An energy management model for isolated microgrid community considering operation flexibility

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Abstract. The isolated microgrids adjacent to each other form an isolated microgrid community, which can realize optimal resource allocation among microgrids with different source-load characteristics through energy sharing, thereby improving the economical, reliability and renewable energy utilization of regional power system operation. Aiming at the energy management problem of the isolated microgrid community, a hierarchical energy management architecture of the isolated microgrid community was established. On this basis, the flexibility index is introduced to evaluate the impact of renewable energy output uncertainty on system operation. A multi-objective optimization energy management strategy as well as a community layer energy allocation strategy is constructed. The linearized model is solved by the tolerant lexicographic method. Finally, an isolated microgrid community consisting of four microgrids is taken as an example to verify the effectiveness of the proposed energy management strategy.

1. Introduction

As a kind of micro-energy system integrating “source-load-storage”, microgrid can cope with the safety and stability problems brought by a large number of distributed energy sources to the power distribution system through internal control, thus improve the acceptability and utilization efficiency of distributed renewable energy [1-2]. On this basis, by connecting multiple adjacent microgrids via feeders to form an integrated network of interconnection, namely microgrid community, the dispersion, randomness, intermittence and volatility of distributed power sources can be effectively compensated. In terms of the operation mode of the microgrid community, it can be divided into two types: grid-connected type and isolated-type. The isolated type is mainly used in two cases. First, it is difficult to connect to the distribution network due to geographical or natural environment, such as islands and other isolated areas; Second, when the power grid is seriously faulty, in order to ensure reliable supply of critical loads, the microgrid disconnects with the distribution network into the isolated operation. Due to the lack of interaction with the outside system, the operation of the isolated-type microgrid community is more susceptible to the allocation of resources within the system. Studying its internal energy management mechanism is of great significance to the economics and reliability of the isolated microgrid community.

The energy management of microgrids is a process of optimization and decision-making. In the existing research on microgrid management and control, its models can be divided into three
categories: centralized, hierarchical and distributed. The centralized system treats the whole system as a whole, and the central node collects data related to the optimization decision problem from all network nodes in a unified manner, and calculates the optimal decision of the optimization problem. Literatures [3-4] use centralized optimization to establish a microgrid energy management model that considers multiple optimization objectives, energy storage strategies, and market transactions, but they rely too much on the central controller and has poor reliability. In the hierarchical architecture, the lower controller operates local data for local optimization calculations, and then sends the local calculation results back to the upper control nodes. In the hierarchical optimization, because each control unit needs to interact to make the decision, the literature [5-6] introduce the multi-agent system to model and optimize the energy management problem of the microgrid. In the literature [7], both centralized and distributed methods are proposed to solve energy transaction problem in the residential microgrid. And the effectiveness of different algorithms in different information scenarios is compared.

A large number of renewable energy power generation equipment such as wind turbines and photovoltaics are connected to the microgrid, and the impact of the uncertainty on the efficient and reliable operation of the system cannot be ignored. The focus of previous research is on optimization based on uncertainty at a certain time [8-9]. However, due to the double uncertainty of meteorological conditions and prediction levels, the fluctuations in the system cause the netload to exhibit a “duck curve” pattern that changes with time [10]. Existing researches on microgrid energy management mainly focuses on the economic operation of a single microgrid, but do not fully consider the coordinated operation of microgrid community composed of different stakeholders and the impact of renewable energy uncertainty on system operation.

In this paper, for the isolated microgrid community, the risk index of flexibility shortage is established to evaluate the impact of RES generation uncertainty on the system operation. The lowest operating cost, the lowest risk of flexibility shortage are optimal objectives of the microgrid. On this basis, considering the differences and autonomy requirements of each microgrid, a hierarchical energy management model for isolated microgrid community is constructed according to the energy interaction intention of each microgrid.

