}$$

The flowchart of entire strategy is shown in Fig. 5. After receiving the information from others, the sub-microgrid controller will go into the trading market as described in Section III-B. Due to the complex weather conditions of the islands, the signal transmission cannot be guaranteed to be stable. Therefore, the acceptance of the signal has a certain time limit. Hence, the proposed DMPC strategy also ensures that the microgrid can exit the transaction in time when the signal could not be sent out, to provide the plug-and-plug function for microgrids and ensure the robustness of the operation of MMGs.

On the other hand, according to the trading method proposed above, the cost function of each MG in MPC will be changed as

$$J_i = \sum_{k \in M} (J_i^G(k) + J_i^B(k) + J_i^L(k) + J_i^T(k)) \tag{27}$$

where

$$J_i^T(k) = \sum_l pr(l,k) \cdot PE_i(l,k) \tag{28}$$

$$pr(l,k) = \frac{price_s(l,k) + price_b(l,k)}{2} \tag{29}$$

TABLE II
MULTI-MICROGRIDS PARAMETERS

	MG 1	MG 2	MG 3
Controllable DG (kW)	1000	600	600
BESS (kWh)	1400	1400	2000
PV (kW)	600	400	700
WT (kW)	600	400	700

TABLE III
DEVICE PARAMETERS

	MG 1	MG 2	MG 3
ΔPG max (kW)	500	400	400
SOC max (p.u.)	0.85	0.85	0.85
SOC min (p.u.)	0.15	0.15	0.05
PB max (kW)	500	500	500
λ (¥/kW^2)	0.4	η^{ch}	0.85
γ (¥/kW)	0.38	η^{dis}	0.9
C^{con} (¥/kWh)	125	*Cycles*	3000
$C^{\deg}$ (¥/kWh^2)	0.2		

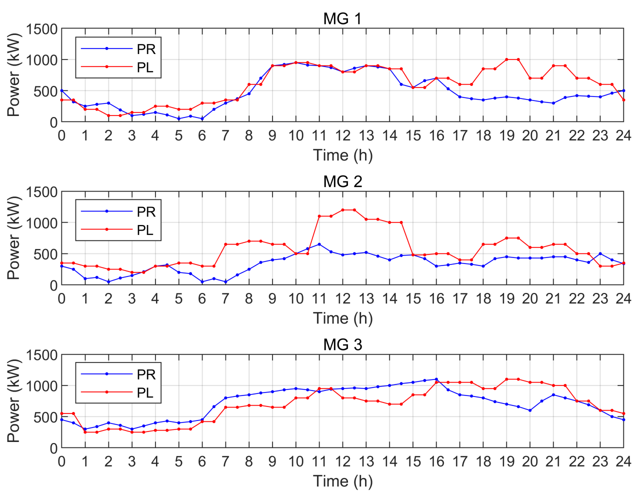

Fig. 6. The forecast curves of renewable energy and loads.

where l indicates the round of trading. pr indicates dealing price in this round.

The dealer will recalculate operating costs. If the cost of all traders is reduced, that is, everyone satisfied with the trade, the deal can be confirmed. If someone is not satisfied with the outcome, this means the match is unsuccessful, and the unsatisfied party withdraws from the current round of trading ($tr = [0,0]$) to wait for the next round. The rest of the traders will return to the trading market to rematch. Confirmation of the deal leads to the end of the current round of trading. Each MG will be forced to resend information according to the new system status into the next round of trading markets. Until the seller or buyer does not exist, the trading market will be closed.

After that, each system will summarize the order and complete the power transfer. The system then enters into autonomous operation with MPC strategy, which will input the control amount ($u^* = [u_1, u_2, \ldots, u_N]$) into its own system.

Finally, the feedback module will be run repeatedly in a smaller time scale before the next sampling time $k+N$.

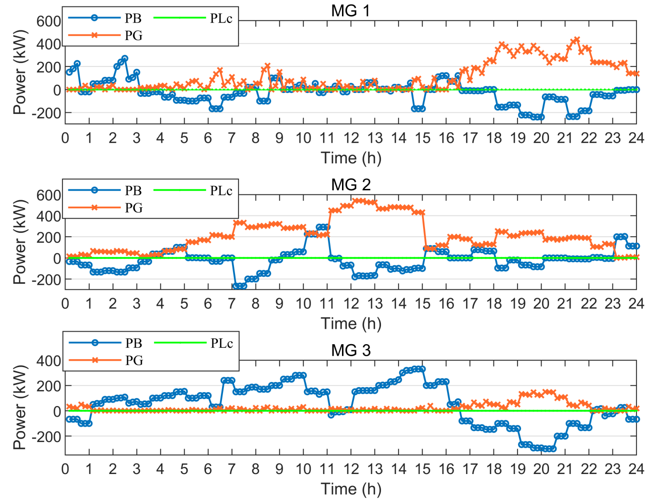

Fig. 7. The operation without communication among microgrids.

