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Distributed Energy Scheduling Problem Based on Learning Algorithm

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Abstract: Compared with traditional fossil energy, new energy has the advantages of large reserves, great development potential, and no pollution. For the current rapidly growing electricity demand, it is of great significance to fully develop and utilize new energy. In this context, the necessity of new energy development and the difficulty of new energy utilization drive the rapid development of distributed energy(DE) optimization scheduling methods. Since the efficient operation of DE optimal scheduling relies on advanced communication technology, this paper implements DE scheduling in the cloud environment. In this paper, the objective optimization scheduling simulation experiment of the economic cost and environmental protection benefit of the DE system is carried out, and the DE system is optimized by three learning algorithms including Bayesian, decision tree and improved decision tree, and the DE economic scheduling problem is solved , and compared with the other two algorithms, the effect of improving the decision tree algorithm to reduce the economic cost is more obvious.

1. Introduction

Since the DE system is concentrated on the user load side, the operation is easily affected by load changes. At the same time, changes in external environmental factors such as temperature, light and wind speed will also have a great impact on the safe and stable operation of the DE system. The utilization rate of clean energy is low and it is difficult to achieve a dynamic balance with user needs. DE systems are usually difficult to operate under optimal operating conditions, resulting in problems such as high investment costs and low operating efficiency for DE systems.

So far, scholars have been researching DE scheduling problems based on learning algorithms. For example, a scholar proposed an optimal scheduling model based on a CCHP-type DE system. The experimental results show that the method can effectively reduce the daily economic cost by optimizing the operation mode and output of each equipment of the CCHP-type DE system [1] . A scholar proposed a new chemical reaction algorithm, aiming at the characteristics of DE with strong randomness, and comprehensively considering the reactive power optimization mathematical model of the output of DE and the change of electric energy load [2]. Some researchers include energy storage as a separate source into adjustable resources, and propose optimal scheduling methods for wind storage and solar energy storage aiming at the lowest total operating cost and high clean energy consumption rate, proving that dynamic modeling of energy storage can reduce the cost to maximize economic benefits [3]. By studying electric vehicles, an increasingly popular flexible load, a scholar has established a time-of-use electricity pricing mechanism and fully considers the behavioral characteristics of users' travel, taking electric vehicles as an important dispatching resource, effectively alleviating the problem of DE resources. A series of problems brought by large-scale grid connection [4]. Although there are many solutions to the DE scheduling problem, there are few scheduling models for learning algorithms.

This paper first proposes several machine learning algorithms, then introduces the composition and structure of DE, and then builds a DE economic dispatch model, and implements DE dispatch in the cloud environment. Finally, based on three learning algorithms, the DE scheduling problem is analyzed, and the DE multi-objective scheduling with low economic cost and high environmental protection benefits is realized.

2. Related Algorithms and DE Networks

2.1. Learning Algorithms

There are many types of learning algorithms. Machine learning algorithms and deep learning algorithms are typical two types of algorithms, and there are many kinds of algorithms under these two types of algorithms. For example, there are Bayesian algorithms under machine learning algorithms and deep learning algorithms. There are neural network algorithms. This paper introduces the machine learning algorithm [5].

(1) Decision tree algorithm

Decision tree belongs to supervised learning, which is a kind of classification algorithm, which presents the final classification result in the form of tree flow chart. Decision trees explain the response results of categorical variables [6]. Essentially, a decision tree is to classify a series of regular data. The decision tree division selection includes information gain and gain rate. The ID3 decision tree learning algorithm selects the division attributes based on the information gain [7].

(2) Bayesian algorithm

Bayes' theorem is used to describe the relationship between two conditional probabilities and to judge the probability distribution of a phenomenon [8]. Suppose there are two events A and B, and P(A|B) is the probability that A occurs if B occurs, then:

$$P(A \mid B) = P(B \mid A) \cdot P(A) / P(B) \tag{1}$$

where P(A) is the probability of occurrence of A, and P(B|A) is the conditional probability of B given that A occurs.

2.2. Composition and Structure of DE System

According to the different energy demand of users, the composition of DE system is complex and diverse. The DE system is mainly composed of various distributed micro-sources, various types of loads, energy storage devices and energy conversion devices [9]. The system structure diagram and energy flow relationship are shown in Figure 1 below. The figure shows the devices that make up the DE system in detail, as well as the energy transmission and conversion relationship between the devices.

