Design of Renewable Energy Consumption Scheduling Model Based on Quantitative Feedback Theory

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Abstract

In the renewable energy consumption scheduling, due to the large fluctuation of wind power output, the renewable energy consumption rate is low, and the energy consumption scheduling effect is poor. Therefore, a new renewable energy consumption scheduling model based on quantitative feedback theory is designed. For the first time, calculate the output response of wind power generation, obtain the output change rate of the wind farm at the time scale, and determine the response curve of wind power generation according to the power generation process is divided into three stages: the initial stage, the peak stage and the end stage, and the response output during the peak period, so as to obtain the transfer rate of output during the peak period. Build a mathematical model of renewable energy power generation, calculate the output state of wind power generation, and analyze the output characteristics of renewable energy storage system; Secondly, the objective weight coefficient of renewable energy consumption is determined by using quantitative

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feedback theory, the objective function of renewable energy consumption is constructed, the power injected by parameter nodes is determined, the quantitative feedback controller is designed by using loop shaping technology, the control structure of two degrees of freedom is determined, the objective function of renewable energy consumption is constructed, and the constraint range of renewable energy consumption capacity is determined according to static constraints such as current constraints and voltage constraints; Then, the quantitative feedback theoretical controller is designed, the input and output transfer functions of the consumption system are determined, and the renewable energy consumption scheduling model is constructed. The renewable energy consumption scheduling model is solved by particle swarm optimization through a variety of index parameters in the renewable energy consumption determined by the QFT controller. The experimental results show that the proposed model can effectively improve the renewable energy consumption rate and optimize the consumption scheduling effect.

Keywords: Quantitative feedback theory, renewable energy, consumption scheduling model, photovoltaic power generation, particle swarm optimization, transfer function.

1 Introduction

In recent years, with the rapid development of social economy, the problem of ecological environment is becoming more and more serious. Energy conservation and emission reduction has become a key concern in this development process. All sectors of society call for ensuring the safety and health of ecological environment while developing economy. At present, the energy crisis is very serious, and the continuous change of energy structure will become the key link of future economic development [1]. Therefore, renewable energy has become an important means to change the energy structure and improve the ecological environment. With years of research and development, renewable energy occupies an important position [2]. Renewable energy consumption refers to the process of dispatching excess electric energy to the place where it is needed after generating electricity through clean energy and sending part of the electric energy to the transmission network, which can not be effectively stored in real time [3]. In order to improve the ecological environment, promote the development of renewable energy such as solar energy, wind energy and tidal energy, and improve the level of this kind of energy has become an important direction of development in this field. However, due to the influence of many factors such as nature and all sectors of society, the development of renewable energy has been unstable, and this defect will become an obstacle to the effective scheduling of renewable energy [4]. With the continuous expansion of the scale of renewable energy grid connection, its consumption and dispatching capacity continues to decline. The traditional dispatching mode relying on the generation side can not achieve its efficient consumption, resulting in the waste of energy. With the continuous development of electronic information technology, the Internet has played a key role in the consumption of renewable energy. Relying on this technology can effectively reduce the instability of renewable energy output and ensure its effective consumption scheduling [5]. However, with the continuous expansion of energy scale, the consumption problem is becoming more and more serious. Therefore, researchers in this field have done a lot of research and achieved some results.