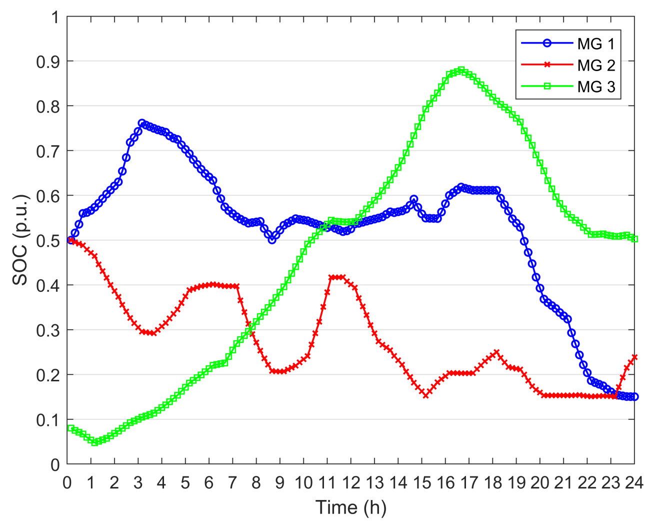

Fig. 8. The change in battery power within one day.

IV. VERIFICATION RESULTS AND DISCUSSIONS

The proposed control strategy is applied in an islands MMGs system which consists of three microgrids, and each microgrid comprises PV, WT, BESS, gas turbine and loads, as presented in Fig. 1. The MMGs parameters and the device parameters of the three MGs are presented in Table II and Table III, respectively. It should be noted that unlike general residential microgrid, due to land occupation and investment restrictions on the islands, the capacity of energy storage systems cannot be configurated too large [34]. Each MG is controlled by MPC for 24 hours. The rolling layer $P = 24$, the prediction layer $M = 8$, and the control layer $N = 1$. This means that the sampling interval is 0.5 hour. In addition to this, the time interval of the feedback layer is 10 minutes. All simulations were run in MATLAB with YALMIP solver.

A. Single Microgrid Operation

The renewable energy and loads forecast curves of the three MG are shown in Fig. 6. 10% of the random disturbances is added to simulate the actual renewable energy curve.

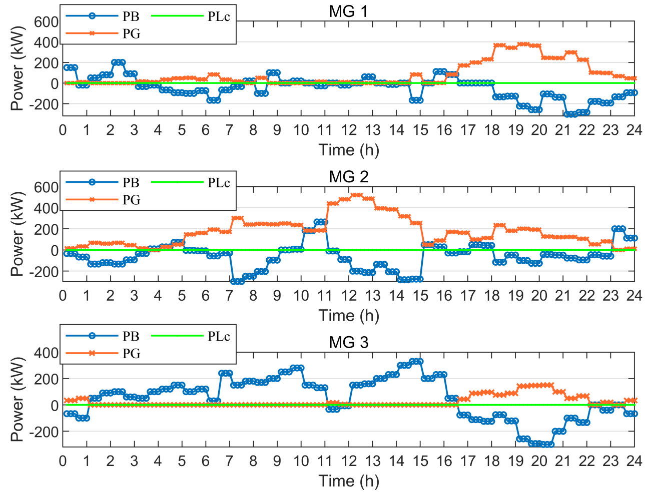

Fig. 9. The operation of MPC without feedback module.

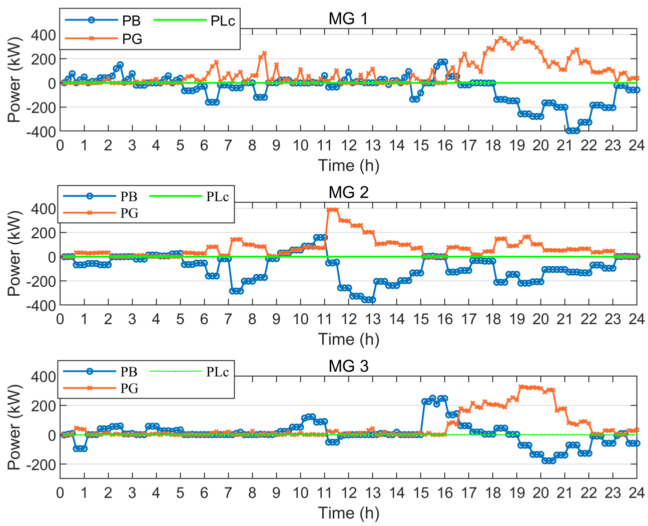

Fig. 10. The simulation of operation with DMPC strategy.

