Research Article

Big Data Energy Scheduling Game Management Algorithm Based on Dual Carbon Goals

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"Carbon peak and neutrality" are an important strategic decision to promote the transformation of China's energy economy and build a community with a shared future for mankind. China is a big energy consumer, and the whole society is facing huge challenges under the goal of carbon peak and neutrality. The realization of the goal of carbon peak and neutrality requires the guidance of correct theoretical methods and scientific deployment. This paper mainly studies the energy consumption scheduling, demand response management, and energy trading problems of microgrid. In view of the shortcomings of the existing energy optimization scheduling methods in the microgrid, a variety of energy resources such as electric energy, natural gas, heat energy, and cold energy are considered into the microgrid model. Based on the noncooperative game and Stackelberg game, a new energy optimal dispatch model is constructed with a variety of game methods such as two-layer game. Maximize the personal benefits of the microgrid while meeting the reliable operation of the system and the electricity demand of users. The three-stage noncooperative game problem is solved based on the reverse bootstrap method, and the closed expression of the optimal strategy in each stage is obtained. The power generation forecasting technology based on big data is studied, and a power forecasting method is proposed, which can effectively guide the energy consumption of the microgrid. The simulation results show the effectiveness of the proposed renewable energy management model based on big data, which verifies that the accurate wind power prediction results are conducive to better theoretical analysis of energy management.

1. Introduction

On December 12, 2020, Xi Jinping, General Secretary of the Central Committee of the Communist Party of China, solemnly announced at the UN Climate Ambition Summit that China will strive to achieve Carbon peak by 2030 and strive to achieve the "Carbon peak and neutrality goal" of Carbon neutrality by 2060. On April 30, 2021, General Secretary Xi Jinping emphasized at the 29th collective study meeting of the Political Bureau of the CPC Central Committee that realizing carbon peak and neutrality is China's solemn commitment to the world, is also a broad and profound economic and social change, and is by no means easy to achieve. Party committees and governments at all levels must have the energy to grasp the traces of iron and stamp on the stone, clarify the

timetable, roadmap, and construction drawings, and promote economic and social development based on the efficient use of resources and green and low-carbon development [1, 2].

Facing the great and arduous goal of Carbon peak and neutrality, what challenges will China face? What exactly does this goal require of Chinese society? The author believes that there are two major requirements in summary: one is energy saving on the energy demand side, and the other is zero carbonization on the energy supply side. The dual carbon goal is a huge subject covering multiple industries and disciplines in the whole society [3–5]. This paper only analyzes and judges the challenges and countermeasures of the energy industry under the mission of Carbon peak and neutrality from the perspective of energy supply, that is, to gradually realize the "primary energy" "Zero-carbon,

secondary energy electrification" direct use of zero-carbon energy and electrified secondary use.

Renewable energy sources such as wind power and photovoltaics have attracted widespread attention from all over the world due to their environmentally friendly and renewable characteristics. However, the uncertainty of its primary energy has a certain impact on the operation and power quality of the power system, to alleviate the fluctuation of the power supply, and the power grid dispatching usually limits its output scale, thus causing a serious phenomenon of curtailment of wind and solar power [6–8].

Distributed energy system (DES) is one of the development directions to solve the problem of renewable energy consumption. Compared with the traditional centralized energy supply system, DES is composed of small distributed power sources (such as gas internal combustion engines, and gas turbines). An energy system is composed of loads and energy transmission equipment according to a certain topology. The main advantage of the distributed energy system is that it can realize the cogeneration of cooling, heating, and power, which can maximize the "cascade utilization" of energy and improve the utilization rate of energy [9, 10]. Connecting several distributed energy systems to the grid gas network to establish an energy network can realize the regional interconnection of multiple energy sources. The established energy network is also called a distributed energy network system (DENS). It realizes the information-energy cooperative control through information network technology and forms a safe, efficient, and intelligent new energy network system. Among them, the autonomous dispatch strategy refers to the optimal operation strategy of the distributed energy network system aiming at system stability, economy, and environmental benefits, coordinating regional controllable power sources, loads, and energy storage facilities to achieve a balance between supply and demand at different time scales. The distributed energy network system can be connected to a large power grid and run in a grid-connected mode and can also be disconnected and run independently when the power grid fails [11–13].