2. Microgrid operation flexibility

For the isolated microgrid system, the flexibility requirement refers to the netload fluctuation caused by the fluctuation of the load and the renewable energy output within a certain time window, and can be divided into the upward flexibility demand \( FRU \) and the downward flexibility demand \( FRD \) according to the fluctuation direction. The expression is:

\[
FRU(t, \Delta t) = \max \{ P_{\text{var}}(t, \Delta t) + P_{\text{an}}(t, \Delta t), 0 \} \tag{1}
\]

\[
FRD(t, \Delta t) = \max \{ -P_{\text{var}}(t, \Delta t) - P_{\text{an}}(t, \Delta t), 0 \} \tag{2}
\]

\[
P_{\text{var}}(t, \Delta t) = \overline{P_{\text{net}}}(t + \Delta t) - \overline{P_{\text{net}}}(t) \tag{3}
\]

where \( P_{\text{var}}(t, \Delta t) \) is the fluctuation value of the netload during the time period \( t \) to \( \Delta t \), the uncertainty part \( P_{\text{an}}(t, \Delta t) \) is the error fluctuation range of the netload prediction value, \( \overline{P_{\text{net}}}(t + \Delta t) \) and \( \overline{P_{\text{net}}}(t) \) are the expected value of the current netload forecast value for time \( t \) and \( t + \Delta t \) respectively.

In the isolated operation mode, the microgrid flexibility supply is mainly composed of the controllable distributed generation (CDG, diesel generation, microturbine, etc.) and the energy storage system (ESS). Corresponding to the need for flexibility, the flexibility supply is also divided into an upward flexibility supply and a downward part in flexibility supply. For the whole system, the flexibility margin for up and down is:

\[
FP^{U}(t, \Delta t) = \sum_{j=1}^{I} \min \{ P_{\text{CDG,j}}^{\text{max}} - P_{\text{CDG,j}}(t), R_{\text{CDG,j}}^{U, \text{max}}(\Delta t) \} + \\
\sum_{j=1}^{I} \min \{ P_{\text{ESS,j}}^{\text{max}} - P_{\text{ESS,j}}(t) - P_{\text{ESS,j}}^{d}(t) - P_{\text{ESS,j}}^{d}(t), P_{\text{SOC,ESS,j}}^{\text{max}}(t, \Delta t) - P_{\text{ESS,j}}^{d}(t) - P_{\text{ESS,j}}^{d}(t) \} \tag{4}
\]
\[
FPD(t, \Delta t) = \sum_{i=1}^{n} \min \{ P_{CDG,i}(t) - P_{min_{CDG,i}}, R_{D, max_{CDG,i}} \Delta t \} + \\
\sum_{i=1}^{m} \min \{ P_{e, ESS,i}(t) + P_{d, ESS,i}^{max}(t) - P_{min_{ESS,i}}, P_{e, ESS,i}(t) + P_{d, ESS,i}^{min}(t) - P_{SOC_{min}}^{ESS,i}(t, \Delta t) \}
\]

where: \( P_{max_{CDG,i}}, P_{min_{CDG,i}} \) and \( P_{CDG,i}(t) \) are the maximum and minimum output power and output power at time \( t \) of the \( i \)th CDG, respectively, and \( R_{D, max_{CDG,i}}, R_{D, max_{CDG,i}} \) are the maximum upward and downward ramp rates of the \( i \)th CDG. \( P_{min_{ESS,i}}, P_{max_{ESS,i}} \) are the maximum and minimum output power of the ESS respectively, \( P_{SOC_{min}}^{ESS,i}(t), P_{SOC_{max}}^{ESS,i}(t) \) are the power required to charge from the current state of charge to the upper limit and discharge to the lower limit, \( P_{e, ESS,i}(t) \) is the charging power of the \( i \)th energy storage unit at time period \( t \), \( P_{d, ESS,i}^{max}(t) \) is the discharging power of the \( i \)th energy storage at period \( t \).