Obviously, different requirements and output characteristics will result in different operating curves, which will bring about the possibility of energy exchange and trading between systems.

When there is no communication between the MGs, each MG will be operated by MPC independently. The operation is shown in Fig. 7. It should be noted that the capacity of each microgrid is different. Fig. 8 shows the change in battery power.

As shown in Fig. 7, the curve of renewable energy basically meets the loads in MG 1 from 0 am to 4 pm. The system is in a state of smooth operation. However, MG 2 represents a microgrid of insufficient supply, which is in a state of power shortage for most of the time from 0 am to 4 pm. Especially from 11 am to 2 pm, the demand gap is pulled to the maximum, and the generator output is close to full load. If the load at this time is greater during actual operation, the generator will enter the hazardous operating area or agent must consider the load shedding.

On the other hand, as presented in Fig. 8, MG 3 has surplus power. As shown in Fig. 6, from 0 am to 4 pm, the supply curve is basically above the demand curve, which means that the main cost source is the charging of the battery, and the more battery

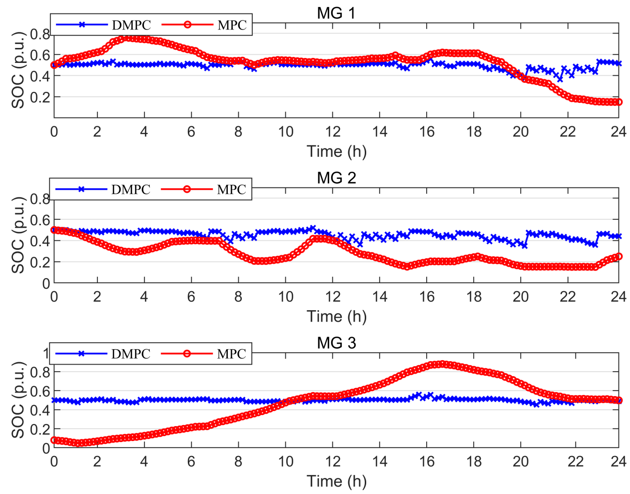

Fig. 11. The comparison of energy storage in operation of MPC and DMPC.

capacity must be considered before construction. In addition, at the end of a day, the remaining power of the BESS is about 50%, which makes pressure on energy storage capacity for the BESS of MG 2. Therefore, agent will have to discard a portion of the energy for the next day operation.

Moreover, all three MGs have different levels of power shortage from 4 pm to 12 am.

B. Comparison with MPC without Feedback Module

The operation results of a single microgrid under the MPC strategy without a feedback module in smaller time scale like [35] are shown in Fig. 9. The fluctuations caused by the uncertainty of the renewable energy will generally be borne by the controllable generator when there is no feedback module in the control strategy of the real microgrid project. Especially for MG 2, due to the lack of renewable energy, the controllable generator will run in a high output state from 11 am to 2 pm. In this case, even small fluctuations will pose a security threat to the microgrid, and the output margin of the generators is also low which cannot withstand greater fluctuations.

Compared with Fig. 7 for the MPC strategy, in the small-time scale, BESS will share part of the pressure of the generator according to the redistribution rules of the MPC strategy with the feedback module and reduce the output variation of the controllable generator effectively. However, at other times, due to the larger operating margin of the generator, the redistribution principle will actively use the generator to suppress fluctuations. In general, the feedback module enhances the stability of microgrid operation timely and effectively.

C. Non-Cooperative Game-Based DMPC Strategy

The proposed DMPC control strategy in this paper is adopted in the operation of the MMGs system, and the results are shown in Fig. 10. The strategy effectively reduces the operating range of the equipment in the system and avoids large fluctuations of the output of the controllable generators and BESS. This not only reduces the loss of equipment life but also significantly improves the utilization rate of renewable energy from the perspective of the entire multi-microgrids system.