Since China's energy resources and energy demand are characterized by reverse distribution, in order to promote the optimal allocation and utilization of energy resources, the concept of demand-side response is proposed in the existing technology, that is, through various ways and means (such as through legal, administrative, economic, technological, and other means) to guide and encourage users to actively change the conventional energy consumption. As a virtual controllable resource, demand-side response can be combined with a variety of energy supply types to effectively overcome the impact of the reverse distribution of energy resources and energy demand on the power system. Therefore, in view of the above status quo, it is urgent to develop an energy Internet dispatching system based on big data analysis to overcome the deficiencies in current practical applications [14, 15].

Game theory is also known as "game theory," and in Taiwan, China is translated as "game theory," as shown in Figure 1. In a broad sense, game theory refers to the process in which multiple entities (agents) use the information they

Figure 1: Game theory.

have (the decisions of each participant) to make decisions under certain constraints (the rules of the game). It is also a branch of applied mathematics and an important discipline in operations research and has a wide range of applications in computer, psychology, economics, and other disciplines. Taking computer science as an example, according to incomplete statistics, researchers who are active in wireless networks, distributed computing, databases, algorithm analysis, and other branches have long been concerned about the application of game theory in computer science [16–18]. Game theory is a direction of mathematical theory research and has become an important research method in economics. It mainly solves decision-making problems and finds the optimal solution by studying the rational interaction between multiple game participants. Game theory only has five basic elements: game players, strategy sets, payoffs, information, and Nash equilibrium. Games can be divided into different categories according to different classification conditions. In general, we think that there are two main categories of games, namely, cooperative games and noncooperative games. According to whether there is a constrained agreement between the interacting participants, the game is divided into cooperative game (constrained agreement) and noncooperative game (unconstrained agreement). In addition, the game can be divided into static game and dynamic game, complete information game, and incomplete information game according to the time sequence of participants' behavior and the degree of information mastery in the game process [19–21]. In order to further improve the efficiency of distributed energy utilization, the competition and cooperation mechanism with multiple target entities has been widely used in the energy management research of microgrids.

Despite the advantages of cooperative analysis among systems, noncooperative game models do not require mutual commitment among various market players and have the advantage of lower communication overhead. Furthermore, through noncooperative game analysis in various noncooperative game models, it is possible to effectively model hierarchical levels among players in which leaders have market dominance over followers and can adapt their strategies to imposed on followers. Most of the current research on microgrid energy consumption scheduling, energy trading, and demand response management only considers one energy source, namely, electricity [22–24]. However, with the consideration of various energy networks such as electric power, natural gas, and thermal energy into the microgrid, the microgrid system will become more complex and

unpredictable. How to comprehensively manage multiple energy resources and ensure the efficient and stable operation of the system is particularly critical. Therefore, it is necessary to carry out corresponding research on the energy optimization scheduling method of the microgrid, which comprehensively considers various energy resources such as electric energy, natural gas, and cold energy.

To sum up, in order to effectively utilize renewable energy while further ensuring the reliable operation of the system and meeting the electricity demand of users, this paper studies the problem of distributed energy management and maximizes the individual objective function of each market participant. The method based on the fusion of noncooperative game idea and big data solves the problem of microgrid energy management in the energy Internet. In order to effectively reduce the uncertainty caused by wind turbines, a short-term wind power prediction algorithm based on deep learning is proposed. In the pretraining process, an adaptive evolutionary algorithm with a three-layer hidden layer structure is used to extract features from the training sequence, and in the fine-tuning process, the backpropagation algorithm is used to calculate the weights of the entire neural network. Numerical results show that accurate wind power prediction results are beneficial for better energy management [25, 26].

2. Game Theory Model

In recent years, with the continuous advancement of the goal of "Carbon peak and neutrality," the large-scale grid connection of distributed energy such as solar energy and wind energy, due to the uncontrollable, fluctuating, variable, and intermittent characteristics of distributed energy, large-scale, high-proportion Access will bring certain challenges to the stability of the power system. In addition, the installed capacity of the microgrid is limited, and only relying on its own energy supply may not meet the user's power demand. When the user's power supply is insufficient, the power plant and the energy storage company should be coordinated to purchase the corresponding power to meet the user's energy demand in time.