Reference [6] designed a wind power consumption scheduling method with improved whale optimization algorithm. This method analyzes the current situation of wind power consumption, designs the scheduling method for scheduling high load energy, takes the maximum consumption capacity as the overall goal, takes the cost as the research direction, introduces the improved whale algorithm to solve the constructed optimization model, adjusts the global search ability according to the obtained results, and improves the convergence with the help of differential variation. This method considers the overall scheduling, but the effect is not significant in the improvement of wind power consumption capacity, which needs to be further improved. Reference [7] designed a waste air consumption scheduling method with the help of combined electric and thermal energy storage. Firstly, the reason of wind power fluctuation is analyzed, and the reason of wind power being abandoned is analyzed in detail. Then, according to the joint operation method of heat storage cogeneration and wind farm, with the help of the system, the power characteristics of wind power are adjusted, and the energy of wind farm is effectively transferred to improve the consumption capacity. This method integrates the benefits and other objectives, and improves the dissipation capacity of energy storage and discharge. However, it only works well for this mode in the research, so it can not be widely used. Reference [8] designed a multi energy load coordination and optimization scheduling method based on space-time complementarity. Using the space-time complementarity characteristics of multiple energy sources, the wind, light, water, fire and pumped storage, high load load coordination and optimization scheduling, and established a multi energy power system source load coordination and double-level scheduling model with the goal of minimizing system operation cost, maximizing renewable energy consumption and minimizing net load fluctuation, The improved locust optimization algorithm and particle swarm optimization algorithm are used to solve the upper and lower two-level optimal scheduling model respectively. This method can effectively improve the energy storage and discharge capacity, but leads to low renewable energy consumption rate.

Based on the above research methods, this paper designs a renewable energy consumption scheduling model based on quantitative feedback theory.

2 Analysis of Renewable Energy Power Generation Characteristics

2.1 Mathematical Model of Renewable Energy Power Generation

Wind turbine can convert natural wind energy into industrial production and daily necessary electric energy. It is a major and very common renewable energy utilization device. As wind energy is a kind of clean energy that is abundant and will not cause any pollution in the process of power generation, and can play a key role in national energy supply, energy structure, economic development, energy conservation and emission reduction, wind power generation has developed rapidly in China in recent years, and China's wind power installed capacity is increasing year by year, as shown in Figure 1.

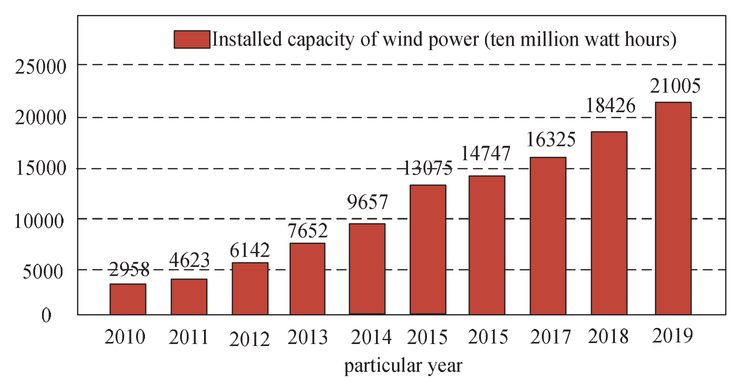

Figure 1 Growth trend of China's wind power installed capacity from 2010 to 2019.

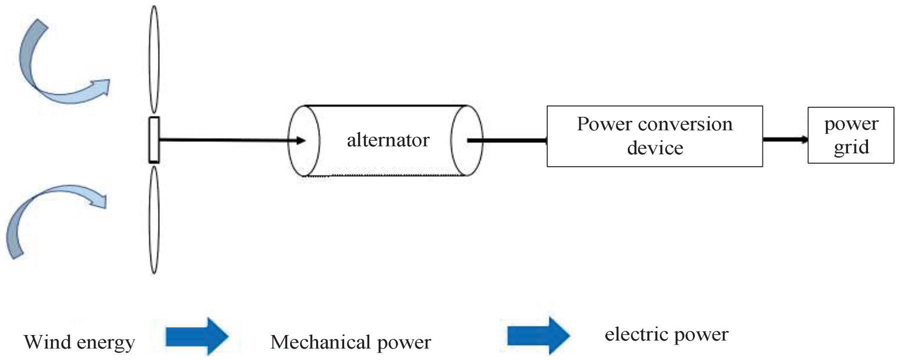

Figure 2 Basic schematic diagram of wind turbine.

The main principle of wind turbine generator is that the wind turbine blades are driven to rotate by the wind, and the rotation of the blades drives the generator to generate electric energy. The process can be briefly described as the conversion of wind energy into mechanical energy, and then mechanical energy into electric energy. Its basic principle is shown in Figure 2.

