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An Improved Scheduling Approach for Multi-Energy Microgrids Considering Scenario Insufficiency and Computational Complexity

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Abstract: With the increasing energy demands and concern for environmental protection, researching and optimizing multi-energy systems have become prominent issues in the energy field. To improve the overall performance of multi-energy systems, there are two main difficulties that must be overcome: the first is the issue regarding the coupling relationships between energy sources, and the second is the uncertainties related to multiple types of energy and loads. Particularly with regard to the second difficulty, it is necessary to generate a large number of effective scenarios, as many multi-energy systems have only been built recently, and operational data exhibit uncertainties. However, at the same time, the introduction of a large number of random scenarios can lead to computational difficulties, making it impossible for a model to solve this problem. To this end, in this paper, we propose an improved scheduling approach for multi-energy microgrids, balancing scenario insufficiency and computational complexity. Latin Hypercube sampling is creatively used to generate enough uncertain scenarios, and hierarchical clustering is employed to create representative scenarios to reduce the computational complexity. Then, based on these effective clustered scenarios, a multi-energy collaborative optimization method considering the coupling relationship between energy sources is proposed. The effectiveness of this method is verified through numerical tests and sensitivity analysis. The results show that the economic cost of this method is only 0.305% higher than that of the deterministic method and that it has a certain degree of robustness and a good economic performance, but it is limited by its computational efficiency. In summary, this study provides an effective solution for collaboratively optimizing the operation of multi-energy systems, aiming to provide valuable insights for research in the energy field.

Keywords: multi-energy microgrids; hierarchical clustering; Latin Hypercube sampling; scenario generation

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1. Introduction

The global energy demand continues to grow; however, traditional energy resources are becoming increasingly scarce, and environmental pollution is becoming more serious. Through the application of renewable energy and multi-energy collaborative optimization systems, energy structures can be better optimized while carbon emissions and the dependence on fossil energy can be reduced [1], thus promoting sustainable development of the environment.

As the specific application platform of an energy network, multi-energy microgrid systems integrate electrical energy, cooling energy, and thermal energy storage and renewable energy and realize the joint supply of electrical, heating, and cooling energy at a given terminal. This not only greatly improves the energy utilization capacity of the system but also realizes efficient conversion and has a significant energy-saving effect. However, the uncertainty of renewable energy [2,3], the complexity of the coupling relationship between multiple energy sources, and the difference between energy sources increase the complexity of optimal scheduling problems.

As a result of the increasing importance of multi-energy collaborative optimization in integrated energy systems, researchers in this field have explored several innovative research paths [4]. Liu [4] proposed a comprehensive energy system containing hydrogen and used probability information to deal with uncertain information by pushing back the horizon to avoid risks, but there was no cooling demand in the system. Wei [5] proposed a bidirectional operation strategy with regional energy management as the core, not only focusing on the configuration of energy conversion equipment but also deeply analyzing the multi-energy complementarity between the system and user sides to optimize how the system adapts to the multi-energy demand. However, its reliability in actual operation still needs to be verified. Xu [6] focused on integrated energy systems of industrial parks and studied the effective regulation and optimization of multiple energy sources through the application of an energy cascade. In addition, the detailed modeling and analysis of all kinds of equipment in the energy system were carried out, but the implementation cost was relatively high, and the practical application still needs to be carefully balanced. Wang [7] proposed a user collaboration model of shared energy storage and cogeneration, providing a scientific basis for cost allocation by accurately analyzing users' electricity consumption behavior. However, there is still room for improvement in its performance regarding reducing emissions. Wu [8] described a multi-microgrid integrated energy system in detail and used the energy coefficient method to construct an economic- and thermal-efficiency-oriented optimization scheduling model, effectively overcoming the shortcomings regarding the heuristic algorithm efficiency. Li [9] proposed a new framework for multi-energy microgrids that participate in multi-energy market trading as well as a multi-agent master–slave game trading model based on the characteristics of energy interaction at all levels of an integrated energy system. Du [10] proposed a multi-microgrid integrated energy system optimization scheduling model that takes into account electricity price uncertainty and game fraud and introduces demand response and cloud energy storage mechanisms. Based on the Nash bargaining game mechanism, Gu [11] established an improved operation model of a multi-microgrid integrated energy system under a carbon-trading mechanism and adopted ADMM to solve it. Li [12] proposed a sizing optimization and energy management strategy for hybrid energy storage using multi-objective optimization and random forests, while Wang [13] presented a new improved method for home energy management based on the Internet of Things. This method is a multi-objective optimization method that considers two main goals: energy consumption cost and user satisfaction. Zhong [14] investigated the impact of carbon emission limitations on multi-energy microgrids and proposed an improved energy management strategy for multi-energy microgrids.

As a typical algorithm for solving random factors, robust optimization has also been applied in multi-energy microgrids. However, over estimating the worst-case scenario of uncertain information leads to overly conservative scheduling. Ou [15] proposed a two-stage stochastic robust optimization model for a multi-energy microgrid, taking into account the structure of the power grid and the heat network to optimize and minimize the cost of a two-stage microgrid in the worst wind power output scenario. Zhao [16] used

a robust optimization method to deal with the uncertainty of renewable energy output, and a two-tier game model was designed in the first stage of the two-stage RO. Sang [17] proposed a two-stage RO model based on the expected scenario that considers the influence of the uncertainty of wind power and photovoltaic output on microgrid operation, taking the optimal operation cost of the expected scenario as the objective function. Zhou [18] proposed a novel multi-stage adaptive stochastic–robust optimization (MASRO) approach for hydrogen-based multi-energy microgrids, which combines the concepts of stochastic programming and multi-stage robust optimization. The established model has the objective of optimizing the expected operation cost, and the solution's feasibility is ensured by designed constraints rather than the "min–max" structure. Zhao [19] proposed a distributed robust model predictive control (DRMPC)-based energy management strategy for island multi-microgrids, while Chen [20] proposed a novel cumulative relative regret decision-making strategy to optimize the energy management of grid-connected multi-energy microgrids considering uncertainties. By considering these uncertainties, the robustness of the microgrid can be ensured and the conservatism of microgrid operation can be reduced compared with the traditional robust optimization method. Yang [21] proposed a robust optimization model of microgrids considering uncertainty, taking into account the economy and robustness of microgrid operation.