In recent years, in addition to the economic field, game theory has also been applied in the field of microgrids. In the microgrid, a simple economic model can no longer describe the complex energy network including a variety of renewable energy and energy storage devices, and the use of noncooperative game, alliance game, Stackelberg game, and other game theory methods together with the economic behavior of each individual in the energy network can be effectively modeled and analyzed. There are generally three important basic elements in game models: players, strategies, and benefit functions. The behavior of the players is selfish and rational, by adjusting their game strategies to maximize their benefits. The general idea of applying game theory to the field of microgrid research is as follows: on the basis of the system model of microgrid, the three basic elements in the game model must be clarified first, the corresponding game model must be constructed, and the game model must be proved by relevant proof methods. Whether there is a corresponding equilibrium, then design a corresponding

algorithm to solve the game process, and finally analyze the characteristics of the game model through simulation. The performance decisions between multiple entities are made through cooperation or competition strategies, thereby effectively improving the microgrid.

The basic assumption of the game model establishment: each game participant is rational and pursues the maximization of his own interests, and each participant needs to consider his own knowledge information and the behavior expectations of other participants. From the perspective of game types, big data energy scheduling game models can generally be divided into three categories: (1) noncooperative games, where each participant chooses his own actions independently from other participants; (2) cooperative games, where the participants in the game act in the form of alliances and cooperation; (3) semicooperative games, where players choose one player to cooperate. This paper constructs a noncooperative game model of dual energy consumption scheduling among household users in the energy interconnected microgrid. In this game model, household users compete with each other to adjust the electricity and natural gas consumption of hybrid gas-electric equipment to maximize its benefits. The employed functions are shown in Figure 2.

Assuming that the players in the game are each household m_i, then there are M households in a certain area, and then,

$$\{m_1, m_2, \ldots, m_M\}. \tag{1}$$

The resource allocation strategy of a single family can be expressed as a resource allocation matrix $A(m_i)$:

$$A(m_i) = \begin{bmatrix} \overline{a_1}(m_i) \\ \overline{a_2}(m_i) \\ \cdots \\ \overline{a_n}(m_i) \end{bmatrix}. \tag{2}$$

The benefit function of household user n is defined by the consumption cost of electricity and natural gas, namely,

$$U_n = -Pex_n - Pgy_n. \tag{3}$$

Here, a control variable n_z is defined to describe the dual-energy scheduling strategy of the hybrid gas-electric equipment of household user n, namely,

$$z_n = ax_n - \frac{A_n}{2},$$

$$ax_n - \frac{A_n}{2} = -by_n + \frac{A_n}{2}. \tag{4}$$

The benefit function for home user n can be described as

$$U_n(z_n) = -\left[Pe + \lambda \sum_n \left(Ea_n - Sp_n + \frac{A_n/2 + z_n}{a} \right) \right] \frac{A_n/2 + z_n}{a}$$