In this paper, the output mathematical model of wind turbine generator is selected as cubic subsection function, and its mathematical model formula is as follows:

$$P_{wind,t} = \begin{cases} 0, & v < v^{in}, v > v^{out} \\ P_{wind}^{nom} \dfrac{v^3 - (v^{in})^3}{(v^{nom})^3 - (v^{out})^3}, & v^{in} \leq v < v^{nom} \\ P_{wind}^{nom}, & v^{nom} \leq v < v^{out} \end{cases} \tag{1}$$

Where, $P_{wind,t}$ represents the generating power of wind turbine in t period; P_{wind}^{nom} refers to its rated generating power; v represents the actual wind speed in t period; v^{in}, v^{out} and v^{nom} represent cut in, cut-out wind speed and rated wind speed respectively. According to the mathematical model, the output curve of a wind turbine can be obtained by inputting its own parameters and the local wind data, as shown in Figure 3.

2.2 Calculation of Wind Power Output Response

In renewable energy, in addition to solar energy is the key energy for power generation, wind power generation is also a key power generation mode.

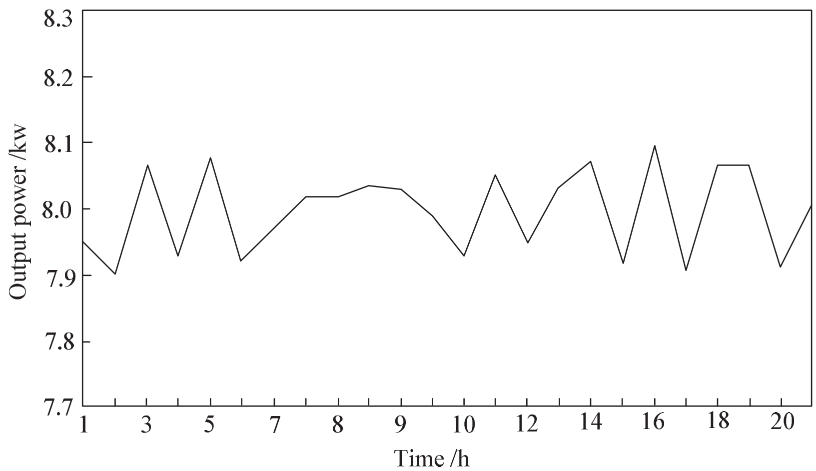

Figure 3 Output curve of a wind turbine.

There is great randomness in the process of wind power generation. There is also a problem of poor coordination in the connection of wind power to the power grid. The traditional sharp power generation mode can only determine the summary of controllable characteristics of giants, and can not realize the circular development of diversified energy. The short-term fluctuation of wind power output in the power generation process is not very obvious. Due to the influence of wind turbine operation and other factors, the second power of wind farm can be balanced to a certain extent. When the time scale continues to expand, the fluctuation force of single fan power generation increases. If multiple fans work together, the mutual auxiliary effect can be improved [10]. Therefore, it is very important to grasp the output change rate of wind farm in time scale.

The calculation formula of wind power output response at time *t* is:

$$e_i = \frac{\partial d}{\partial q_i}\left[A(x,y)\frac{q_i - q_0}{q_i}\right] \tag{2}$$

In formula (2), d represents the power demand at time t, q_i represents the motor speed during wind power generation, q_0 represents the motor speed during the starting wind power generation, and $A(x, y)$ represents the power output point during power generation.

It is assumed that the wind power generation process is divided into three stages: initial stage, peak stage and end stage. In these three stages, the response curve of wind power generation is shown in Figure 4:

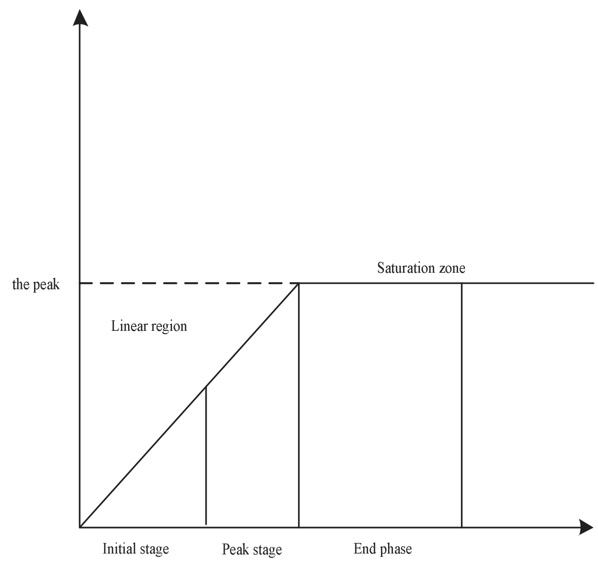

Figure 4 Schematic diagram of response curve of wind power generation in different stages.

It can be seen from Figure 4 that the response of power generation at different nodes is different in the process of wind power generation. Among them, the response from the initial stage to the peak stage is high and develops most rapidly, and the change of the response curve from the peak stage to the end stage remains at the same level [11]. Therefore, in this study, the response output during peak hours is studied, and the calculation formula is:

$$\gamma_{high} = b_i(\Delta b_i - c_i) \sum \frac{\gamma_i^{max}}{b_i} + c_i \tag{3}$$

In formula (3), b_i represents the inflection point of the peak time transfer rate curve, c_i represents the saturation region value, and γ_i^{max} represents the transfer rate of the peak time output.

2.3 Analysis on Output Characteristics of Renewable Energy Storage System

In the place where photoelectric renewable energy is more abundant, in order to improve the utilization efficiency of photoelectric and save energy, the construction of renewable energy storage system is the key to improve the consumption capacity. In this system, in order to expand the energy storage space, it is necessary to determine the electric heating power of cogeneration unit under the minimum working condition, and its expression formula is:

$$s_i = f_i h_i \tag{4}$$

Specifically, s_i represents the electric power of hotspot cogeneration, f_i represents the heat capacity ratio, and h_i represents the thermal power value.

During renewable energy power generation, the output system of the heat storage device stabilizes the balanced operation state of the energy storage system according to other output conditions. In the process of heat storage, it can solve the problem that the energy supply and demand cannot be matched, achieve the problem of energy conservation and emission reduction, and improve the flexibility and economy of the power grid. The heat storage characteristics of the device are calculated through thermal efficiency, and the following results are obtained:

$$\alpha_i = \frac{E_i}{E_j} \tag{5}$$

In formula (5), α_i represents the heat efficiency, E_i represents the released heat, and E_j represents the stored heat value.

While the output of renewable energy energy storage system is, its state of charge should also be fully considered. The ratio of the electric quantity of energy storage at time t to the rated capacity is its operation state. At this time, this state can be expressed as:

$$\mathrm{V(t) = V(t-1)} + \varepsilon_\mathrm{i} \frac{\mathrm{l_i(t)\Delta t}}{\mathrm{R_i}} \tag{6}$$

In formula (6), $\Delta\mathrm{t}$ represents the time interval, $\mathrm{R_i}$ represents the rated discharge power, $\mathrm{l_i(t)}$ represents the heat energy released by the energy storage system, and ε_i represents the rated capacitance.

3 Design and Implementation of Renewable Energy Consumption Scheduling Model

3.1 Objective Function of Renewable Energy Consumption

In the renewable energy system, this paper also considers the maximum local consumption of renewable energy, namely distributed wind power and photovoltaic, as the objective function. This chapter uses quantitative feedback theory to define the established objective function of renewable energy consumption.

The quantitative feedback theory endows each objective with corresponding weight coefficients according to its importance, and then optimizes its linear combination. The basic basis for weight distribution of linear combination is as follows: first, remember that event 1 is S_1 and event 2 is S_2; The weights corresponding to the two events are recorded as ψ_1 and ψ_2. If the decision-maker thinks that S_1 is more important than S_2, the corresponding weight relationship is $\psi_1 > \psi_2$; If the decision maker thinks that S_1 and S_2 are of the same importance, the corresponding weight relationship satisfies $\psi_1 \approx \psi_2$; If the decision-maker thinks that S_2 is more important than S_2, the corresponding weight relationship is $\psi_1 < \psi_2$.