In some studies, reinforcement learning has been used to make scheduling decisions in multi-energy microgrid systems. However, using reinforcement learning often leads to constraint violations and poor convergence when dealing with complex coupling constraints. This is very dangerous for the safe operation of power systems. Yao [22] proposed a solution to this based on multi-agent reinforcement learning. Their method not only ensures the voltage of the system is stable but also optimizes the scheduling strategy of the distributed power supply and realizes an efficient energy balance. Yang [23] detailed the problem related to the multi-scenario and variable complexity of multi-microgrid optimization as well as source load uncertainty and data privacy protection problems. To solve these problems, the authors proposed a reinforcement learning optimization method based on hierarchical constraints to improve the overall performance of the system. Wang [24] proposed a data-driven strategy for MMG systems with shared energy storage. Mixed attention is applied to fit the conditions of the equipment, and Multi-Agent Soft Actor–Critic (MA-SAC) and MA-WoLF-PHC are proposed to solve the partially observable dynamic stochastic game problem. Nakabi [25] designed an advanced energy management system and implemented and empirically compared seven deep reinforcement learning algorithms to enhance the well-known asynchronous advantage Actor–Critic algorithm**.** Lissa [26] proposed that a deep reinforcement learning algorithm should be developed for indoor, domestic hot water temperature control, aiming to reduce energy consumption by optimizing the usage of PV energy production. Ji [27] proposed a novel energy management approach using deep reinforcement learning for the real-time scheduling of an MG that considers the uncertainty of the load demand, renewable energy, and the electricity price, while Zhou [28] developed an improved deep reinforcement learning (DRL) method to achieve dynamic optimal energy dispatch and linked the stochastic optimization model to a Markov decision process.

Some studies have also used scenarios and historical data to deal with random factors in multi-energy microgrid systems. Si [29] established a model for the multi-objective optimization of a multi-energy microgrid configuration and constructed a typical scenario set by using a hidden Markov model based on simplifying the historical data of the system. Dong [30] and Wen [31] constructed a multi-scenario, multi-energy microgrid model based on the uncertainties in multi-energy system planning. However, their model focuses on the configuration problem. Meanwhile, Xiu [32] established a multi-microgrid integrated

energy scheduling optimization model based on historical data, which uses a BP neural network to predict the photovoltaic power generated in the following year to ensure the rationality of the configuration of microgrid equipment capacity.

In brief, in previous studies, there is a poor balance between scenario insufficiency and computational complexity, which is the focus of this paper. Based on the previous work, in this study, we adopt a new method of optimizing multi-energy microgrid scheduling. Our main contributions are summarized as follows.

- An improved economic dispatch model for multi-energy microgrids incorporating renewable energy; electricity, heating, and cooling load demands; heating, cooling, and electric energy storage; electric heaters; and a chiller is established.
- Latin Hypercube sampling is used to generate simulated scenarios to solve the problem of a lack of scenarios for five random factors: photovoltaic (PV) power, wind power, electricity load, cooling load, and heat load.
- The hierarchical clustering method is used to obtain representative scenarios to reduce the complexity of model calculations caused by an excessive number of scenarios.

2. Problem Formulation and Analysis

2.1. Multi-Energy Microgrid

As shown in Figure 1, the multi-energy microgrid system considered in this paper includes photovoltaic (PV) and wind power; electrical load demand; heating, cooling, and electrical energy storage; electric heating; and a chiller, and it can exchange power with the main grid. Due to the temperature requirements of the equipment in the microgrid system, the demand for cooling and heating loads should be catered for. There are complex coupling relationships among various devices, which will be introduced in Section 3.1, which greatly complicates the scheduling of multi-energy microgrids.

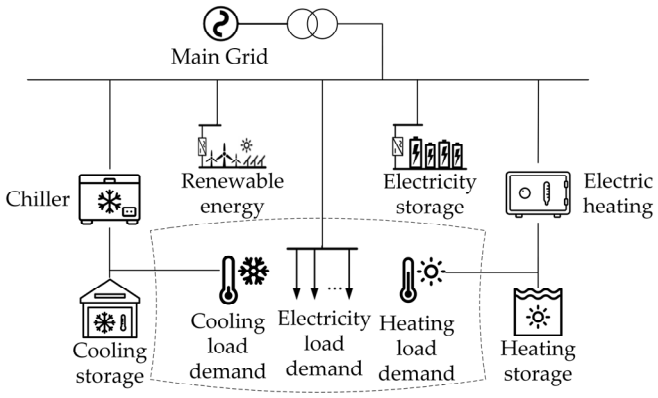


Figure 1. The structure of a multi-energy microgrid.