When measuring the impact of operation flexibility of the system, the degree of flexibility of supply and demand mismatching and the different severity of potential risks arising from the upward and downward of flexibility shortage should be considered. This paper establishes an index called Risk of Flexibility Shortage (RFS) based on Chance Constrained Goal Programming (CCGP) [11]. This index is able to reflect the degree of inadequacy of the upward and downward flexibility shortage and the corresponding degree of risk to the system operation. It is then introduced into the objective function of the subsequent scheduling model in section 4.1.

\[
RFS(t, \Delta t) = C_{U}^{C}PFSU(t, \Delta t) + C_{D}^{C}PFSD(t, \Delta t)
\]

\[
\text{s.t.} \quad \Pr \{ FRU - FPU \leq FSU (t, \Delta t) \} \geq \beta^{U} \]

\[
\text{s.t.} \quad \Pr \{ FRD - FPD \leq FSD (t, \Delta t) \} \geq \beta^{D}
\]

In the formula: \( FSU(t, \Delta t) \) and \( FSD(t, \Delta t) \) are the maximum up and down flexibility deficiencies that may occur in the microgrid under the current scheduling plan between \( t \) and \( t+\Delta t \). \( PFSU(t, \Delta t) \), \( PFSD(t, \Delta t) \) are the corresponding flexibility deficiency probability, and \( \beta^{U}, \beta^{D} \) are the confidence level of the netload deviation, \( C_{U}^{C}, C_{D}^{C} \) are the risk severity factor after the occurrence of flexibility deficit. When the uncertainty part can be partially separable, equations (7) can be converted into the determined forms of equations (8) and (9).

\[
FSU(t, \Delta t) = \max \{ \bar{P}_{m}(t+\Delta t) - \bar{P}_{m}(t) - FPU + \phi^{1}(\beta^{U}), 0 \} \quad (8)
\]

\[
FSD(t, \Delta t) = \max \{ \bar{P}_{m}(t) - \bar{P}_{m}(t+\Delta t) - FPD - \phi^{1}(1-\beta^{D}), 0 \} \quad (9)
\]

Where: \( \phi^{1}(\beta^{U}), \phi^{1}(1-\beta^{D}) \) are the values of the inverse of the cumulative distribution function of \( P_{m}(t+\Delta t) \) at \( \beta^{U} \) and \( 1-\beta^{D} \). This paper ignores the error of load forecasting, and assumes that the uncertainty part is composed of random errors of wind and PV prediction. They are subject to a normal distribution \( N(0, \sigma_{\mu}^{2}(t)) \) and \( N(0, \sigma_{\nu}^{2}(t)) \).

\[
\sigma_{\mu}(t) = e_{\mu} \bar{P}_{W}(t) + \varepsilon_{\mu} P_{W}
\]

\[
\sigma_{\nu}(t) = e_{\nu} \bar{P}_{PV}(t) + \varepsilon_{\nu} P_{PV}
\]

Where: \( P_{W}(t) \) and \( P_{PV}(t) \) are the predicted expected value of wind power, photovoltaic power generation in period \( t \), respectively. \( P_{W} \) and \( P_{PV} \) are the installed capacity of wind power and
photovoltaic power generation. $\epsilon_{fu}$, $\epsilon_{fpv}$, $\epsilon_{iw}$, $\epsilon_{ipv}$ are the corresponding prediction error coefficients. Therefore, the sum of errors is subject to the normal distribution $N(0, \sigma^2_w(t) + \sigma^2_p(t))$.

3. Three-stage energy management strategy
The microgrid community structure and its hierarchical control architecture proposed in this paper are shown in Figure 1. Each microgrid consists of an ESS, distributed energy resources DG (including CDG and renewable energy RES), and load (LD), and each microgrid is connected to each other through a tie line. The community layer optimization is carried out by the microgrid community management controller agent MGCM according to the energy sharing willingness of each microgrid and its uploaded operational data.

![Figure 1. Structure of microgrid community.](image)

The hierarchical energy management strategy of the isolated microgrid community proposed in this paper is divided into three stages.

The first stage: each microgrid in the microgrid community performs internal optimization according to its own optimization goal using the prediction data from its RES agent, load agent, CDG agent and ESS agent. At this stage, each microgrid determines whether to participate in the community layer collaborative optimization, and informs the MGCM agent.
The second stage: the MGCM agent performs the community layer energy sharing according to the allocation strategy, and informs the participating microgrids of the distribution results.

The third stage: each microgrid MGC agent performs re-optimization according to the allocation results from MGCM agent, and carries out re-optimization to finally determine the scheduling plan. The strategy flow is shown in Figure 2.