Specifically, after quantifying the value of its weight comparison, the range is as follows: if S_1 is much more important than S_2, there is $\psi_1 \geq 2\psi_2$; If S_1 is more important than S_2, $1.2\psi_2 < \psi_1 < 2\psi_2$; If S_1 is almost as important as S_2, $1/1.2\psi_2 \leq \psi_1 \leq 1.2\psi_2$; If S_2 is more important than S_1, $0.5\psi_2 < \psi_1 \leq 1.2\psi_2$; If S_2 is much more important than S_1, it is $\psi_1 \leq 0.5\psi_2$.

The objective function of renewable energy consumption can be expressed as:

$$\min F = \psi_1 F_{Cost} + \psi_2 F_{New} \tag{7}$$

Where, ψ_1 and ψ_2 are linear weighting coefficients, and $\psi_1 + \psi_2 = 1$.

3.2 Renewable Energy Consumption Capacity Constraints

During the grid connection period, the grid connected power value of the energy has reached a limit number. When its power exceeds this value, the system will break the static constraints such as current constraints and voltage constraints. At this time, this limit value is its absorption capacity. In the fixed distribution system, the load value and power value are unique to the consumption capacity of renewable energy [12]. Generally, it is controlled by controlling the power injected by different parameter nodes, that is:

$$F_i + F_j - F_Y + \delta\Delta F_x = G \sum_{i,j \in Y} \sum v_i^k cos\vartheta_j^k + c_j^k sin\vartheta_j^k \tag{8}$$

In formula (7), F_i, F_j represents the active power and reactive power of the traditional generator set of the bus, F_Y, δ represents the active power and reactive power of different phases respectively, ΔF_x and v_i^k represent the real-time position of the phase power change, and c_j^k represents the voltage of the node phase.

The capacity of the system to absorb renewable energy is expressed as:

$$S_{RMAX} = \sum S_{R_i} + \alpha \Delta p_{R_i} \tag{9}$$

Among them, S_{R_i} represents the standardized renewable energy consumption capacity and R_i represents the power margin.

3.3 Design of Renewable Energy Consumption Scheduling Model

Quantitative feedback theory is a controller with good robustness, which is called QFT controller for short. The controller has an independent input unit with uncertainty and has the advantage of strong independence. This theory is based on the frequency domain analysis, which transforms the performance indexes that the uncertain system needs to meet, and uses the loop forming technology to meet the requirements of the controller [13]. The object of the theory is the existence of uncertainty. The uncertain object of the research is simplified into a mathematical model as follows:

$$\mu = (\mathrm{H} + \Delta)\mathrm{U} + \mathrm{M} \tag{10}$$

In formula (10), μ represents the output, U represents the input, H represents the transfer function, Δ represents the unknown perturbation of the uncertain object, and M represents the unknown noise or interference.

Assuming that both Δ and M each belong to different set units, each generated output will correspond to an input, this model is a model of uncertainty. Therefore, in the design of quantitative feedback theory controller is a two degrees of freedom control structure, the design structure is shown in Figure 5:

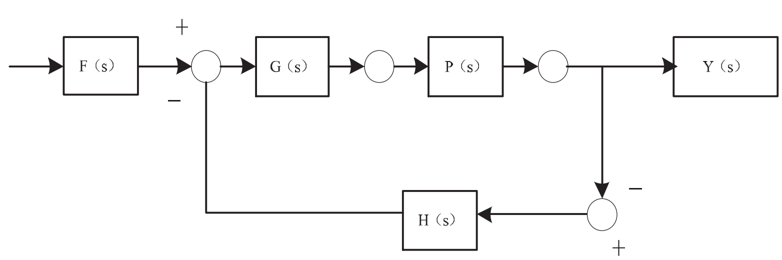

Figure 5 Structure diagram of two degree of freedom feedback control.

In Figure 5, $\mathrm{R(S)}$ represents the input value, $\mathrm{Y(s)}$ represents the output value, $\mathrm{P(s)}$ represents the set of charged objects, $\mathrm{H(s)}$ represents the external interference input, $\mathrm{G(s)}$ represents the controller, represents the front filter, $\mathrm{F(s)}$ represents the feedback gain.