2.2. The Uncertainty of Random Factors

There are five random quantities to consider in multi-energy microgrid scheduling optimization, which are the photovoltaic (PV) and wind power and electricity, heating, and cooling loads. In this paper, $t (t = 1, 2, \ldots, T)$ represents the discrete period in the scheduling process, $\mathbf{d}_t$ represents all random factors in period t; $\mathbf{d}_t^{real}$ represents the actual realized values of all random factors in period t, as shown in Equation (1); and $\mathbf{d}_{[t]}$ represents the actual realized values of all random factors before period t (including period t).

$$\mathbf{d}_{[t]} = \left\{ \mathbf{d}_1^{real}, \mathbf{d}_2^{real}, \cdots, \mathbf{d}_t^{real} \right\} \tag{1}$$

Since it is impossible to determine the value of the random quantity at a future time when deciding period t, the decision made at period t will affect the feasibility of the

decision at this future time. Thus, the problem of the uncertainty of random factors brings great challenges to solving the model. In this study, we use a scenario-based method to simulate the uncertainty of random factors and deal with this uncertainty problem through simulating deterministic scenarios.

2.3. Lack of Scenarios

For some newly built multi-energy microgrids, there are too few operating scenarios, for which we only know the fuzzy boundaries. In this case, it is difficult to use scenario-based methods to solve the model, so we need to generate scenarios. If the traditional Monte Carlo method is used to sample random factors, most of the scenarios generated under a small amount of sampling are distributed near the mean value with a high probability, and thus the simulated scenarios do not reflect actual scenarios that will occur in the future. Thus, it may be impossible to apply these simulation scenarios to solve the model using scenario-based methods. Therefore, in this paper, we use the Latin Hypercube sampling method to a better effect so that simulated scenarios can sufficiently cover the sample space.

3. Optimal Scheduling Approach for Multi-Stage, Multi-Energy Microgrids

To solve the problem of the insufficient number of operation scenarios for multi-energy microgrids, we use Latin Hypercube sampling to create more scenarios. However, the computational complexity of using a lot of scenarios is too high for scenario-based methods; thus, we adopt hierarchical clustering to obtain representative scenarios and add these to ensure the robustness of scheduling schemes. Finally, rolling optimization is adopted for the real-time scheduling of multi-energy storage microgrids. The steps of our methodology are shown in Figure 2.

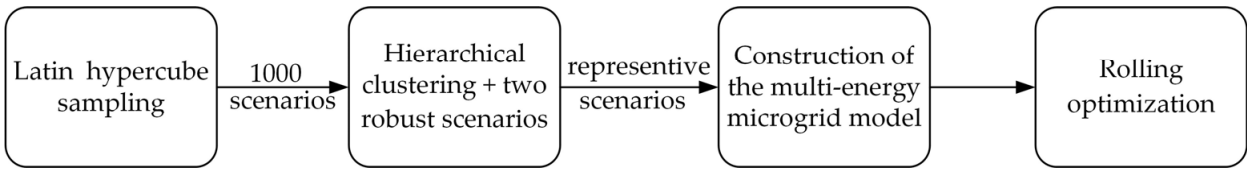


Figure 2. Steps of the proposed methodology.

3.1. Latin Hypercube Sampling

For newly constructed multi-energy systems for which there are limited historical operating scenarios, it is essential to extract as much information as possible from the available data to generate representative scenarios. Initially, we assume that the random factors follow a normal distribution, which is a common approach widely adopted in numerous studies [33]. Subsequently, the upper and lower bounds and expected values of four random factors can be determined based on the limited scenarios and operational experience of similar systems. At this point, the inputs are obtained to generate scenarios.

To improve the sampling effect of scenarios composed of random factors, the Latin Hypercube sampling [34] (LHS) method is adopted in this study, which has a better sampling effect compared with traditional Monte Carlo sampling (MCS). The sample distributions of Latin Hypercube sampling (LHS) and traditional Monte Carlo sampling (MCS) are shown in Figures 3 and 4. Both methods were sampled 1000 times, and it can be seen that the LHS method has a better fitting effect than MCS.

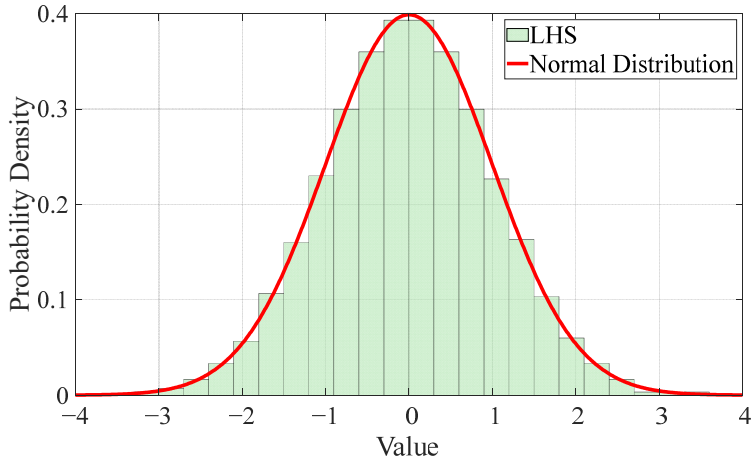


Figure 3. Sample distribution of Latin Hypercube sampling.