Fig. 11 shows the comparison results of battery power when the proposed non-cooperative game-based DMPC strategy and

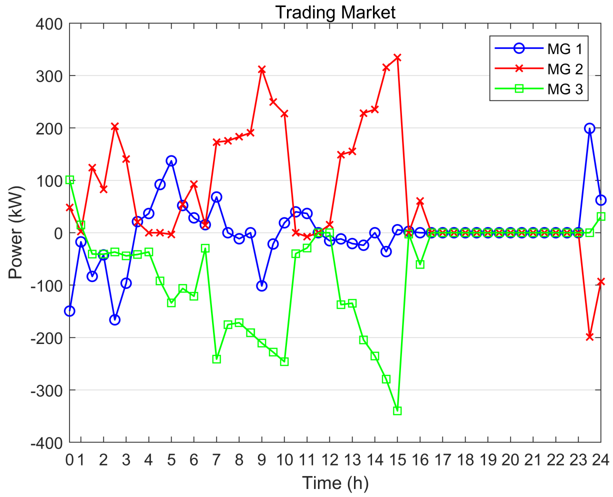

Fig. 12. Electricity trading amount among microgrids in one day.

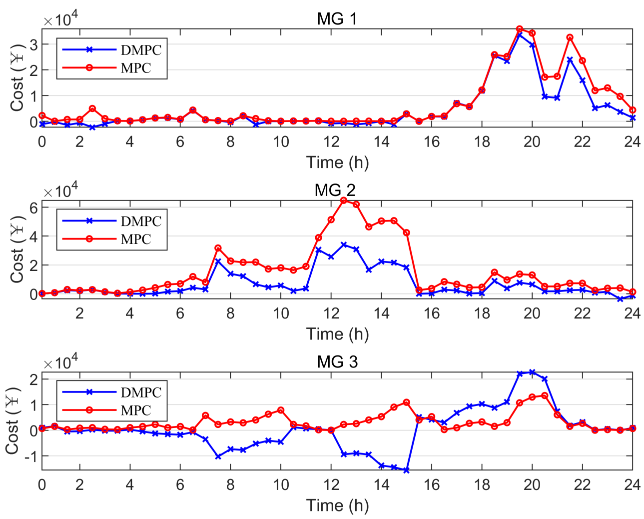

Fig. 13. Comparison of operation costs in a day with MPC and DMPC strategy.

TABLE IV
COST STATISTICS

MG	STRATEGY	
	MPC ($1\text{x}10^4$ ¥)	DMPC ($1\text{x}10^4$ ¥)
1	30.608	21.732
2	74.442	32.939
3	15.172	2.4074

TABLE V
RELATIVE ERROR OF THE NET LOAD FOR DIFFERENT CONTROL STRATEGIES

MG	STRATEGY			
	Rolling optimization (single MG) (%)	MPC (single MG) (%)	Rolling optimization (MMGs) (%)	DMPC (%)
1	2.7576	2.2597	2.3260	1.9133
2	1.0258	0.8849	1.1683	1.1338
3	1.1265	0.8588	7.2763	3.4485

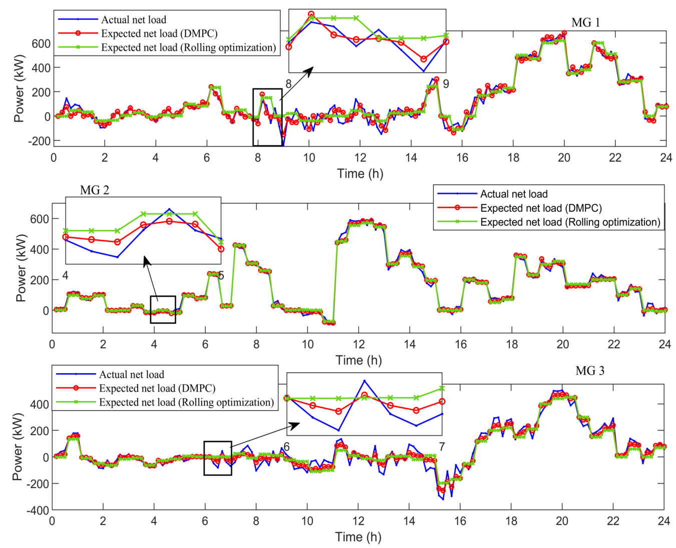

Fig. 14. Comparison of net load in a day with rolling optimization and the proposed DMPC.

the conventional MPC strategy are applied respectively.

The proposed DMPC strategy enables the MG to get external power replenishment in time, slows down the trend of self-discharge, and makes the running curve BESS more gradual. Especially for MG 3, since the excess energy is sold in time, the battery does not need to bear the same storage pressure as before. It means that the owner has more selectivity and can reduce the investment cost of a large part of the upfront.