4. The optimal operation model of the microgrid

4.1. Objective function

4.1.1. Microgrid layer. This paper aims at optimizing the minimum operating cost and the lowest RFS. The operating costs include fuel costs, operation and maintenance costs, renewable energy abandonment costs, load shedding costs, and microgrid interaction costs.

\[
\begin{align*}
\min f_1 &= C_{DG} + C_{ESS} + C_{LS} + C_{Cw} + C_{EX} \\
\min f_2 &= \text{RFS}
\end{align*}
\]

\[
f_i = \Delta t \left\{ \sum_{j=1}^{m} (c_{f,j} P_{CDG,j}^f(t) + c_{om,j} P_{CDG,j}^o(t)) + \sum_{j=1}^{m} c_{c,j} (P_{ESS,j}^l(t) - P_{ESS,j}^r(t)) + c_{L,j} P_{ES,j}^l(t) + c_{c,j} P_{ES,j}^p(t) \right\}
\]

Where \( l \) is the total number of controllable distributed generation, \( c_{f,j}, c_{om,j} \) are the fuel cost, operation and maintenance cost of each controllable distributed power source, \( P_{CDG,j}^f(t) \) is the output power of the \( j \)th CDG during time period \( t \); \( m \) is the total number of energy storage units, \( c_{c,j} \) is the penalty costs for the abandonment of the RES the load, respectively. \( P_{Cw}(t) \) and \( P_{EX}(t) \) are the cutting load power and RES output power during period \( t \). \( c_s \) is the price of electricity purchase and sale between the microgrids. \( P_{ES,j}(t) \) is the interaction power at time \( t \), the value of the positive value represents the willingness to sell electricity, and the negative one represents the willingness to purchase electricity.

The optimization model of this paper contains two objective functions, which are difficult to solve by analytical methods. Considering the difference of importance between the two objectives, the tolerant lexicographic method in [12] is used to solve it. In this way, the two objectives can be compromised by setting the priority and a tolerance value. The primary goal in (12) is to minimize the operation cost, and secondly to solve the problem of minimizing the RFS in the tolerance domain of the operation cost. It means the value of the minimized cost would be used as the boundary when solving the minimized RFS problem. And the tolerance value is a non-negative number set by the decision maker to increase the cost boundary in order to gain better flexibility level. In other words, this value can reflect the decision maker’s willingness to accept the risk caused by uncertainties. A bigger tolerance value indicates that the decision maker tends to pay more to keep the microgrid maintain a lower risk level.

4.1.2. Community layer. After the first stage optimization is completed, the MGCM agent performs community layer power allocation according to the interaction intention of each MGC agent. In the community layer, the MGCM agent first classifies the received data, and divides the microgrids into the demand side and the supply side. In the case where both the supply side and the demand side exist, MGCM will make an assignment according to the total supply and demand energy. There may be three types of supply and demand matching relationship in this process.

Case 1:

\[
\sum_{j=1}^{N} P_{es,j}^s = \sum_{j=1}^{N} P_{es,j}^d
\]
In this case, supply and demand are balanced, and both the supply and demand sides can be satisfied according to their willingness. Where $\sum_{i=1}^{M} P^{S}_{ex,i}$ is the sum of the power that the supplier can provide, $\sum_{j=1}^{N} P^{D}_{ex,j}$ is the sum of the power required by the demand side.

Case 2:

$$\sum_{i=1}^{M} P^{S}_{ex,i} > \sum_{j=1}^{N} P^{D}_{ex,j}$$

(15)

In this case, the supply of interactive power is greater than the required interactive power. According to the supply capacity of each supplier, the microgrid with higher supply capacity and lower $RFS$ is assigned to supply more power. Defining the supply sharing factor as follows.

$$F^{S}_{share,j} = \frac{P^{S}_{ex,j} \max \{RFS_j, \delta \}^{-1}}{\sum_{i=1}^{M} P^{S}_{ex,i} \max \{RFS_i, \delta \}^{-1}}$$

(16)

Where $\delta$ is a positive number with a small negative value.