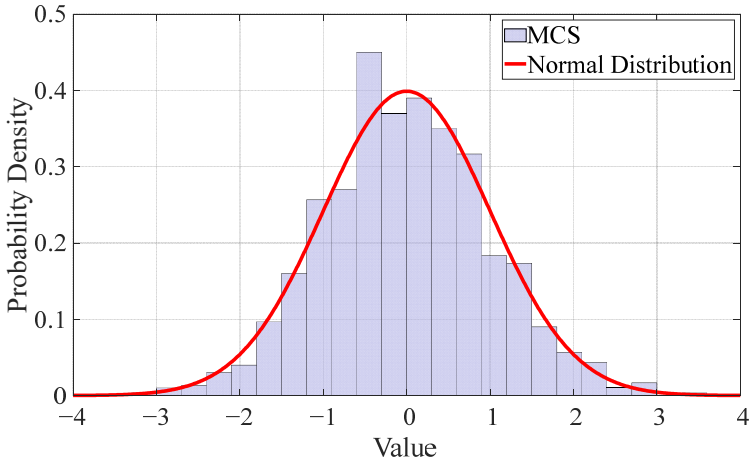


Figure 4. Sample distribution of Monte Carlo sampling.

LHS includes mainly stratified sampling and random sorting.

1. Stratified sampling can ensure that sample points fully cover the joint probability space of multidimensional random variables. As shown in Figure 5, the sampling times of random variables are denoted as N. For a random variable X, its probability interval can be divided into N equidistant non-overlapping sub-intervals, and random numbers $y_n \in Y$ are extracted according to a uniform distribution for each sub-interval. If the cumulative probability distribution function of X is $Y = F(X)$, then a random sample $\{x_1, x_2, \cdots, x_N\}$ of X can be obtained according to the inverse function $x_n = F^{-1}(y_n)$ of the cumulative probability distribution function, thus obtaining a $1 \times N$-dimensional sample sequence of random quantities. A commonly used interval median stratified LHS method is given here. The formula is as follows.

$$y_n = \frac{n - 0.5}{N}, n = 1, 2, \cdots, N \tag{2}$$

$$x_n = F^{-1}(y_n) \tag{3}$$

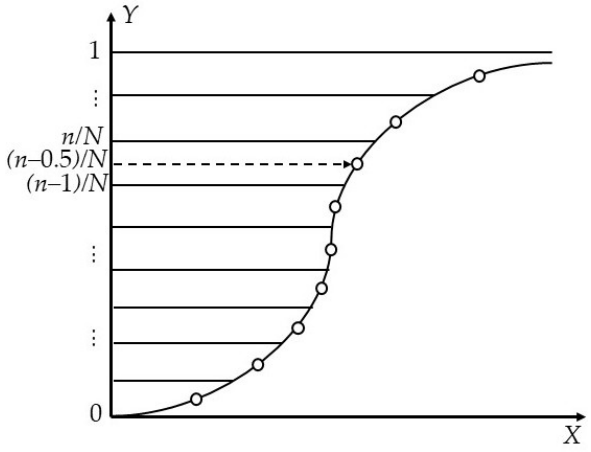


Figure 5. Description of Latin Hypercube sampling.

2. Random sorting is used to shuffle the order of samples in the initial sample. The order of the initial samples obtained by stratified sampling is strictly arranged according to the cumulative probability of the samples. However, for a single random variable, random sorting is more consistent with the actual sampling situation, and when sampling multiple random variables, there is often a correlation between these variables. Random ordering can reconstruct this correlation between random variables.

When the number of random variables is M, the method of random ordering is as follows. An $M \times N$-dimensional random order matrix L with the same dimension as the initial sample is generated. The initial sequence matrix L is modified using the Cholesky decomposition method to control the correlation of the sampling results. The correlation coefficient matrix corresponding to L is denoted as ρ_L, and the correlation coefficient matrix ρ_S is obtained according to the historical observations of random quantities. On the premise that both ρ_L and ρ_S are symmetric positive definite matrices, the Cholesky decomposition is performed.

$$\rho_L = QQ^T \tag{4}$$

where Q and D are the lower triangular matrices obtained by decomposition ρ_L and ρ_S, respectively. Then, the correlation matrix G is derived from Q, D, and L.

$$G = Q^{-1}L \tag{5}$$

When the elements in G are not integers, an association matrix with all positive elements can be constructed based on the relative sizes of the elements in G, and the elements in the original sample of X can be reordered according to this association matrix.

3.2. Hierarchical Clustering

When there are too many sampled scenarios, it is difficult to solve the model. Assuming that the number of sampled scenarios is 1000, the model cannot obtain a scheduling scheme that conforms to all 1000 scenarios feasibly within a limited solving time. Therefore, after sampling is completed, in this study, we use the hierarchical clustering method to cluster the sampled scenarios and obtain a small number of representative economic scenarios. Meanwhile, robust scenarios are added to ensure the robustness of the model.

The steps of the hierarchical clustering algorithm [35] are shown in Algorithm 1.

Algorithm 1 Hierarchical Clustering

Input: Dataset $D = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_m\}$;
Clustering distance measurement function d;
Number of clusters k.
Steps:
for $j = 1, 2, \ldots, m$ **do**
  $C_j = \{\boldsymbol{x}_j\}$
end for
for $i = 1, 2, \ldots, m$ **do**
for $j = 1, 2, \ldots, m$ **do**
    $M(i, j) = d(C_i, C_j)$;
    $M(j, i) = M(i, j)$
  end for
end for
Set the current cluster number: $q = m$
while $q > k$ **do**
  find the two closest clusters: C_{i^*} and C_{j^*};
merge C_{i^*} and C_{j^*}: $C_{i^*} \cup C_{j^*}$;
  for $j = j^* + 1, j^* + 2, \ldots, q$ **do**
renumber cluster C_j to C_{j-1}
  end for
  delete rows j^* and column j^* of the distance matrix M
  for $j = 1, 2, \ldots, q - 1$ **do**
    $M(i^*, j) = \mathrm{d}(C_{i^*}, C_j)$;
    $M(j, i^*) = M(i^*, j)$
  end for
  $q = q - 1$
end while
Output: Cluster $C = \{C_1, C_2, \ldots, C_k\}$

As shown in the above pseudo-code, the initial cluster contains only one sample and the corresponding distance matrix is initialized. Then, the nearest cluster is continuously merged, and the distance matrix of the merged cluster is updated. The above process is repeated until the preset number of clusters is reached to obtain the required number of economic scenarios.