$$- \left[Pg + \mu \sum_n \left(Ga_n + \frac{A_n/2 - z_n}{b} \right) \right] \frac{A_n/2 - z_n}{b}. \tag{5}$$
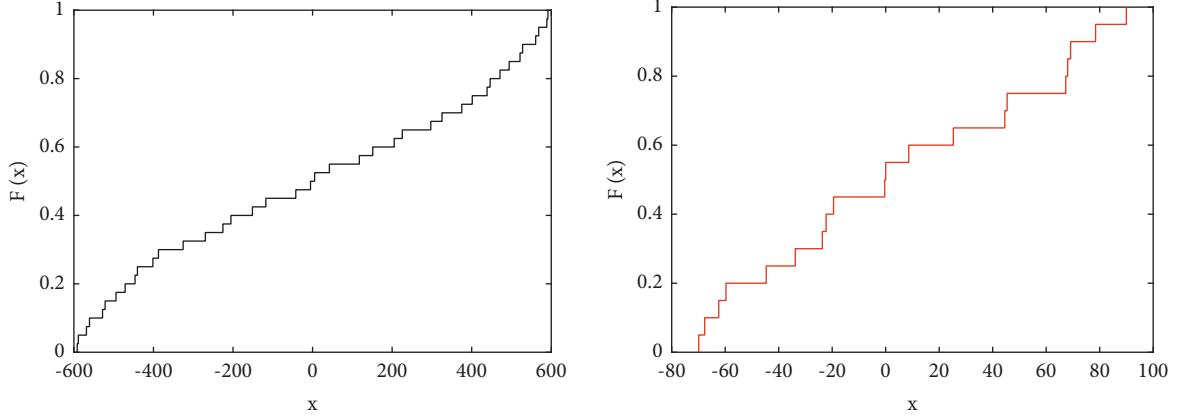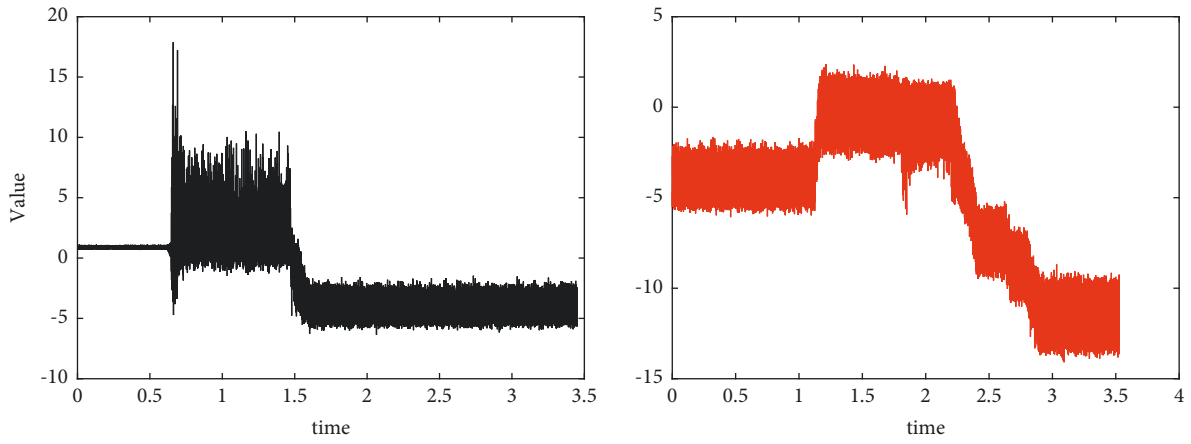
Figure 2: Employed function.

Figure 3: Predicted value.

In the noncooperative game model of dual energy consumption scheduling among household users, there are participants, namely, all household users n. In strategy, each household user n controls the control variable z_n of its mixed gas-electric equipment to adjust its electricity and natural gas consumption. The predicted is shown in Figure 3. In the benefit function, each household user maximizes its benefit U_n and is defined in equation (5). The set of strategies for all feasible dual-energy consumption scheduling for home user n is expressed as

$$S_n = \left\{ z_n | z_n^{\min} \leq z_n \leq z_n^{\max} \right\}. \tag{6}$$

Among them, $z_{\min}$ and $z_{\max}$ respectively represent the smallest and largest controllable variable value. For each household user n, the optimal response strategy of its dual energy consumption scheduling is defined as

$$z_n^{best} = \arg \max U_n(z_n). \tag{7}$$

The energy supplier resource game (NYGYS) can be represented by a quadruple:

$$\text{NYGYS} = \{M, \text{Req}, S, \text{Utility}\}. \tag{8}$$

Among them, M is the participant of the game, Req is the request matrix, S is the alternative strategy of the game participant, and Utility is the profit.

$$S = \{S(m_i) | i = 1, 2 \dots, M\},$$
$$\text{Utility} = \{\text{Utility} | i = 1, 2 \dots, M\}. \tag{9}$$

How to make the most reasonable and effective use of data center resources, meet user requirements, improve resource utilization efficiency, and reduce resource waste is worth the attention. The mathematical model of the energy game can be expressed as the following equation:

$$\text{Max} - \text{Utility s.t.} \begin{cases} s_i(m_i) \in N, \\ \sum_i s_i(m_i) \cdot r \leq R_k(m_i), \\ 0 \leq ERT_i \leq RT_i, \\ 0 \leq \sum_k a_{ik} \cdot \text{prace} \leq \text{Cos } t. \end{cases} \tag{10}$$