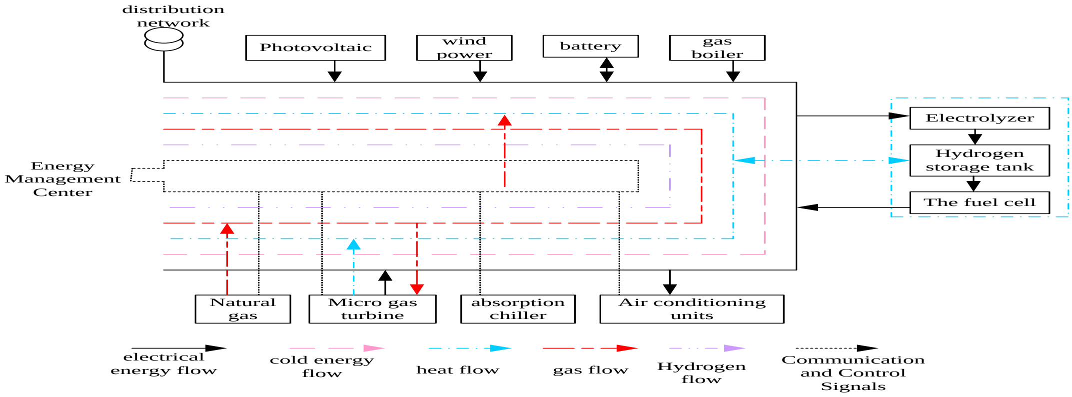

Figure 1. The relationship between DE system structure and energy flow

As can be seen from the above figure, the DE system mainly includes five parts: energy input, energy output, energy conversion, energy management, and distribution and energy storage [10]. The energy input part includes the input of renewable energy and the input of conventional energy. The input of renewable energy includes solar energy, wind energy and electric energy injected from external power grids. The advantages are low carbon and environmental protection, while the disadvantage is that solar energy and wind energy are affected by external environmental factors The energy supply is relatively large, and the energy supply is unstable, and the electricity injected into the external power grid is affected by the time-of-use electricity price, which may be less economical; the conventional energy input, namely the natural gas sold by the gas company, has a relatively stable supply and good economy, but poor environmental protection [11-12]. Energy output, including electrical energy output, cooling energy output and thermal energy output. Photovoltaic cells and wind turbines in the energy conversion part convert renewable energy solar and wind energy into electrical energy, gas boilers convert natural gas energy in conventional energy into heat energy, and micro gas turbines can convert natural gas energy into a part of heat energy and electricity. The unit can use the electric energy in the system to selectively convert it into heat energy or cold energy according to the demand of the load, and the absorption refrigeration unit can convert the waste heat generated by the micro gas turbine into cold energy [13-14]. The energy management and distribution are in charge of the energy management center, which realizes the optimal scheduling and control of the entire DE system through communication and control signals. Energy storage is mainly used to store electrical energy in batteries and hydrogen storage devices to store hydrogen energy [15].

3. DE System Scheduling Model and Implementation Mode

3.1. Economic Dispatch Model

The objective function of the economic dispatch model of the DE system is to minimize the operating cost J, and the objective function is as follows:

$$\min G = G1 + G2 + G3 + G4 \tag{2}$$

Among them, G1, G2, G3, and G4 represent the satellite gas turbine cost, grid exchange cost, electrolyzer loss cost, and fuel cell loss cost of the DE system, respectively [16].