3.3. Optimal Scheduling Model

3.3.1. Cooling

The cooling power of the chiller in the multi-energy microgrid system can be expressed by (6), where the cooling generated by the chiller and the electric power consumed are linearly affected by the coefficient κ^{Fq}.

$$q_t^{CO}(\mathbf{d}_{[t]}) \cdot \tau = \kappa^{Fq} \cdot p_t^{cFC}(\mathbf{d}_{[t]}) \cdot \tau; \forall t \in \mathcal{T} \tag{6}$$

The cooling energy storage contained in the system can cope with the uncertainty of the cooling load to a certain extent, as shown in (7). The cooling energy storage is affected by the initial cooling storage energy E_0^{CL}, the cooling power q_t^{ST}, and environmental losses q_t^{Loss}, and it must be within the upper and lower limits $[\underline{E}_t^{CL}, \overline{E}_t^{CL}]$. The lost cooling storage

is considered to be a definite amount in this study. As shown in (4), the input and output of cooling energy storage q_t^{ST} must be within the upper and lower limits.

$$\underline{E}_t^{CL} \leq E_0^{CL} - \sum_{t'=1}^{t} q_{t'}^{ST}(\mathbf{d}_{[t]}) \cdot \tau - \sum_{t'=1}^{t} q_{t'}^{Loss} \cdot \tau \leq \overline{E}_t^{CL}; \forall t \in \mathcal{T} \tag{7}$$

$$\underline{q}_t^{ST} \leq q_t^{ST}(\mathbf{d}_{[t]}) \leq \overline{q}_t^{ST}; \forall t \in \mathcal{T} \tag{8}$$

As shown in (9), the system must meet the cooling balance constraint. To meet the demands of the system, the cooling load must be equal to the sum of the cooling generated by the chiller and the cooling exchanged with the cooling energy storage system.

$$q_t^{CO}(\mathbf{d}_{[t]}) + q_t^{ST}(\mathbf{d}_{[t]}) = q_t^{D}; \forall t \in \mathcal{T} \tag{9}$$

Finally, to achieve sustainable scheduling of the cooling load, as shown in (10), the final cooling energy storage needs to be equal to the initial cooling energy storage.

$$E_0^{CL} = E_T^{CL} \tag{10}$$

3.3.2. Heating

The power of the electric heating in the multi-energy storage microgrid system can be expressed by (11), where the heat generated by the fuel cell and the amount of electric power consumed are linearly affected by the coefficient κ^{Fh}.

$$h_t^{FC}(\mathbf{d}_{[t]}) \cdot \tau = \kappa^{Fh} \cdot p_t^{hFC}(\mathbf{d}_{[t]}) \cdot \tau; \forall t \in \mathcal{T} \tag{11}$$

Similar to cooling energy storage, the system's heating energy storage can cope with the uncertainty of the heat load to a certain extent, as shown in (12). The thermal energy storage is affected by the initial thermal storage energy E_0^{HT}, the heating power h_t^{ST}, and environmental losses h_t^{Loss}, and it must be within the upper and lower limits of heating energy storage $[\underline{E}_t^{HT}, \overline{E}_t^{HT}]$. The lost heat is also regarded as a definite amount in this study. As shown in (13), the input and output of heating energy storage q_t^{ST} must be within the upper and lower limits.

$$\underline{E}_t^{HT} \leq E_0^{HT} - \sum_{t'=1}^{t} h_{t'}^{ST}(\mathbf{d}_{[t]}) \cdot \tau - \sum_{t'=1}^{t} h_{t'}^{Loss} \cdot \tau \leq \overline{E}_t^{HT}; \forall t \in \mathcal{T} \tag{12}$$

$$\underline{h}_t^{ST} \leq h_t^{ST}(\mathbf{d}_{[t]}) \leq \overline{h}_t^{ST}; \forall t \in \mathcal{T} \tag{13}$$

As shown in (14), the system must meet the thermal balance constraints. To meet the system's heating load demand, it must be equal to the sum of the heat generated by the heater and the heat exchanged with the heating energy storage.

$$h_t^{FC}(\mathbf{d}_{[t]}) + h_t^{ST}(\mathbf{d}_{[t]}) = h_t^{D}; \forall t \in \mathcal{T} \tag{14}$$

Similar to cooling energy storage, to achieve sustainable scheduling of the heating load demand, the final heating energy storage, as shown in (15), should be equal to the initial heating energy storage.

$$E_0^{HT} = E_T^{HT} \tag{15}$$

3.3.3. Electricity

As shown in (16) [2], the electric energy storage is affected by the initial stored electric energy E_0^{POW} and the charging and discharging power p_t^{ST}. In addition, the stored energy

at every moment should be within the upper and lower limits $[\underline{E}_t^{POW}, \overline{E}_t^{POW}]$, and the charging and discharging power is affected by the physical equipment and also needs to be within the upper and lower limits $[\underline{p}_t^{ST}, \overline{p}_t^{ST}]$. However, the functional relationship between the electric energy storage and the charging and discharging power in (18) is not linear. Before solving the model, it needs to be linearized via the Big M method or other methods. As shown in Figure 6, when x is negative, it represents the charging stage; when x is active, it represents the discharge stage.

