Penalty Adjustment-Based Sizing Method for Flexible Resources in Isolated Microgrids

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This work was supported in part by the Natural Science Foundation of Guangdong Province under Grant 2017A030313288.

ABSTRACT The fixed and subjective setting of the penalty coefficient is a significant drawback of existing penalty-based programming models used to determine the size of flexible resources (FRs), such as microturbines and battery energy storage systems, for isolated microgrids (IMs). Generally, most researchers set the penalty coefficient to a sufficiently large value to ensure a satisfactory operational performance of IMs, which often leads to redundant and uneconomical configurations. How to balance the operational performance and economic configuration is an intractable problem confronted by many researchers. In this paper, a penalty adjustment-based sizing method is proposed to solve the aforementioned problems. Specifically, four indicators are defined to evaluate the size of FRs. Based on the assessment metrics, a trade-off sizing method is proposed to attain the FR size with the maximum marginal benefit. This method is combined with mixed integer programming to propose a penalty adjustment-based sizing algorithm to solve the optimal penalty coefficient and size of FRs. Simulations verify that the proposed method can avoid subjectivity and improve the traditional conservative configuration.

INDEX TERMS Flexible resources, isolated microgrid, penalty adjustment, sizing method.

I. INTRODUCTION
Isolated microgrids (IMs) are regarded as a highly efficient way to supply power in remote and unconnected areas [1]. However, the intermittent power output of renewable energy resources causes drastic power fluctuations of the net load (load-renewable energy), which complicate the operation of IMs [2]. Flexible resources (FRs) are perceived as an effective way to reduce the power fluctuation of the net load [3], [4]. To improve the operation of IMs and smooth the power imbalance between renewable energy and the load, sizing methods for FRs in IMs have recently been a hot topic of research [5], [6].

Generally, FRs can be classified as the power generation type or storage type, and the operational functions of these two types are quite different. Specifically, power generation-type FRs, such as microturbines (MTs), can generate energy and power to fill shortages in the net load [7]. Storage-type flexible resources, such as battery energy storage systems (BESSs), do not have the ability to generate energy but can store and release energy as needed [8], [9]. The flexibility of the energy and power balance in IMs can be improved using MTs and BESSs, [10]. However, to guarantee the power supply reliability and renewable energy consumption ability of IMs, the size of FRs is generally determined conservatively, which results in an uneconomical configuration [11], [12].

In the existing literature, some researchers formulate sizing models of FRs as a multi-objective optimization problem, while others formulate the models as a single-objective optimization problem containing penalty terms. In [13], the authors formulate a multi-objective model considering the levelized cost of energy and the loss of load probability and propose a Pareto-based fuzzy decision-making method to present a capacity compromise scheme for IMs between the two objectives. In [14], the authors propose a multi-objective compound difference evolution algorithm to solve the optimal capacity of BESS and use information entropy theory to select the compromise scheme between the cost and robustness. In [15], the authors propose a multi-objective bilevel optimization problem to determine the sizes, sites and types of renewable generation and BESS and use crowding-distance assignment to select the best solution. Using the multi-objective optimization method, a set of Pareto optimal solutions can be obtained. Therefore, many
The main contributions of this paper can be summarized as the optimal setting of the penalty. A penalty adjustment-based method is proposed to determine the FR size that yields the maximum marginal benefit by balancing the robustness and cost. A penalty adjustment-based algorithm that combines the trade-off sizing method with MIP is proposed to solve the optimal penalty coefficient and FR size. The algorithm can effectively prevent subjective setting of the penalty coefficient and improve the conservative configuration.

The rest of this paper is organized as follows: The size assessment system and the trade-off sizing method are presented in Section II. In Section III, a general MIP model for determining the size of FRs is formulated. In Section IV, the penalty adjustment-based algorithm is proposed to solve the optimal penalty coefficient and FR size. A simulation and results analysis are presented in Section IV, and the paper is concluded in Section V.

II. SIZE ASSESSMENT SYSTEM AND TRADE-OFF SIZING METHOD

A. SIZE ASSESSMENT SYSTEM

The proposed size assessment system for FRs contains four indicators that represent the power supply reliability, renewable energy consumption ability, operational robustness of IMs and economy of the configuration.