Under the effect of the sharing factor, the cumulative supplied power of each supplier’s microgrid after each round of allocation is:

$$P^{S}_{ex,j,r, t+1} = P^{S}_{ex,j,r, t} + \min \left\{ P^{S}_{ex,j} - P^{S}_{ex,j,r, t+1} F^{S}_{share,j} \left( \sum_{i=1}^{M} P^{S}_{ex,i} - \sum_{j=1}^{N} P^{D}_{ex,j,r} \right) \right\}$$

(17)

where $P^{S}_{ex,j,r}$ is the sharing power value provided by the $j$th supply microgrid until the $r$th allocation round, if the sharing power of any microgrid reaches its expected supply power value, the microgrid exits the allocation. When $\sum_{i=1}^{M} P^{S}_{ex,i} - \sum_{j=1}^{N} P^{D}_{ex,j,r} = 0$, the community layer power allocation ends.

Case 3:

$$\sum_{i=1}^{M} P^{S}_{ex,i} < \sum_{j=1}^{N} P^{D}_{ex,j}$$

(18)

In such cases, the available power is less than the required power, considering the power demand of each microgrid and the degree of risk of its flexibility, defining the demand sharing factor to measure the degree of demand for the interactive power of each demanding microgrid, the expression is as follows:

$$F^{D}_{share,j} = \frac{P^{D}_{ex,j} \max \{1 - RFS_j, \delta \}^{-1}}{\sum_{j=1}^{N} P^{D}_{ex,j} \max \{1 - RFS_j, \delta \}^{-1}}$$

(19)

Similar to case 2, under the effect of the demand sharing factor, the cumulative power generated by each demanding microgrid after each round is

$$P^{D}_{ex,j,r, t+1} = P^{D}_{ex,j,r, t} + \min \left\{ P^{D}_{ex,j} - P^{D}_{ex,j,r, t+1} F^{D}_{share,j} \left( \sum_{i=1}^{M} P^{S}_{ex,i} - \sum_{j=1}^{N} P^{D}_{ex,j,r} \right) \right\}$$

(20)

4.2. Constraints

4.2.1. The electrical energy balance constraint.

$$\sum_{i=1}^{M} P^{ESS}_{ex,i}(t) + \sum_{j=1}^{N} \left( P^{S}_{ESS,j}(t) + P^{D}_{ESS,j}(t) \right) + P_{ex}(t) - P_{ex}(t) = P_{ex}(t) - P_{ex}(t)$$

(21)
4.2.2. CDG constraints.

\[
P_{CDG,i}(t) \leq P_{CDG,i}^u(t) \leq P_{CDG,i}^l(t)
\]

\[
P_{CDG,i}^l(t) = \max \left\{ P_{CDG}(t-1) - P_{CDG,i}^{max} + P_{CDG,i}^{min} \right\}
\]

\[
P_{CDG,i}^u(t) = \min \left\{ P_{CDG}(t-1) + D_{CDG,i}^{max} + P_{CDG,i}^{max} \right\}
\]

Where \( P_{CDG,i}^u(t) \) and \( P_{CDG,i}^l(t) \) are the upper and lower limits of the output power of the CDG during the period \( t \) respectively, \( R_{CDG,i}^{max}, D_{CDG,i}^{max} \) are the maximum upward climbing rate and the maximum downward rate of the output power, and \( P_{CDG,i}^{min}, P_{CDG,i}^{max} \) are the upper and lower limits of the CDG output power.

4.2.3. ESS constraints.

\[
SOC(t) = SOC(t-\Delta t) - \left( \frac{P_{ESS,i}^h(t)\Delta t}{E} + \frac{P_{ESS,i}^d(t)\Delta t}{E} \right)
\]

\[
0 \leq P_{ESS,i}^d(t) \leq S_{ESS}^d P_{ESS,i}^u(t), S_{ESS}^d \in \{0,1\}
\]

\[
S^h P_{ESS,i}^d(t) \leq P_{ESS,i}^{h^*}(t) \leq 0, S^h \in \{0,1\}
\]

\[
S^h + S^d = 1
\]

Where \( E \) is the total capacity of the battery, \( \eta^h, \eta^d \) are the charging and discharging efficiency of the battery respectively. \( S^h, S^d \) are integer variables, representing the state of charge and discharge, the value of 1 means that the battery is in the corresponding state, otherwise it is taken as 0, \( P_{ESS,i}^u(t) \) and \( P_{ESS,i}^l(t) \) are the upper and lower limits of the output power of the battery in the period \( t \).