$$\underline{E}_t^{POW} \le E_0^{POW} - \sum_{t'=1}^{t} f^{POW}(p_{t'}^{ST}(\mathbf{d}_{[t]})) \le \overline{E}_t^{POW}; \forall t \in \mathcal{T} \tag{16}$$

$$\underline{p}_t^{ST} \le p_t^{ST}(\mathbf{d}_{[t]}) \le \overline{p}_t^{ST}; \forall t \in \mathcal{T} \tag{17}$$

$$f^{POW}(x) = \begin{cases} x \cdot \tau / \eta^{Edis}, \ if \ x \ge 0 \\ x \cdot \tau \cdot \eta^{Ech}, \ otherwise \end{cases} \tag{18}$$

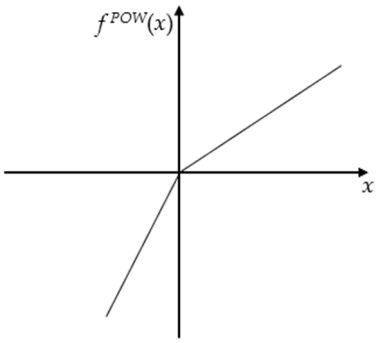


Figure 6. The functional relationship between electric energy storage and the charging and discharging power (when x is negative, $f(x)$ represents the charging stage; when x is positive, it represents the discharge stage) [2].

In addition, for power scheduling to be sustainable in the future, as shown in (19), the final energy storage needs to be equal to the initial energy storage.

$$E_0^{POW} = E_T^{POW} \tag{19}$$

When too much renewable energy is generated, it may be impossible to consume it; at this point, the power needs to be abandoned to ensure the safe operation of the power system. As shown in (20), the power discarded from renewable energy sources must not exceed the power they generated at any moment.

$$0 \le p_t^{cur}(\mathbf{d}_{[t]}) \le p_t^{ren}; \forall t \in \mathcal{T} \tag{20}$$

Finally, as shown in (21), the power exchanged between the microgrid system and the main grid needs to be within the upper and lower limits.

$$\underline{p}_t^{GD} \le p_t^{GD}(\mathbf{d}_{[t]}) \le \overline{p}_t^{GD}; \forall t \in \mathcal{T} \tag{21}$$

3.3.4. Load Balance Equation

In addition, the above constraints are coupled through the load-balancing equation shown in (22).

$$p_t^{ren} - p_t^{cur}(\mathbf{d}_{[t]}) + p_t^{ST}(\mathbf{d}_{[t]}) + p_t^{GD}(\mathbf{d}_{[t]}) = p_t^{cFC}(\mathbf{d}_{[t]}) + p_t^{hFC}(\mathbf{d}_{[t]}) + p_t^{D}; \forall t \in \mathcal{T} \tag{22}$$

3.3.5. Objective Function

In (23), λ_t^{POW} is the electricity price, which is considered to be a known quantity in this study. The electricity price varies in different periods. $\mathcal{D}^s$ is the set of representative scenarios. The overall objective function is the expected cost of the transaction with the main grid in each scenario in $\mathcal{D}^s$. $\underset{\mathbf{d}\in\mathcal{D}^s}{Exp}[\cdots]$ is the weighted sum of all scenarios' economic costs, and the weighting coefficient of each representative scenario is related to the number of clustering scenarios.

$$\min_{q,h,m,p} \underset{\mathbf{d}\in\mathcal{D}^s}{Exp}\left[\sum_{t\in\mathcal{T}}\left(\lambda_t^{POW}\cdot p_t^{GD}(\mathbf{d}_{[t]})\right)\cdot\tau\right] \tag{23}$$

3.4. Rolling Optimization

To further cope with the uncertainty of random factors introduced in Section 2.2, we adopt a rolling optimization scheduling strategy; that is, all decisions within 24 h are not solved at once in advance, as demonstrated in Figure 7. As time goes on, random factors become deterministic at different moments, and the decisions made at each moment are not only dependent on the realized value of random factors at the present moment but are also related to the simulated future scenarios.

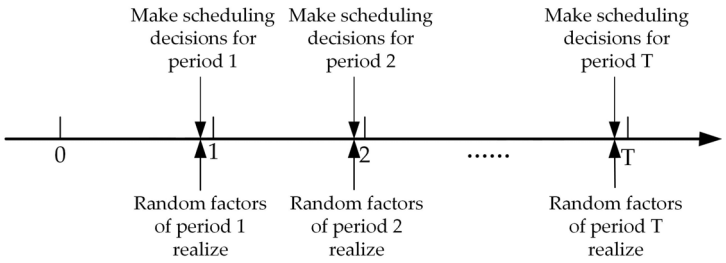


Figure 7. Rolling optimization diagram.

4. Numerical Tests

Numerical tests were implemented on real multi-stage, multi-energy microgrids. All tests were simulated using MATLAB R2022a and Gurobi 10.0.3 on a desktop with Intel i5-9300H CPU @ 2.40 GHz with 16 GB RAM manufactured by Hewlett-Packard in Palo Alto, CA, USA.