The first constraint is expressed as an overall planning problem, and the second constraint states that the total resources of virtual units allocated in each user do not exceed
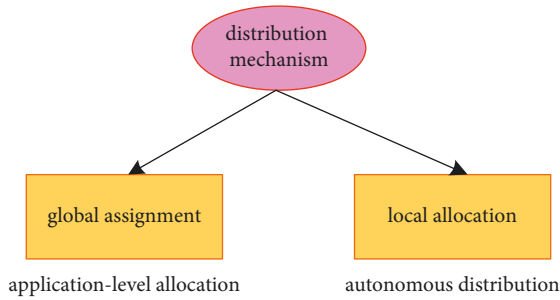
FIGURE 4: Common allocation mechanisms.

the total amount of available resources. The third constraint indicates that the actual response time of each user to each subtask is within the maximum response time in the constraint. The fourth constraint indicates that the cost is within the budget in the constraint. Through the design of the profit function in the game model, its optimization algorithm can solve the appropriate available resource scheduling strategy $S(m_i)$ for each user. The benefit function is a trade-off of resource utilization of energy centers, fairness of resource allocation, and multitype optimization objectives.

Based on the introduction of the above knowledge, the grid participants in the economic model include various resource providers and consumers, and some models also require auctioneers. Whether they are resource providers or resource consumers, they are all selfish, and their fundamental goal is to maximize their own benefits. Generally, the commonly used economic models adopt two-level distribution mechanisms, namely, global distribution and local distribution, as shown in Figure 4. Global allocation is application-level allocation. Resources are allocated to maximize benefits according to consumer information and utility functions. Local allocation can support the autonomy of grid nodes, and complete task execution according to the system's resource allocation strategy. Correspondingly, we can use the knowledge of game theory to solve the problem of grid resource allocation. The overall energy dispatching level is based on the competitive game analysis in multiple energy systems.

The grid resource consumer agent submits jobs to the grid resource provider agent. Different types of jobs are allocated to specific grid nodes through a certain global strategy. Generally, the resource consumer agent will calculate the job execution according to certain strategies. In the same way, the resource provider agent will also make a general calculation according to the operating capacity, load, and quantity of resources, so as to formulate a price suitable for the value of resources. Grid resource consumer agents and grid resource provider agents trade, buy, and sell resources through grid information services.

We can abstract the global allocation problem as a game model in which multiple grid users (i.e., resource consumers) buy resources competitively, or a game model in which multiple resource providers compete to find users. In the former, there are multiple users who need to perform their jobs, and each user has a certain budget, but the resources are limited, so they must successfully buy resources

and execute jobs through a bidding game. The latter situation occurs when some resources are oversupplied. Instead of wasting resources there, it is better for the resources themselves to actively seek out users who need resources to obtain certain benefits.

3. System Implementation and Simulation Analysis

The big data energy management system proposed in this paper is a comprehensive energy consumption management system based on the Industrial Internet of Things and big data analysis. Large-scale, multiregional, network-wide synchronization of data collection, aggregation, and centralized uploading requires cloud networks and cloud storage resources with extremely high performance levels. The overall system construction and operation and maintenance are most suitable for the three major telecom operators to undertake, not to mention the need for different energy consumption. The unit establishes a one-to-one corresponding multidimensional related energy consumption and emission model. For the self-control and reliable energy-consuming units, the simulation results of the model are used to implement the reverse switch standby operation for the relevant energy-consuming equipment to realize the dynamic energy efficiency optimization of the energy-consuming equipment. This in turn requires extremely powerful cloud computing resources, and the implementation of such control should be in the hands of mainstream state-owned central enterprises, and the cloud computing resources of the three major operators are basically guaranteed. The network management system and dynamic environment monitoring system built by telecom operators are responsible for the collection and integrated access of the operators' own energy consumption data. Or the existing system of the enterprise is forwarded and connected to the operator's energy management cloud platform according to the unified energy consumption and emission data collection and interface standard specifications, and the operator charges the traffic fee and function fee. For example, if users use the energy auditing and diagnosis function to request energy use consulting reports, additional consulting fees can be charged. The government pays financial subsidies, maintenance fees, traffic fees, and service fees to operators to purchase services, and operators can also collect energy consumption and emission source data, transaction fees, and management fees for the government. The operator pays the development fee and technical support fee to the system technology supplier.