1) LOAD LOSS RISK

Load loss risk (LLR) is the weighted sum of the load loss ratio that is used to represent the power supply reliability of IMs [21]. The LLR indicator $\omega_{LLR}$ is defined as follows:

$$\omega_{LLR} = \frac{\sum_{s=1}^{n} \left( \sum_{t=1}^{T} P_{LL}(s, t) \right) \times 100\%}{\sum_{s=1}^{n} \left( \sum_{t=1}^{T} P_{net}(s, t) \right)}$$

$$P_{net}(s, t) = \min(P_{ren}(s, t) - P_{load}(s, t), 0)$$

$$P_{ren}(s, t) = P_{pv}(s, t) + P_{wt}(s, t)$$

In the formula, $p^s$ denotes the probability of the sth scenario, $P_{LL}(s, t)$ denotes the load loss, $P_{net}(s, t)$ denotes the power shortage of the net load, $P_{load}(s, t)$ denotes the load, $P_{ren}(s, t)$ denotes the renewable power, $P_{pv}(s, t)$ denotes the photovoltaic power and $P_{wt}(s, t)$ denotes the wind power, respectively.

2) RENEWABLE CURTAILMENT RISK

The renewable curtailment risk (RCR) is the weighted sum of the renewable curtailment ratio, which is used to represent the renewable energy consumption ability of IMs. The RCR
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indicator $\omega_{RCR}$ is defined as follows:

$$\omega_{RCR} = \frac{\sum_{s=1}^{n} \left[ \sum_{t=1}^{T} P_{RC}(s, t) \right]}{\sum_{s=1}^{T} \sum_{t=1}^{T} P_{net}(s, t)} \times 100\%$$

(4)

$$P_{net}^{+}(s, t) = \max \left( P_{ten}(s, t) - P_{load}(s, t) , 0 \right)$$

(5)

where $P_{RC}(s, t)$ and $P_{net}^{+}(s, t)$ denote the renewable curtailment and the power surplus of the net load, respectively.

3) SCENARIO ACCOMMODATION LEVEL

The scenario accommodation level (SAL) is an accumulative probability indicator used to represent the operational robustness of IMs. In this paper, the scenarios are power curves of the net load combining renewable power and load. Each scenario occurs within a day (24 h) with a dispatch period of one hour.

The size of FRs corresponding to the scenario can be obtained from the data of a scenario. The scheme corresponding to the $s^{th}$ scenario can be formulated as $x_{s}^{i}$.

$$x_{s}^{i} = \left( P_{s}^{MT}, P_{s}^{BESS}, E_{s}^{BESS} \right)^{T}$$

(6)

Here, $P_{s}^{MT}$, $P_{s}^{BESS}$ and $E_{s}^{BESS}$ denote the power capacity of the MT, the power capacity of the BESS and the energy capacity of the BESS, respectively.

A set of scenarios can be used to obtain a set of schemes formulated as $X_{s}^{i} = \left\{ x_{s}^{i1}, x_{s}^{i2}, \cdots, x_{s}^{in} \right\}$. The final configuration size of FRs is defined as $x_{s}^{i} = \left( P_{s}^{MT}, P_{s}^{BESS}, E_{s}^{BESS} \right)^{T}$. If all the variables in $x_{s}^{i}$ are larger than those in $x_{s}^{j}$ ($s = 1, 2, \cdots, n$), $x_{s}^{i}$ can accommodate the $s^{th}$ scenario. The SAL indicator $\omega_{SAL}$ is defined as follows:

$$\omega_{SAL} = \sum_{j=1}^{m} p_{j}, \ m \leq n$$

(7)

where $m$ denotes the number of scenarios that can be accommodated by $x_{s}^{i}$.

The larger the size of the FRs deployed in IMs, the more scenarios to which the IMs can adapt, indicating that the IMs have higher operational robustness.

4) SIZING COST

The sizing cost (SC) is an indicator used to represent the economy of capacity deployment. The SC indicator $\omega_{SC}$ is defined as follows:

$$\omega_{SC} = C_{si} x_{s}^{i}$$

$$C_{si} = (c_{MT}, c_{P}, c_{E})$$

(8)

(9)

In the formula, $c_{MT}$ denotes the cost of the unit power capacity of the MTs, $c_{P}$ denotes the cost of the unit power capacity of the BESS and $c_{E}$ denotes the cost of the unit energy capacity of the BESS.