3.2. Implementation Mode of DE Optimal Scheduling

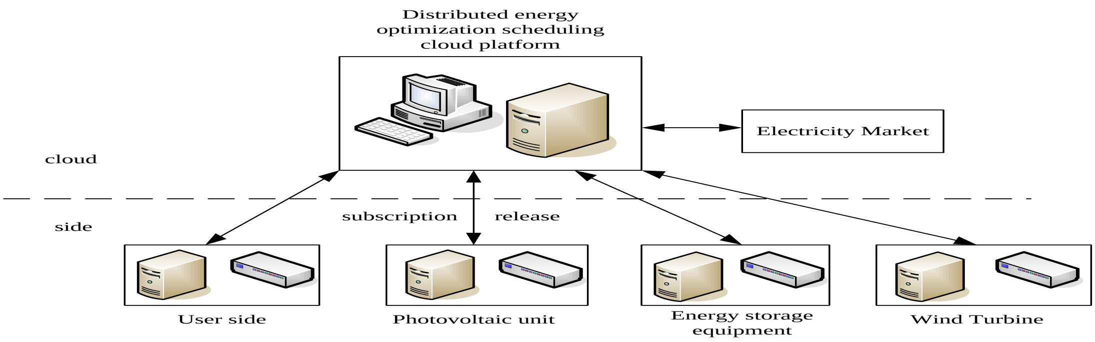

Figure 2. DE scheduling implementation based on cloud environment

As shown in Figure 2, DE scheduling is realized in the cloud environment. The side calculator subscribes the control instructions of the cloud platform to the side server, and processes and publishes the control instructions. The terminal devices subscribe to the relevant control instructions from the side server, obtain the instructions and implement them, so as to realize the control of the terminal by the cloud [17]. Through the "cloud-side-end" communication architecture based on MQTT, a large number of devices on the edge do not need to be directly connected to the cloud, which reduces the connection pressure on the cloud. At the same time, the private data from the terminal is protected on the edge, ensuring the privacy and security of users. At the same time, it also alleviates the difficulty of mass data storage in the cloud. In addition, the original cloud computing pressure is distributed to the edge closer to the terminal, which can make the calculation more accurate and efficient [18-19].

4. Simulation Experiment

4.1. Multi-Objective Optimal Scheduling Simulation of DE Network System

DE network system scheduling needs to meet the lowest economic cost and the best environmental benefit at the same time. The purpose of this experiment is to verify the effectiveness and rationality of the research on the optimal scheduling of the DE network system for the two objectives of economic cost and environmental benefit. In this paper, the experiment is divided into the following five schemes for the analysis and comparison of the simulation results of the example:

Scheme A: Under the independent operation mode, each DE system conducts optimal scheduling analysis with the goal of the lowest economic cost.

Option B: Under the independent operation mode, each DE system conducts optimal dispatch analysis with the goal of the lowest pollutant emission.

Scheme C: The DE network system is optimized for scheduling analysis with the goal of the lowest economic cost.

Scheme D: The DE network system takes the lowest pollutant emission as the goal to carry out optimal dispatch analysis.

Scheme E: The DE network system is coordinated to optimize the scheduling analysis with the two goals of the lowest economic cost and the lowest pollutant emission.

Table 1. Time-of-use tariff table

	Period (24h)	Electricity purchase price/(yuan ·kwh-1)	Electricity price/(yuan ·kwh-1)
Peak hours	10:00-15:00 18:00-21:00	1.00	0.6
Valley period	23:00-6:00	0.42	0.37
Normal period	Other	0.8	0.55

As shown in Table 1 is the time-of-use electricity price, and the DE system uses this electricity price to calculate the economic cost. During the period from 0:00 to 6:00, the electricity purchase price is low, and the DE output is small, and the start-up cost and power generation cost of dispatchable units are greater than the electricity purchase cost. Therefore, electricity is purchased from the external power grid to meet the load demand, and the energy storage is charged at the same time. At 6 o'clock, the price of electricity becomes higher, and the output of DE resources gradually increases. At this time, the start-up cost and power generation cost of dispatchable units are still greater than the cost of electricity purchase, so the load demand is still met by means of electricity purchase.

Starting from 10:00, the output of DE has a significant increase trend. At this time, the electricity price is also high. The unit can be dispatched to start, which is basically close to full power, and the energy storage begins to discharge. At the same time, the incentive signal is used to stimulate users to respond to demand. When the energy service provider sells electricity to the outside world, it can improve the economic benefit of the energy service provider.

After 15:00, the electricity price will be reduced, and the micro-gas turbine will have an operating cost, so it will not stop but continue to meet the load demand with the minimum output. At this time, the energy storage is charged in an appropriate amount to meet the large load demand of the peak electricity price in the subsequent period.

At 18:00, the electricity price peaked again. At this time, the predicted load was very high, and the incentive cost of reducing the load was less than the income from selling electricity to the outside world. Therefore, incentives will be applied to reduce the load significantly. In addition, the micro-gas turbine is basically full, and the energy storage is discharged. , as far as possible to sell electricity to improve the income of energy service providers.

After 21:00, the price of electricity is greatly reduced, and energy service providers purchase more electricity from the grid to meet the needs of the load reduced by the peak electricity price and transfer it to the demand for use during this time period, such as water heaters. At the same time, the energy storage is also charged to meet the constraint demand, and the micro-gas turbine is shut down.