4.1. Data Preparation

To deal with the uncertainties of photovoltaic and wind power, electricity load, and cooling and heating demands as much as possible, in this study, we generated 1000 scenarios for these five uncertainties through Latin Hypercube sampling. However, if the model introduced above is used to determine a feasible solution for these 1000 scenarios, it is difficult to solve in terms of time and memory. Therefore, in this study, we perform hierarchical clustering of these 1000 scenarios, clustering similar scenarios into one representative scenario to obtain the 10 most representative scenarios. Figure 8 shows the electricity prices used in this article, while Figures 9 and 10 show the photovoltaic power and electricity load in the 10 scenarios obtained by clustering, in which S1 to S10 refer to the 10 representative scenarios obtained by hierarchical clustering, ub is upper bound, and lb is lower bound. In addition, two additional robust scenarios are added to the scenario set to ensure the robustness of the scheduling scheme.

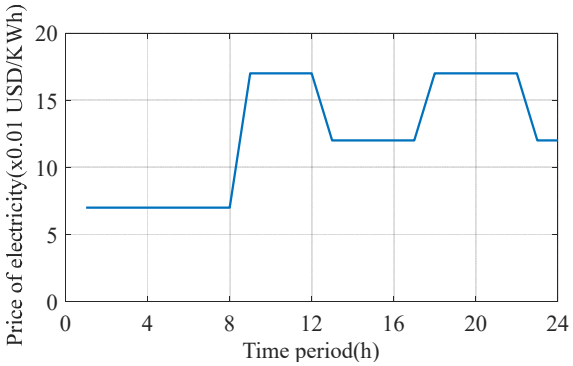


Figure 8. The price at which power is exchanged with the main grid.

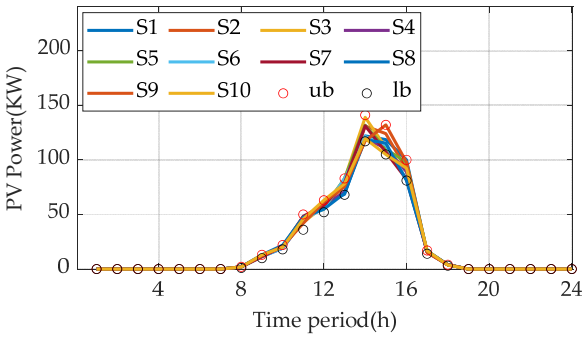


Figure 9. The clustering results for photovoltaic power.

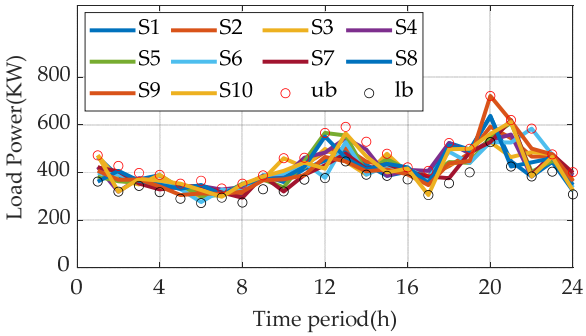


Figure 10. The clustering results for electricity load.

Other data for the tested regional microgrid were taken from real multi-stage, multi-energy microgrids. The regional microgrid includes one ES system (30 KW/100 KWh), one wind farm (240 KW), one photovoltaic (PV) station (150 KW), one heating storage unit (300 KW/600 KWh), one cooling storage unit (300 KW/600 KWh), electric loads (720 KW), heating loads (400 KW), and cooling loads (50 KW). Other detailed data can found in [36].

The initial energy stored in the ES unit is set to 50 KWh and the cycling efficiency is 0.92. The power transfer limits between the microgrid and the main grid are $\pm$1.5 MW.

4.2. The Output of the Decision for Each Period

To visually display the dispatch results, we take the electric power traded with the main grid as an example, as shown in Figure 11. To reduce the cost, the direct power transferred between the microgrid and the main grid is different at different times. By considering the electricity price changes shown in Figure 8, it can be seen that in the period of low electricity prices, both the dispatching scheme and the deterministic method are more inclined to buy electricity, while in the period of high electricity prices, both schemes

are more inclined to sell electricity, meeting the requirements of minimum cost in the objective function.

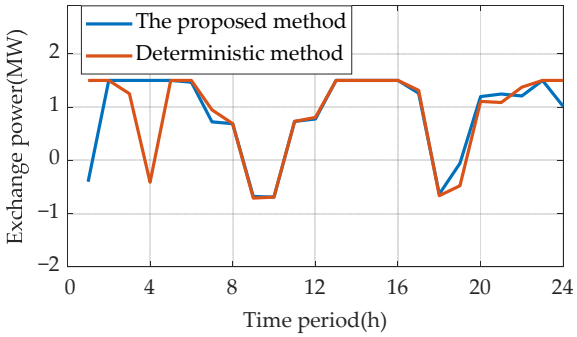


Figure 11. Decision results of power exchange with the main grid.

4.3. Comparison with Other Methods

For the deterministic method, in any scheduling period, the real values of random factors in the future time are known; that is, it has complete information on future period scheduling. Therefore, using the deterministic method, the decision made in each period is the most economical throughout the whole process. However, it is impossible to completely and accurately predict random factors in the future during the actual scheduling process; thus, a comparison is used in this study to reflect the economical and computational efficiency of the presented scheme.

The robust scenario refers to two worst-case scenarios for multi-energy storage microgrids. (1) Renewable energy generation reaches a maximum, but the electricity, heat, and cooling demands are minimal. (2) Renewable energy generation is at a minimum, but the demands for electricity, heat, and cooling are maximal. When the robust scenario is used as the simulation scenario, the economic benefits may be low because the prediction of future situations is too conservative.