B. MARGINAL-BENEFIT FUNCTION

In this paper, the marginal benefit is defined as the ratio of the increment in the SAL to the increment in the SC, which represents the added cost of an improvement in operational robustness.

Generally, researchers determine the size of FRs based on cost, neglecting the significance of the marginal benefit. This paper takes the marginal benefit as the standard to improve the conservative configuration of FRs. The marginal-benefit function $h_{mb}$ is defined as follows:

$$h_{mb} = \frac{\Delta \omega_{SAL}}{\Delta \omega_{SC}}$$

(10)

where $\Delta \omega_{SAL}$ and $\Delta \omega_{SC}$ denote the increment in the SAL and the increment in the SC, respectively.

C. TRADE-OFF SIZING METHOD

The adaptability of an isolated microgrid to handle power fluctuations largely depends on the size of the FRs. However, many researchers adopt robust sizing methods based on the worst case, which may lead to redundant and uneconomical configurations. Therefore, a trade-off sizing method is required to solve this problem.

To eliminate the effects of different units, the three variables in vector $x_{s}^{i}$ are normalized using the following equations:

$$x_{s,j}^{i} = \frac{x_{s,j}^{i} - x_{s,j}^{\min}}{x_{s,j}^{\max} - x_{s,j}^{\min}}, \ j = 1, 2, 3, \ n = 1, 2, \cdots, n$$

(11)

$$x_{s,j}^{\min} = \min \left\{ x_{s,j}^{1}, x_{s,j}^{2}, \cdots, x_{s,j}^{n} \right\}, \ j = 1, 2, 3$$

(12)

$$x_{s,j}^{\max} = \max \left\{ x_{s,j}^{1}, x_{s,j}^{2}, \cdots, x_{s,j}^{n} \right\}, \ j = 1, 2, 3$$

(13)

where $x_{s,j}^{i}$, $x_{s,j}^{\min}$ and $x_{s,j}^{\max}$ denote the normalized value of the $j^{th}$ variable in $x_{s}^{i}$, the value of the $j^{th}$ variable in $x_{s}^{i}$, the minimum of the $j^{th}$ variable in $X_{s}^{i}$ and the maximum of the $j^{th}$ variable in $X_{s}^{i}$, respectively.

The trade-off scheme for FRs can be found in a range of SAL values set according to decision requirements. Different levels of SAL are contained in $W_{SAL}$. The difference between each level is equal and is denoted as $\Delta \omega_{SAL}$.

$$W_{SAL} = \left\{ \omega_{SAL,1}, \omega_{SAL,2}, \cdots, \omega_{SAL,n} \right\}$$

(14)

$$\omega_{SAL,i} \leq \omega_{SAL,i+1}, \quad i = 1, 2, \cdots, n$$

(15)

$$\Delta \omega_{SAL} = \omega_{SAL,i+1} - \omega_{SAL,i}, \quad i = 1, 2, \cdots, n$$

(16)

Here, $\omega_{SAL,i}^{\min}$ and $\omega_{SAL,i}^{\max}$ denote the minimum SAL and the $i^{th}$ level of SAL, respectively.

The relationship between the two power capacity variables is linear, and the relationship between the power capacity variables and the energy capacity variable is nonlinear. Thus, in the three-dimensional coordinate system, all the normalized vectors can be surrounded by an equilateral right-angle triangular prism.
The space of the triangular prism can be formulated as \( \theta \).

\[
\theta = \begin{cases}
0 \leq x_{P_{MT}} + y_{P_{BESS}} \leq 1 \\
0 \leq z_{E_{BESS}} \leq 1
\end{cases}
\]  

(17)

Here, \( x_{P_{MT}} \), \( y_{P_{BESS}} \) and \( z_{E_{BESS}} \) denote the variable of the power capacity of the MTs, the variable of the power capacity of the BESS and the variable of the energy capacity of the BESS.

By introducing the similarity coefficient \( \lambda_s \) into (13), the accommodation space \( \theta_d \) can be formulated as follows:

\[
\theta_d = \begin{cases}
0 \leq x_{P_{MT}} + y_{P_{BESS}} \leq 1 - \lambda_s \\
0 \leq z_{E_{BESS}} \leq 1 - \lambda_s
\end{cases}, \lambda_s \in [0, 1]
\]  

(18)

where \( \lambda_s \) is 0 or 1 to indicate that none of the scenarios or all the scenarios are accommodated, respectively.