The communication operator's energy big data management system grasps the energy consumption situation in real time, improves the real-time energy consumption model of each energy-consuming equipment to predict the energy use trend, realizes the dynamic optimization of energy consumption management of various energy-consuming equipment, and takes timely dispatching measures to improve the operation efficiency. Maintain the management level of the department, timely discover and forecast operating equipment failures in advance, realize preventive
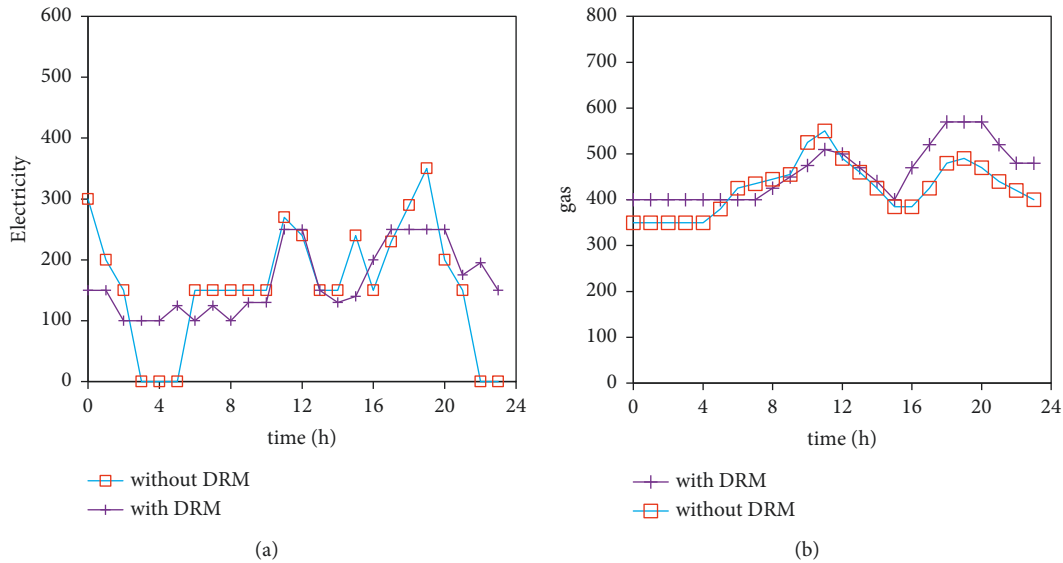
Figure 5: Performance with or without DRM. (a) Electricity. (b) Gas.

maintenance, make all energy-consuming equipment operate in the best state as much as possible, and minimize the impact on energy consumption, which is in line with the 12th Five-Year Energy Saving of the General Office of the State Council. Emission reduction proposes policy guidance, fulfills the responsibility of enterprises for energy conservation and emission reduction, and contributes to accelerating the construction of a resource-saving and environment-friendly society.

The energy management big data cloud platform establishes a benchmark computer room/base station by clustering and correlation analysis of massive energy consumption data of large-scale computer rooms/base stations and establishing energy consumption models of energy-consuming sites. The system constitutes a knowledge base by constructing theoretical knowledge, experimental data, expert experience, and related definitions and theorems related to energy consumption analysis, and stores, organizes, implements, and uses a set of interconnected knowledge bases in the computer to effectively realize knowledge performance and performance. Reasoning, closely combined with data mining and OLAP, helps users analyze, give reasonable conclusions and suggestions, and improve social and economic benefits.

In this section, we use concrete cases to evaluate the performance of the proposed game method for solving multienergy demand response management problems. Assume that there are 1 energy supplier and 10 residential smart energy hubs in the system in a day, and there are 24 time periods in a day. The efficiency parameters of transformers, electric refrigerators, gas boilers, and CCHPs in each residential smart energy hub can range from the interval [0.91, 0.97], [0.4, 0.5], [0.4, 0.5], [0.35, 0.45], respectively. [0.4, 0.5] and [0.4, 0.5] are randomly selected. The coefficients of the cost function for electrical energy are 4, 2, and 5, respectively. The coefficients of the cost function for natural gas are 3, 1, and 4, respectively. The coefficients in the

benefit function of each residential smart energy hub are randomly selected from the interval [10, 20] in the time period 12:00–14:00 and the time period 18:00–21:00. For other time periods of the day, the coefficients are randomly selected from the interval [5, 10]. The coefficient for all residential smart energy hubs is set to 0.5. For the scheduling parameters that do not use the above algorithm, they are set to 0.7 and 0.6, respectively.