4.2.4. Tie line constraints.

\[
P_{EX}^l(t) \leq P_{EX}(t) \leq P_{EX}^u(t)
\]

5. Case study

5.1. Basic data settings

| Table 1. Parameter settings of microgrid community. |
|-----------------------------------------------|
| MG1 | MG2 | MG3 | MG4 |
|---|---|---|---|
| ESS Capacity(kWh) | 200 | 150 | 100 | 200 |
| CDG (kW) | 150 | 120 | 80 | 150 |
| PV(kW) | 300 | 300 | 80 | 150 |
| WT(kW) | 200 | / | / | 100 |
| ESS Operation Cost(yuan/kW) | 0.027 |
| CDG Fuel Cost(yuan/kW) | 1 |
| CDG Operation Cost (yuan/kW) | 0.2 |
| Load Shedding Cost(yuan/kW) | 2 |
| RES Curtaining Cost(yuan/kW) | 1.3 |
| Energy Sharing Cost(yuan/kW) | 0.5 |

In this paper, the microgrid community system consisting of four microgrids is used for simulation analysis. Equations (1)-(10) are linearized by Big-M method [13]. Finally, the problem can be converted into a MILP problem. This paper uses JADE platform to build an energy management architecture based on multi-agent system [14], and the optimal problem is solved by IBM CPLEX 12.9.
The net load curve of each microgrid is shown in Figure 3. Take 1h as simulation time step and the confidence level of the netload deviation is 0.95, $\varepsilon_{fw}$ and $\varepsilon_{fw}$ are set to 0.5 and 0.05, respectively. The parameters of each microgrid device are shown in Table 1.

5.2. Operation cost analysis
It can be seen from Table 2 that in the community mode, the operating costs of each microgrid are lower than the isolated mode. The overall economic improvement of the system comes mainly from two aspects:

First, the interaction benefit brought by energy sharing. As shown in Figure 4, there are energy sharing in 14 periods during 24 scheduling periods. It can be seen from Figure 3 that the MG1 has a large netload during the period from 0:00 to 6:00. Since the energy sharing cost is less than the CDG power generation cost, MG1 preferentially purchases power from the community. At the same time, the rest of the microgrids’ netload remains at low level. And the operating cost of the energy storage system is lower than the benefit of energy sharing. Therefore, after satisfying the internal power supply, MG2, MG3 and MG4 firstly sell electricity to the community by discharging energy from storage energy. During the period from 6:00 to 11:00, due to the increase in the netload of MG2 and MG4, the shared energy in the community is reduced, and MG1 is mainly powered by CDG to meet the energy supply demand. Due to the timing fluctuation characteristics of photovoltaic and wind turbine output, the netload of microgrids shows a trend of decreasing at first and then increasing between 11:00 and 17:00. During this period, MG2 and MG3 are the main beneficiaries. MG4 becomes the main energy demand side. Although the netload of MG1 has also risen to around 70kW, its netload is mainly balanced by the energy storage system by releasing the energy absorbed by the negative netload during the period from 11:00 to 14:00.

Second, the cost of abandoning RES, and the reduction of the amount of load shedding. It can be seen from Figure 5 that the amount of abandoned RES and load shedding under community operation is significantly lower than that of isolated operation. For MG2, the netload is negative during the period from 11:00 to 13:00. In the isolated mode, if there is power surplus after the energy storage system is charged to the upper limit, the RES must be discarded. In the community mode, MG2 can reduce the loss caused by the abandonment of new energy by nearly 20% through energy sharing. For MG4, in the isolated mode, there is a large netload shortage in the period from 11:00 to 17:00, and the number of load shedding can be reduced by nearly 70% through interaction within the community.

| Table 2. Operation cost of microgrids. |
|----------------------------------------|
| MG1 | MG2 | MG3 | MG4 |
| Isolated | 2302.823 | 1344.104 | 1253.222 | 2231.996 |
| Community | 2095.346 | 1189.403 | 1164.141 | 2125.139 |

**Figure 3.** Netload in each microgrid.  
**Figure 4.** Exchange power within microgrid community.
5.3. **RFS analysis**

The operation mode of the microgrid and the tolerance value used in optimization will change the resource allocation within the microgrid, which will affect the RFS.