The similarity coefficient \( \lambda_s \) can then be used to obtain a list of optional schemes corresponding to the different levels of SAL in \( W_{SAL} \). The normalized value can then be transformed into the actual value using the following equation.

\[
x_{s_{i,j}} = (1 - \lambda_s) \left( x_{s_{i,j}}^{\text{max}} - x_{s_{i,j}}^{\text{min}} \right) + x_{s_{i,j}}^{\text{min}}
\]  

\[
 i = 1, 2, \ldots, n
\]  

\[
 j = 1, 2, 3
\]  

(19)

Here, \( x_{s_{i,j}} \) denotes the \( j \)th capacity variable of the \( i \)th optional scheme.

The maximum rates of LLR and RCR are formulated as \( \omega_{LLR}^{\text{max}} \) and \( \omega_{RCR}^{\text{max}} \), respectively. These two rates can be limited using the following constraints.

\[
0 \leq \omega_{LLR,i} \leq \omega_{LLR}^{\text{max}}, \quad i = 1, 2, \ldots, n
\]  

(20)

\[
0 \leq \omega_{RCR,i} \leq \omega_{RCR}^{\text{max}}, \quad i = 1, 2, \ldots, n
\]  

(21)

The penalty cost \( C_{pen} \) includes the renewable curtailment cost and the load loss cost.

\[
C_{pen} = \beta \sum_{t \in T} \left( P_{RC}^{(s,t)} + P_{LL}^{(s,t)} \right) \Delta t
\]  

(30)

Here, \( \beta \) denotes the penalty coefficient.

2) CONSTRAINTS

The power balance in IMs can be described using the following equations:

\[
P_{RC}(s, t) + P_B(s, t) = P_{MT}(s, t) + P_{LL}(s, t) + P_{net}(s, t)
\]  

(31)

\[
P_{net}(s, t) = P_{pen}(s, t) - P_{load}(s, t)
\]  

(32)

\[
P_B(s, t) = \lambda_1 P_{BC}(s, t) - \lambda_2 P_{BD}(s, t)
\]  

(33)
where $P_{BC}(s, t)$ denotes the charging power of the BESS in the $s$th scenario at time $t$.

The dynamic power and energy constraints of the BESS must be satisfied. Binary variables $\lambda_1$ and $\lambda_2$ are used to separate the charging and discharging states of the BESS. According to references [2] and [22], the charging efficiency $\eta_C$ and the discharging efficiency $\eta_D$ can be assumed to be equal. In this paper, we use $\eta_B$ to represent the efficiency of the BESS, and most researchers set the efficiency coefficient $\eta_B$ to 0.9 [14].

$$e(s, t + 1) = e(s, t) + (P_{BC}(s, t)\lambda_1 \eta_B - \frac{P_{BD}(s, t)\lambda_2}{\eta_B})\Delta t$$

(34)

$$\lambda_1 + \lambda_2 = 1$$

(35)

$$soc_{min} E_{BE} \leq e(s, t) \leq soc_{max} E_{BE}$$

(36)

$$e(s, 0) = e(s, T) = soc_{ini} E_{BE}$$

(37)

Here, $e(s, t)$, $e(s, 0)$ and $e(s, T)$ denote the energy of the BESS at times $t$, 0 and $T$, respectively. $\eta_B$, $soc_{min}$, $soc_{max}$ and $soc_{ini}$ denote the efficiency coefficient, minimum energy coefficient, maximum energy coefficient and initial energy coefficient, respectively.

Generally, the remaining energy of the BESS at the end of a day should be equal to that at the beginning of the day. Constraint (37) is called the energy conservation constraint, and it is widely adopted in the literature and in practice. The purpose of setting this constraint is to ensure that the BESS can store sufficient energy to counter potential uncertainties occurring the next day.