Based on the above analysis, the equation of two degree of freedom feedback control system is defined as:

$$\mathrm{T(s)} = \frac{\mathrm{G(s)}}{1 + \mathrm{P(s)}} \mathrm{F(s)} \tag{11}$$

Based on the analysis of the advantages of quantitative feedback theory, this paper designs a renewable energy consumption scheduling model with the help of this theory. In the quantitative feedback theory, the uncertainty and demand of the renewable energy system can reach a stable margin, which is described according to its tracking performance and anti-interference performance. These values are quantified to measure the cost of feedback energy consumption, in which the feedback cost is estimated by the bandwidth of the open-loop function of the system uncertainty [14]. In the energy consumption scheduling, the quantitative feedback theory controller first considers the transfer function of the input and output of the system, which is set as:

$$\mathrm{W(x)} = \frac{\mathrm{GF}}{(1 + \mathrm{GL})} \tag{12}$$

Whene F represents the filter. When the filter gain is close to 1, the gain of the feedback controller in the energy consumption meets the demand.

When the input and output suppression indexes of the renewable energy consumption scheduling object are determined, the transfer function of the input and output is expressed as:

$$\frac{Y(x)}{D_i(x)} = \frac{P}{1 + GL} \tag{13}$$

Where, x represents the system sensitivity function.

Then, further determine the suppression index of the interference output in the renewable energy consumption scheduling, that is, noise, expressed as:

$$\frac{Y(x)}{H(x)} = \frac{-GL}{1 + \tau} \tag{14}$$

Where, $H(x)$ represents the complement sensitivity function value, τ represents the noise wave value.

3.4 Solution of Renewable Energy Consumption Scheduling Model

On the basis of various index parameters of renewable energy consumption determined by QFT controller, the remaining quantity to be consumed and dispatched is determined, and the renewable energy consumption and dispatch is completed by solving the objective function. Set the margin of renewable energy consumption scheduling in a D-dimension area, where there is a population composed of multiple particles, and the particles in this area are expressed as:

$$\frac{U(x)}{E(x)} = \frac{Q_i}{1 + Q_0} \tag{15}$$

Where, $E(x)$ represents the controlled energy size, and Q_0 represents the initial energy size, Q_i representing the amount of energy lost during the input.

On the basis of various index parameters in renewable energy consumption determined by QFT controller, determine the remaining amount to be consumed and scheduled, use particle swarm optimization algorithm [15] to build renewable energy consumption and scheduling model, and complete the design of renewable energy consumption and scheduling model through the setting of objective function and the determination of scheduling constraints.

Set the allowance of renewable energy consumption scheduling in a D-dimensional region with a population of multiple particles, with the particles represented in this region as:

$$X_i = \{x_{i1}, x_{i2}, \ldots x_{in}\} \tag{16}$$

The position of the particle in the particle swarm in the above formula is taken as the potential solution. Bring the surplus of the remaining consumption scheduling into it to obtain the fitness of each particle. Through the calculation of the fitness, it is determined that the particle, that is, the electricity of the consumption scheduling, is in the best position.

In the process of initializing any attribute value of the particle, the larger the weight value corresponding to the attribute, the better the effect of consumption scheduling. Therefore, the attribute weight of the scheduling object in the consumption scheduling is calculated to obtain:

$$x_i = \begin{cases} 1 & rand \geq w(i) \\ 0 & rand < w(i) \end{cases} \tag{17}$$

Where, $rand$ represent constants with random greater than zero and less than 1.

According to the determined weight value, the fitness function is defined to reflect the comprehensive attributes of the consumption scheduling object, namely:

$$f_i = k_i \frac{r_i}{r_c} + \frac{c(x)}{c(y)} \tag{18}$$

Where, f_i represents the fitness function value and k_i represents the attribute value of the scheduled object.