From Table 2, it can be seen that compared with Scheme A, scheme B reduces pollutant emissions by 52.27%, which has excellent environmental protection, but the economic cost increases by 86.67%, which is very poor in economy; compared with scheme A, scheme C, The economic cost has been reduced by 29.53%, and the economy has been improved, but the pollutant discharge has increased by 42.94%, and the environmental protection is still poor; compared with the scheme A, the pollutant emission has been reduced by 90.6%, and the environmental protection has been improved. , but the economic cost has increased by 93.42%, and the economy is very poor. Therefore, Scheme E proposes a coordinated optimization of the total economy, cost and pollutant discharge of the DE network system. Compared with Scheme C, the economic cost of Scheme E increases by 16.51%, but the pollutant discharge is reduced by 40.91%; Compared with scheme D, the pollutant emission of E has increased, but the total economic cost has been reduced by 57.55%. From this, it can be seen that the economic cost of Scheme E is between the economic costs of Scheme C and Scheme D, and the pollutant emission of Scheme E is also between that of Scheme C and Scheme D, achieving the optimal effect of multiple objectives. At the same time, compared with Scheme A, the economic cost of Scheme E is reduced by 17.90%, and the total pollutant emission is reduced by 15.53%. Therefore, the validity and rationality of the research on multi-objective optimal scheduling of DE network system are verified. Among these schemes, scheme E can not only reduce the economic cost, but also have better environmental protection.

Table 2. Economic costs and pollutant emissions under different dispatch schemes

	Economic cost (yuan)	Pollutant emissions (kg)
Plan A	18427.5	4574.8
Plan B	34397.4	2183.6
Plan C	12986.7	6539.1
Plan D	35642.8	1673.5
Plan E	15130.6	3864.2

4.2. DE Economic Cost Scheduling Simulation Based on Learning Algorithm

A learning algorithm is used to optimize the DE network system, as shown in Figure 3. As can be seen from Figure 3, the economic cost of the Bayesian algorithm to optimize the DE system is higher than that of the other two algorithms. Compared with the Bayesian algorithm, the decision tree algorithm has more effective iterations and slower convergence speed, making the optimal The solution can be lower, the cost is reduced more, and the optimization effect is obviously better than the Bayesian algorithm. The improved decision tree algorithm not only improves the convergence of the algorithm, but also has the lowest economic cost among the three algorithms. Figure 3 verifies the feasibility and rationality of the improved decision tree algorithm, which can reduce the economic cost of DE dispatch.

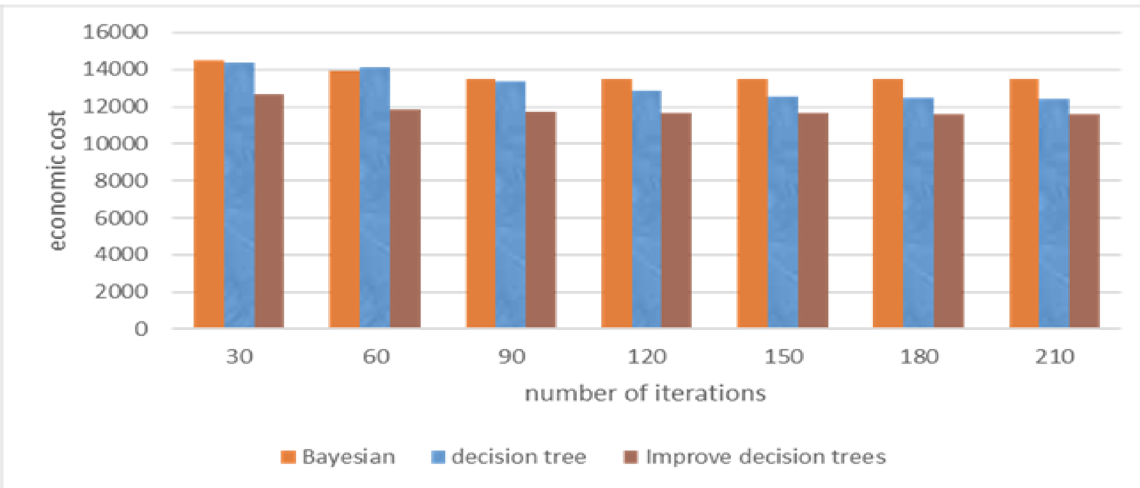

Figure 3. Economic cost of learning algorithm after convergence

5. Conclusion

The optimal operation of DE requires a large amount of data to interact, and requires a reasonable communication framework and operation mode. To this end, this paper builds a communication architecture for DE optimization scheduling based on cloud environment, which is very helpful for energy service providers to achieve optimal scheduling of DE resources. Through this paper, the optimal scheduling problem of DE network system is studied, in order to make full use of DE system technology and give full play to the advantages of DE network system energy complementarity, supply and demand complementarity, and also hope that this research can promote the development of my country's DE system.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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