The size of the FRs must satisfy the power exchange process. Thus, the power capacity variables are required to satisfy the following inequalities:

$$0 \leq P_{MT}(s, t) \leq P_{MT}^i$$

(38)

$$0 \leq P_{BC}(s, t) \leq P_{BC}^i$$

(39)

$$0 \leq P_{BD}(s, t) \leq P_{BD}^i$$

(40)

In contrast to the existing literature, in which the penalty coefficient is used as a parameter, this paper sets the range of the penalty coefficient and solves for the optimal penalty coefficient under the formulated constraint as follows.

$$0 \leq \beta \leq \beta_{max}$$

(41)

It is worth mentioning that in most cases, the nonlinear constraints can be neglected in the current microgrid planning and analysis. Microgrids are small systems, and the problems of power flow congestion and voltage stability are not obvious. Thus, the constraints of aspects such as the bus voltage, line currents and power balance at the buses can be neglected, which helps reduce the complexity of the problem and improve the efficiency of optimization.

**B. MODEL LINEARIZATION**

To prevent the BESS from working in the charging and discharging states simultaneously, two binary variables, $\lambda_1$ and $\lambda_2$, are adopted in the nonlinear constraint (34). However, the binary variables and continuous variables are multiplied, which increases the complexity of the solution. This paper adopts a large constant $M$ ($10^6$) and a binary variable $o_{bin}$ to realize linearization.

The linearization method can be formulated as follows:

$$0 \leq P_{BC}(s, t) \leq Mo_{bin}$$

(42)

$$0 \leq P_{BD}(s, t) \leq (1 - o_{bin}) M$$

(43)

It should be explained that when $o_{bin}$ is 0, $P_{BC}(s, t)$ is equal to 0, and $P_{BD}(s, t)$ must be optimized within a large range from 0 to $10^6$. When $o_{bin}$ is 1, $P_{BD}(s, t)$ is equal to 0, and $P_{BC}(s, t)$ must be optimized within a large range from 0 to $10^6$. Only either the charging state or the discharging state can exist at one time, which is ensured by the newly defined binary variable $o_{bin}$ instead of $\lambda_1$ and $\lambda_2$.

The nonlinear constraints (34) and (35) can be replaced with linear constraints (42)-(44).

$$e(s, t + 1) = e(s, t) + P_{BC}(s, t)\Delta t\eta_B - P_{BD}(s, t)\Delta t/\eta_B$$

(44)

**C. DISCUSSION OF PENALTY**

To guarantee the power supply reliability and renewable energy consumption ability of IMs, the penalty coefficient $\beta$ is adopted in the formulated sizing model. As the penalty coefficient $\beta$ increases, the load loss and renewable curtailment decline. Generally, most researchers set the penalty coefficient to a large number, which may cause redundant deployment of FRs. However, ascertaining the appropriate penalty coefficient is so difficult that a fixed and subjective setting of the penalty coefficient is inevitable.

In view of these intractable problems, it is necessary to develop a penalty-adjustment mechanism to determine the optimal value of the penalty coefficient and improve the traditional conservative configuration.

**IV. SOLUTION ALGORITHM**

As discussed in Section III-C, the general MIP method can be used only to determine the optimal size of FRs under the fixed penalty, which may lead to a redundant configuration. Thus, in this section, the proposed trade-off sizing method is combined with the general MIP method to obtain a penalty adjustment-based sizing algorithm to determine the FR size with the maximum marginal benefit under the optimal penalty and to improve the conservative configuration. A flow chart of the proposed algorithm is shown in Fig 1.

The process of the penalty adjustment-based algorithm can be summarized as follows:

1) Input the generated scenarios and simulation parameters.
2) Set the initial iteration value of penalty coefficient $\beta$.
3) Use the CPLEX solver [26] to solve the formulated MIP-based sizing model under the given penalty coefficient and then obtain the solution set $X_{sij}$, where $x_{sij}$ corresponds to the $s$th scenario (as mentioned in Section II-A).
4) Normalize all the vectors in \( X_a \) using models (11)-(13).
5) Choose one of the input levels of SAL and then increase the similarity coefficient \( \lambda_s \) from 0 to 1 until the chosen level is satisfied.
6) Use model (19) to transform the normalized capacity into the actual value and then verify the LLR and LCR in the generated scenarios.
7) If constraints (20)-(21) can be satisfied, obtain this optional scheme and return to Step 5 until all the input levels have been chosen; otherwise, abandon this scheme.
8) Calculate the marginal benefit of the obtained optional schemes. If the number of iterations is satisfied, move to Step 9; otherwise, change the value of the penalty coefficient \( \beta \) using the pattern search (PS) algorithm [27] and then move to Step 3.
9) Obtain the size of FRs with the maximum marginal benefit.