Figure 5(a) depicts the changes in total electrical energy load of residential smart energy hubs under the unused and used demand response management algorithms. Without using the DRM algorithm, the electrical energy load has obvious fluctuations, and the peaks exist in the period around 13:00 and 20:00. Using the DRM algorithm, the power load becomes smooth, and the peak is reduced by about 20.5% around 13:00, and by about 21.45% around 20:00. Figure 5(b) depicts the variation of total natural gas load of residential smart energy hubs without and with DRM algorithm. When the DRM algorithm is used, the natural gas load becomes smooth, except that two peaks appear around 13:00 and 12:00, respectively. This is due to residential smart energy hubs increasing the utilization of CCHP units to meet their energy load needs during these peak hours.

Changes in the total power consumption of residential smart energy hubs without and using the DRM algorithm are studied in this paper. Compared with Figure 5, the two peaks of the curve using the DRM algorithm are at 13 During the period around 00 and 20:00. Power peak loads are used to support the CCHP units. Figures also describe the changes in the consumption of cold energy and heat energy of residential users without and using the DRM algorithm, respectively. In this figure, after using the DRM algorithm, the cold energy consumption is smoothed, except for two troughs, which is due to the fact that less electricity and natural gas are converted into cold energy output at this time. In this figure, after using the DRM algorithm, the thermal energy consumption is also smoothed, except for
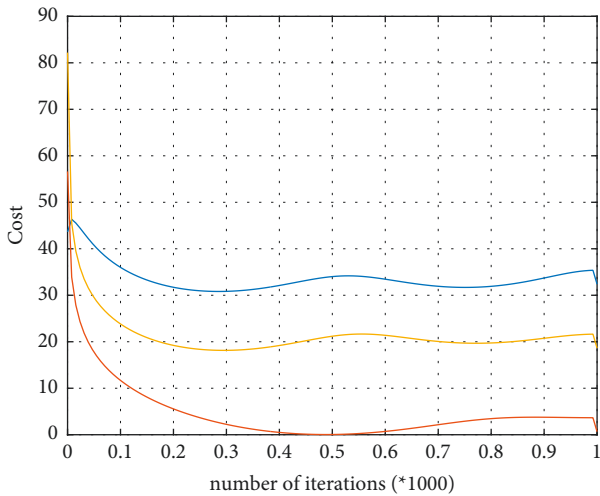
Figure 6: Number of iterations.

Figure 7: MAPE.

Figure 8: Output comparison.

the two troughs, due to the fact that less natural gas is converted into thermal energy output at this time. Figures also describe the changes of dispatch parameters in residential smart energy hubs without and with DRM algorithm, respectively. In this figure, the dispatch parameters have a significant increase in the period around 13:00 and 20:00, which is because the residential smart energy hub needs more natural gas to be converted into electricity for output. On the contrary, in the figure, the dispatch parameters show a significant increase in the period around 13:00 and 20:00, as residential smart energy hubs tend to need to reduce the output in the form of electrical energy converted into heat.

The convergence performance of the Stackelberg game method for multienergy demand response management is shown in Figure 6. There are 3 curves in this figure, and each curve represents the change in energy cost of a residential smart energy hub. According to the figure, at the beginning, the energy cost of residential smart energy hubs and the energy benefits of energy suppliers vary greatly. After about 500 iterations, the energy costs of residential smart energy hubs and the energy benefits of energy suppliers hardly change. At this time, we can think that the Stackelberg game between the energy supplier and the residential smart energy hub has reached the Stackelberg equilibrium. Figure also compares the changes in the total energy cost of residential smart energy hubs without and using the DRM algorithm. As can be seen from figure, after using the above game method, the cost of the residential smart energy hub is reduced by about 30%. Figure also compares the changes in the total energy revenue of energy suppliers without and using the DRM algorithm. It can be seen from the figure that the above game method can effectively improve the income of the energy supplier of electricity and natural gas.