Taking MG2 as an example, as can be seen from Figure 6, although the fluctuation of the expected value of the netload forecast during the period from 14:00 to 15:00 is small, the great uncertainty of the corresponding predicted error exists due to the large PV output during this period. The high level of error results in a possible netload range between [-50 kW, 75 kW] with flexibility requirements in both the upward and downward directions. In the previous period from 11:00 to 13:00, the netload expectation was negative, ESS continues to charge, CDG works near 20 kW, with sufficient upward flexibility supply, and lack of downward flexibility supply. So, under the isolated operation mode, there is a high risk of lack of flexibility in the case of 0 tolerance as shown in Figure 7. In contrast, in the community operation mode, the sales of surplus renewable energy during the period of 13:00 to 14:00 retain the downward flexible supply capacity of the ESS, and make the RFS in the next period less than one-half that of the isolated mode.

At the same time, it can be seen from Figure 7 that although the overall flexibility in the community operation mode is reduced, the RFS for a small period of time is greater than that of the island mode, indicating that the energy sharing between the microgrids in strict accordance with the minimum operating cost may cause the lack of flexibility in supply during certain periods of time. Therefore, it is necessary to relax the cost constraint in order to achieve the purpose of releasing the flexibility supply potential of the system.

The operating costs considering cost tolerance are shown in Table 3.
Table 3. Operation cost of microgrids under different tolerant.

|            | MG1 | MG2 | MG3 | MG4 |
|------------|-----|-----|-----|-----|
| 0.3        | 2487| 1480| 1331| 2773|
| 0.5        | 2682| 1639| 1486| 2917|

It can be seen from Table 3 that under the effect of tolerance value, the feasible cost domain is expanded when solving the problem of minimizing RFS. Microgrids adjust the output of CDG, ESS, the amount of curtailed RES, as well as the amount of load shedding to obtain higher operational flexibility. As can be seen from Figure 7, compared with the flexibility level under 0 tolerance, the risk of insufficient flexibility of MG2 in the whole scheduling period with 0.3 tolerance is reduced by nearly one-half. However, the setting of tolerance is not recommended to be as big as possible. After further increasing the latitude to 0.5, although the RFS is further reduced during 14:00 to 15:00, the flexibility level in other periods is almost the same as the situation of 0.3. It shows that in the cost constraint domain of 0.5 tolerance, the ability of the system to adjust the flexibility level under current resources conditions has tended to be close to the boundary.

6. Conclusions

In this paper, based on the energy management of the isolated microgrid community, a three-stage optimal scheduling strategy based on multi-agent system is established. The benefits of each microgrid are fully considered, and the energy management is optimized in a hierarchical way. Taking economic operation as the main operation goal, considering the impact of renewable energy generation on the netload, the index of risk of flexibility shortage is established, and this index is optimized as the second objective within a certain cost domain through lexicographic optimization.

The proposed strategy for microgrid community energy dispatch has several advantages:

1. Compared with the centralized strategy, the hierarchical strategy gives more autonomy to each microgrid entity to ensure their own operational goals.
2. The scale of the microgrid community is easy to expand without changing the community energy management model.
3. The sharing factors used in community layer are able to allocate power fairly between microgrids to achieve better operational economy and improve the microgrids’ ability to withstand uncertainties.

The simulation examples show that compared with the isolated operation, the community operation improves the operation economically in each microgrid from energy sharing and reducing the abandonment of RES and load. At the same time, within a certain range of operating costs, the introduction of RFS can effectively guide the utilization of resources in the microgrid community and reduce the potential risks caused by the volatility and randomness of renewable energy to the operation of the system.

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