V. CASE STUDY
A. SIMULATION DESCRIPTION
This paper adopts a typical isolated microgrid as an example to verify the effectiveness of the proposed method.

The structure of the isolated microgrid is shown in Fig 2. The renewable generation system in the isolated microgrid is composed of 400 kW PV and 200 kW WT. The peak load in the isolated microgrid is 250 kW. The size of the MT and BESS, which are two major types of FRs, must be solved.

The simulation is conducted on the MATLAB platform, and the YALMIP toolbox is used to implement the CPLEX solver.

As mentioned in Section II-A, in this paper, the considered scenarios are the power curves of the net load, the sum of the renewable power and the load. The historical load, solar power and wind power data and the scenario generation method can be found in [14]. The net load scenarios shown in Fig 3 are used as power parameters in the optimization process.

To improve the life of the BESS and prevent overcharging and discharging, \( \text{soc}_{\text{max}} \) and \( \text{soc}_{\text{min}} \) are set to 0.9 and 0.1, respectively, to limit the energy variation range [28]. Setting \( \text{soc}_{\text{ini}} \) to 0.5 yields the optimal battery storage system performance [29]. The rest of the input simulation parameters are given in Table 1.
TABLE 1. Simulation parameters.

| Parameter | Value         |
|-----------|---------------|
| $c_{MT}$  | 81.2 $/kW$   |
| $c_{P}$   | 354.5 $/kW$  |
| $c_{C}$   | 295.4 $/kWh$ |
| $\alpha_{min}$ | 0.7     |
| $\alpha_{max}$ | 0.01   |
| $\omega_{max}$ | 0.05   |
| $\omega_{min}$ | 0.01   |
| $\gamma_{MT}$ | 20 years |
| $\gamma_{BESS}$ | 10 years |
| $\gamma_{SCR}$ | 2.95 $/kW$ |
| $\gamma_{soc}$ | 73.9 $/kW$   |
| $\gamma_{soc}_{min}$ | 331.6 $/kWh$ |
| $\gamma_{soc}_{max}$ | 295.4 $/kWh$ |
| $\gamma_{a}$ | 7.4 $/kW$    |
| $\gamma_{b}$ | 22.9 $/kW$   |

B. METHOD COMPARISON AND ANALYSIS

To prove the validity of the proposed method, a comparison of three methods is performed. Method 1 is the general MIP method, method 2 is the trade-off sizing method, and method 3 is the penalty adjustment-based sizing method introduced in this paper. The results obtained using these three methods are presented in Table 2.

Using method 1, the size of the FRs is determined using the general MIP method, and as with many studies, the penalty coefficient $\beta$ is set to a fixed large constant of 2.95 $/kW$. The marginal benefit assessment and the penalty adjustment mechanism are not adopted in this method. Thus, the results obtained using this method are subjective and conservative in most cases.

Using method 2, the marginal benefit assessment is introduced into the MIP method, and the size of the FRs is determined using the trade-off sizing method. In contrast to method 1, the results obtained using this method can improve the conservative configuration according to the marginal benefit. However, using method 2, the penalty is still set to a fixed value of 2.9 $/kW$, and the penalty adjustment mechanism is not adopted.

Using method 3, both the marginal benefit assessment and the penalty adjustment mechanism are adopted and combined with the general MIP method. Compared with methods 1 and 2, when using method 3, the subjective setting of the penalty is avoided, and the size of FRs with the maximum marginal benefit can be determined. Thus, the results obtained using this method are subjective and conservative in most cases.

Using method 2, the marginal benefit assessment is introduced into the MIP method, and the size of the FRs is determined using the trade-off sizing method. In contrast to method 1, the results obtained using this method can improve the conservative configuration according to the marginal benefit. However, using method 2, the penalty is still set to a fixed value of 2.9 $/kW$, and the penalty adjustment mechanism is not adopted.