In addition, compared to the single microgrid MPC operation in Fig. 7, it can be found that from 4 pm to 12 am, the curves of the equipment output change little before and after the proposed DMPC strategy is applied. That is because the three MGs are all in a state of power shortage, and the MGs will choose to operate in island mode. The trading market of the whole day is shown in Fig. 12 in which positive power means purchase, and negative means sale.

As depicted in Fig. 12, MG 2 has the largest power shortage and is willing to buy the most energy and accept higher prices. MG 1 rarely participates, and MG 3 basically assumes the role of the seller. Nevertheless, what's important is that this kind of transaction is not monopolized. Every microgrid has the opportunity to participate in trading rounds, so that the total transaction will satisfy everyone.

For the ultimate goal of optimization, the operation costs in a day with MPC and the proposed DMPC strategy is compared in Fig. 13. If the cost is less than zero, it means the system is profitable. It can be observed from Fig. 13 that MG 1 gains some small profits in the early stage. The most obvious change comes from MG 2 and MG 3. The cost curve of MG 2 has dropped significantly from 7 am to 3 pm. The strategy has brought a lot of profit to MG 3 by filling the cost of the afternoon.

The total cost of the day is shown in Table IV. Also, it can be observed from Table IV that the total cost of one day of the MG using the proposed DMPC strategy is significantly reduced compared to the independent operation. Among them, the cost of MG 1 has been reduced by 29 %, and the reason for this has been analyzed in Section IV-A. 55.8 % and 84.1% of the cost is reduced in MG 2 and MG 3, respectively.

Moreover, net load is adopted to evaluate the performance of the proposed control strategy. The net load of the microgrid is calculated as follows:

$$P_{et}(k) = PL(k) - (PR(k) + P_{deal}(k)) \tag{30}$$

where P_{deal} is the trading volume in the trading market. The average relative error of the net load is used as the performance evaluation indicator of the proposed strategy in dealing with the uncertainty of renewable energy, which is calculated as follows [36]:

$$\frac{1}{D}\sum_{k=1}^{D}\frac{\left|P_{et}-P_{ac}\right|}{P_{ac}} \tag{31}$$

where D is the number of data points. P_{ac} indicates the actual net load.

The calculated results are shown in Table V and Fig. 14. It can be seen that the microgrid can predict the future error and track the actual net load well, under the effect of the feedback module for a single MG. Thus, the average relative error is significantly reduced as compared to the rolling optimization method, which reflects that MPC has excellent performance to uncertainty of renewable energy. On the other hand, for the MMGs system, this value has changed based on the energy for the trading. The transaction means that the MGs will receive or lose a part of renewable energy. Therefore, the relative error will change when the absolute error remains unchanged. Therefore, as shown in Table V, the average relative error of DMPC for MG 1 is similar to that of the rolling optimization. For MG 2, the purchase of a large amount of renewable energy will reduce the proportion of the impact caused by the uncertainty of renewable energy in the microgrid. On the contrary, for MG 3, the sale of this part of energy will cause the relative influence of uncertainty to be amplified, which cause the increase of the average relative error using rolling optimization method compared with MPC and DMPC. However, it should be noted that under different control strategies, the absolute deviation caused by this uncertainty to the microgrid is unchanged. As seen from Table V and Fig. 14, the proposed DMPC strategy still predicts the error very well as compared to rolling optimization. The proposed control strategy has good robustness to the uncertainty of renewable energy during MMGs operation.

V. Conclusion

In this paper, a DMPC strategy is proposed to optimize energy management for multi-microgrids systems on islands. The design of this strategy is based on the non-cooperative game theory with two-way auction, which guarantees fair and efficient power trading among microgrids. In the MPC feedback module and considering the stability of the system, a redistribution correction scheme with the minimum change amount as the objective function is designed to prevent the system from being in dangerous operation because of excessive pressure to generators.

Verification results show that the networked operation of microgrids on the islands using the proposed DMPC strategy can significantly improve the utilization rate of the overall renewable resources of the system, reduce the economic operation cost, and increase the service life of batteries and other equipment. The proposed non-cooperative game-based DMPC strategy requires only a minimal amount of information sharing among microgrids, which can help the microgrid to protect its privacy of operating information. In addition, the enabling conditions of the microgrid interaction only depend on the acceptance of the signal, which prevents the damaging of MMGs system operation from communication failure. Furthermore, results show that the interactive strategy based on non-cooperative game can reasonably and efficiently distribute surplus renewable energy in microgrids cluster, which meet interests of multiple owners in MMGs at the same time.

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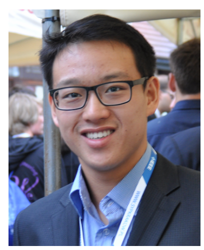

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