The scenario-based method that uses Monte Carlo sampling to generate scenarios and K-means to reduce these scenarios is referred to as the MK scenario-based method in this paper. Pouria [37] used this method for residential energy hubs. To ensure a fair comparison, the input of this method is the same as that for the proposed method.

Figure 12 shows the decision results of the charging and discharging power of the electric energy storage system for the three scheduling schemes (positive values relate to discharging and negative values relate to charging). Because the deterministic method has access to the complete future information, the decision taken at every moment is the best. Both the proposed method and the deterministic method tend to charge when the electricity price is low and discharge when the electricity price is high. Combined with the result of the power exchange with the main grid in Section 4.2, the energy stored by the system that was purchased when the electricity price was low can be released when the electricity price is high to minimize the total cost. The charging and discharging power of the electric energy storage in the scenario scheduling scheme containing only robust scenarios is always 0. This is because the two extreme robust simulation scenarios are very conservative; that is, the two extreme scenarios either have too little demand or too much demand, electricity is bought and sold sufficiently to meet the current needs, and excess electricity is not traded to charge or discharge the electric energy storage unit. Compared with the MK scenario-based method, the decisions of the proposed method are more similar to those of the deterministic method between 1 and 9 h. However, the decisions of the proposed method and MK scenario-based method are the same between 10 and 24 h. There is no doubt that the proposed method has a better performance.

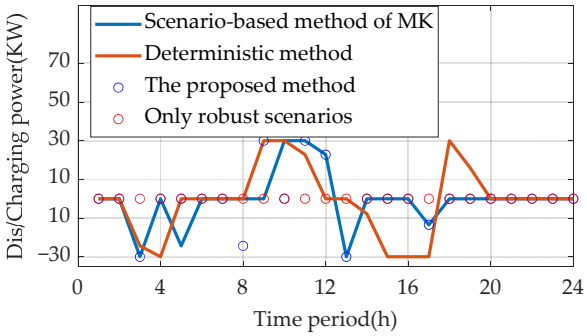


Figure 12. Discharging and charging power decision for electric energy storage (the dark red circles indicate when the decisions of the proposed method and only robust scenarios coincide).

Table 1 shows a comparison of the economical and computational efficiency of the four methods, in which each representative scenario of random factors represents the actual running scenario and cost is the average of the sum of each representative scenario. It can be seen that the economic cost incurred by using our presented method is very similar to that of the deterministic method, far lower than that of the scenario method containing only robust scenarios, and slightly lower than that of the MK scenario-based method, which reflects the economic advantages of this method. However, the computational efficiency of the proposed method is poorer than that of the other methods. This is because only two extreme scenarios are included in the method only considering robust scenarios, which is far less than ten economic scenarios obtained by sampling and the two extreme scenarios guaranteed by robustness considered in the proposed scheme. This increased number of scenarios leads to an increase in solving time; adopting more efficient clustering methods may be one method to improve this solving time.

Table 1. Results of computational efficiency and economy.

Method	Time (s)	Cost (USD)
MK scenario-based method	74	95.7439
Deterministic method	3	94.6622
The proposed method	72	94.9509
Only robust scenarios	38	144.0335

4.4. Influence of Load Levels

With the growth in population and industry, power, cooling, and heat loads have increased. In this study, three load growth levels between 5 and 15% in a scheduling period are tested to analyze their impact on the proposed method. The expected scenario of random factors is used as the actual running scenario for the following tests.

In Figure 13, the "load increase method" indicates that the expected value of electrical, cooling, and heating loads all increase by 5–15%, with the original upper and lower limits [37], and the cost is the economic result of the four methods for the same operation scenario. We can see that the proposed method still remains economically viable with the increase in load, obtaining similar results to the deterministic method with complete information, consistently slightly lower costs than those of the MK scenario-based method and much lower costs than those of the method considering only robust scenarios.

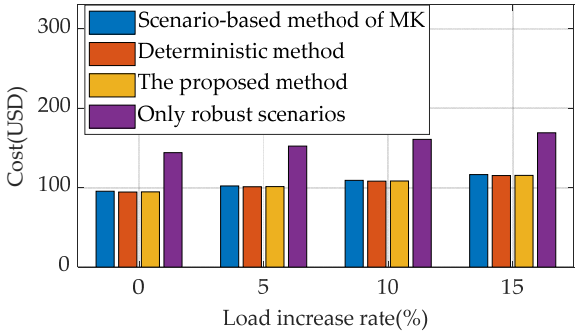


Figure 13. Costs of different methods under four load levels.

4.5. Robustness

After testing, we found that the proposed scheme is feasible for all 1000 scenarios obtained via Latin Hypercube sampling followed by hierarchical clustering. This shows that hierarchical clustering completely inherits the uncertain information present in the original scenario, and our scheme has a certain degree of robustness.

5. Conclusions

In this paper, we discuss a scheduling approach for multi-energy microgrids. Using Latin Hypercube sampling for scenario generation, we solve the problem of the lack of scenarios with random factors. The number of representative scenarios is reduced using the hierarchical clustering method, and then these scenarios are used as the simulation scenarios to solve the scheduling problem of multi-energy storage microgrids. Numerical tests show that our scheduling scheme performs well economically and has a large degree of robustness, but it limited by the solving time. The results show that the method's economic cost only increases by 0.305% compared with that of the deterministic method. Our future work will explore extending the model and scheduling scheme to power systems with transmission constraints and a decreased capacity. In addition, more sustainable development measures and efficient clustering methods will also be studied in future work.

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