Using method 3, both the marginal benefit assessment and the penalty adjustment mechanism are adopted and combined with the general MIP method. Compared with methods 1 and 2, when using method 3, the subjective setting of the penalty is avoided, and the size of FRs with the maximum marginal benefit can be determined. Thus, the results obtained using this method are more reasonable and credible.

Table 2 shows that the FRs obtained using method 1 and method 2 are of equal size under the fixed penalty of 2.95 $/kW$, which indicates that using only the adopted marginal benefit assessment is not sufficient to improve the conservative configuration. The RCR and LCL are both zero, which indicates that a large penalty can guarantee the renewable energy consumption ability and power supply reliability of an IM. By using the penalty adjustment-based algorithm, the optimal penalty is solved as 1.62 $/kW$. The SC is reduced by 150824.15 $, and the marginal benefit is doubled, which indicates that the proposed penalty adjustment-based algorithm can improve the redundant and uneconomic configuration and prevent subjective setting of the penalty coefficient.

From Table 3, we can see that the size of the FRs decreases as the SAL decreases under the same penalty, which indicates that if the isolated microgrid is required to adapt to more scenarios and improve its robustness, more FRs should be deployed. The optional scheme with the SAL of 100% has the highest marginal benefit; thus, it was selected as the optimal size.

C. IMPACT OF THE PENALTY

1) IMPACT OF $\beta$ ON THE MARGINAL BENEFIT

To confirm the optimality of the penalty, which is solved using the proposed penalty adjustment-based sizing algorithm, we conduct simulations with different values of $\beta$.

As shown in Fig 4, the marginal benefit shows an increasing trend when $\beta$ increases from 1 $/kW$ to 1.6 $/kW$. When $\beta$ reaches 1.62 $/kW$, the marginal benefit reaches a maximum. As $\beta$ continues to increase, the marginal benefit begins to decline. When $\beta$ is set to a large value, the marginal benefit is maintained at a low level. The simulation results indicate that setting the penalty coefficient to an excessively large value, as many researchers have done, may lead to a low economic benefit. Thus, the proposed method can prevent uneconomic deployment and identify an appropriate penalty value.

2) IMPACT OF $\beta$ ON THE SIZE

The value of the penalty is an important factor affecting the size of FRs. We now consider how the size of FRs varies with the penalty $\beta$.

As shown in Fig 5 and Fig 6, when $\beta$ increases from 1 $/kW$ to 2.4 $/kW$, the size of the BESS shows an increasing trend, and the size of the MT decreases slightly. The increase in $\beta$ results in a decline in renewable curtailment and load loss, which indicates that larger FRs should be deployed to meet the operational performance of the isolated microgrid. The slight decrease in MT can be explained by the fact that the BESS can help supply power. However, the
sizes of the BESS and MT no longer change when $\beta$ exceeds 2.4 $$/kW, which indicates that no more FRs are required to be deployed.

The results in Table 2, Fig 5 and Fig 6 show that the existing MIP method with a fixed penalty yields a redundant configuration. This drawback can be overcome using the proposed penalty adjustment-based sizing method to determine the size of FRs with the maximum marginal benefit under the given limitations of the RCR AND LCR, which also strikes a balance between operational performance and economic configuration.

### VI. CONCLUSION

This paper proposed a penalty adjustment-based sizing method for FRs in IMs. Numerical simulations and a case analysis of the proposed method were performed, and the general MIP method, trade-off sizing method and penalty adjustment-based sizing method were compared. Both the general MIP method and the trade-off sizing method result in a conservative solution under the fixed penalty conditions. The simulation results show that the proposed penalty adjustment-based sizing method can reduce the SC and double the marginal benefit. The optimal penalty can be solved using the proposed method, which overcomes the drawback of the existing penalty-based programming method and provides a novel way to address the intractable problem of setting penalties. The impact of the penalty on the marginal benefit and the size of the FRs is also investigated. The results confirm the optimality of the penalty obtained by the proposed method.

The introduction of FRs is an effective way to smooth the imbalance between the renewable generation and load and improve the power supply reliability and renewable energy consumption ability of IMs. However, in engineering construction, the redundant deployment of FRs is obvious, which leads to high costs. To overcome these problems, the method proposed in this paper provides a tool for decision makers to determine the size of FRs and contributes to addressing the problem of setting penalties and balancing robustness and economy.

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