Figure 7 shows the MAPE values of the proposed algorithm for three different ways for wind power prediction step. The wind power prediction process based on historical data is called step = 1. New results can be obtained in a similar fashion by adding the forecast results to the historical data, a process called step = 2, and so on. From the simulation results, it can be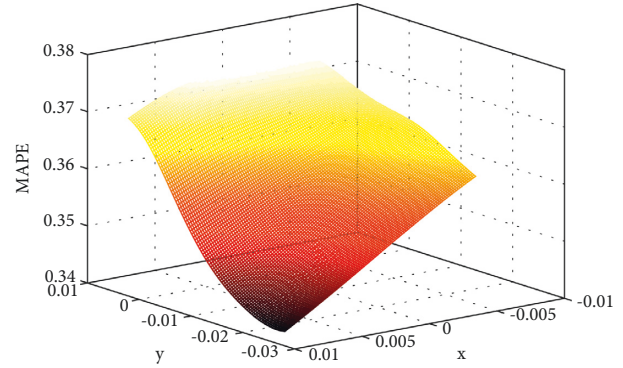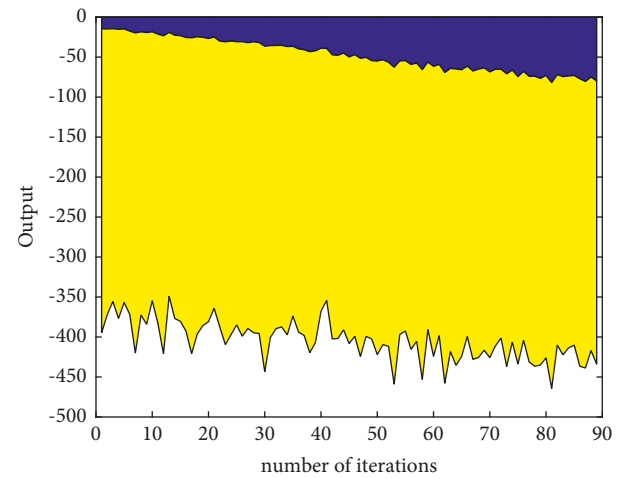 found that MAPE increases with the increase of prediction step size. Thus, it can be concluded that as the step size increases, the result becomes inaccurate. The simulation results show that the algorithm can obtain the smallest prediction error compared with the other two algorithms. Specifically, when step = 5, the absolute error of prediction is reduced by 7.3% compared with the SVM algorithm, and the absolute error of prediction is reduced by 32.4% compared with the Adam algorithm.

Figure 8 is a comparative analysis of the convergence of different algorithms. It can be seen from Figure 8 that, with the increase of the number of iterations, no matter whether the proposed Stackelberg game or the classical Nash non-cooperative game algorithm is used, after a small number of iterations, the very clear convergence can be achieved. However, the proposed big data-based renewable energy management system using Stackelberg game has better convergence than Nash, and at the same time, compared with other algorithms, Stackelberg game can bring more benefits to the microgrid system.

Overall, the Steinberg method is applied to the problem of multi-energy demand response management in residential smart microgrids. In the above game model, the energy supplier, as the leader, adjusts its energy price to maximize its own benefit, while the residential smart energy hub, as the follower, adjusts its energy resource consumption

according to the energy price to minimize its own the cost. We prove the uniqueness of the Stackelberg equilibrium in this game model and present a demand response management algorithm that can achieve this equilibrium. The simulation results show that the above game method can effectively improve the utilization efficiency of various energy resources, improve the energy suppliers' income from selling energy, and reduce the energy consumption cost of users. Through noncooperative game analysis in various noncooperative game models, hierarchical models among players can be effectively modeled in which leaders have market dominance over followers and can impose their own strategies on followers.

4. Conclusion

This paper focuses on energy management systems consisting of power plants, energy storage companies, microgrids, and electricity users. In order to effectively utilize renewable energy, it is proposed to use big data-based power generation forecasting technology to obtain short-term wind power forecasting results to help microgrids implement energy management strategies. On this basis, the paper defines the energy management problem as a three-stage Stackelberg game, which regards each role in the electricity market as a gamer. While ensuring the reliability of the system, it can meet the user's electricity demand and make maximum personal benefits. The three-stage optimization problem is solved by reverse induction, and the closed analytical expressions of the optimal price and demand strategy in each stage are derived. Finally, the effectiveness of the algorithm is verified by simulation, and it is proved that the prediction error will reduce the optimal benefit of the microgrid. The experimental results show that the performance of the genetic algorithm is better than other traditional algorithms, which is beneficial to energy management. In future work, the focus will be on the management of energy cooperation among multiple microgrids based on renewable energy and electricity consumption forecasting.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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