Then, the global search of the consumption scheduling object is carried out through the set particles, and the result of each search is the local optimal value, that is:

$$z_i = max(z_i, f_i(x)) \tag{19}$$

After multiple local searches of particles, determine the optimal value of the scheduling object in the global, that is, the globally optimal scheduling object, that is:

$$z_i' = max(\rho \Sigma f_i(x)) \tag{20}$$

Where, z_i' represents the global optimal value and ρ represents the optimal location point of the scheduling object.

On this basis, according to the objective function of the consumption scheduling model, the response power, wind rejection and load power are the main objects of its scheduling. All scheduling scenarios are divided for the same decision, and the optimized objective function is obtained as follows:

$$\mathrm{min}\sigma_{\mathrm{i}} = \mathrm{v_i} \sum_{\mathrm{i=1}}^{\mathrm{n}} \varphi_{\mathrm{i}}[f_i(x) + z_i']\mathrm{d_x} \tag{21}$$

Among them, φ_{i} represents response, $\mathrm{d_x}$ represents curtailment and $\mathrm{v_i}$ represents load.

Finally, the optimal solution of the renewable energy consumption scheduling model is obtained as follows:

$$^{\circ}\mathrm{F}_i = \sum_{i=1}^{n} D_i + \sum \mathrm{l_i} \tag{22}$$

Among them, D_i represents the user collection of the dispatching grid nodes, and $\mathrm{l_i}$ represents the power load value in the dispatching.

Finally, the renewable energy consumption and scheduling model is constructed as follows:

$$\psi(\mathrm{x}) = {}^{\circ}\mathrm{F}_i \sum_{\mathrm{x}}^{\mathrm{n}} \phi_{\mathrm{i}} \forall \mathrm{s_i} \tag{23}$$

Among them, $\psi(\mathrm{x})$ represents the final scheduling result, ϕ_{i} represents the adjustment coefficient, and $\forall \mathrm{s_i}$ represents the absorption rate. Therefore, the renewable energy consumption scheduling is realized.

4 Experimental Analysis

4.1 Experimental Scheme Design

In the experimental scheme design, the historical annual renewable energy consumption and meteorology of a region are taken as the research objects. The peak value of renewable energy power load in this region is 350 kW, the annual average load value is 210 Kw, and the total annual load is 2000 MW/h. The climate environment of the study area is relatively clear, and the four seasons are clearly divided. The wind speed is suitable for the demand of wind power generation. The wind speed curve is shown in Figure 6:

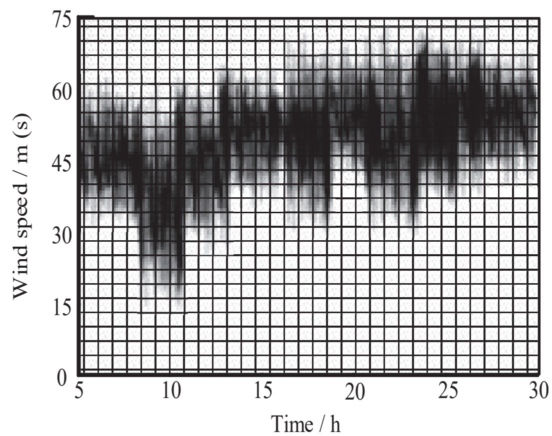

Figure 6 Schematic diagram of wind speed curve.

The illumination curve of the study area is shown in Figure 7:

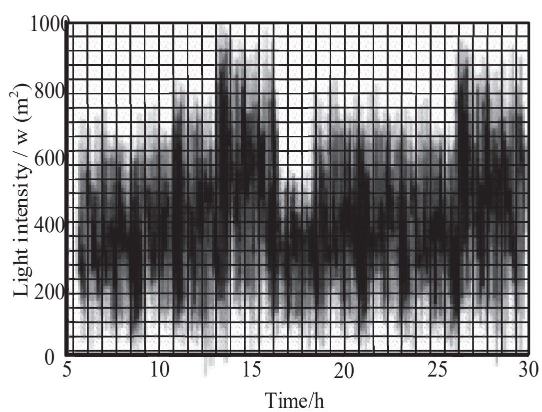

Figure 7 Schematic diagram of illumination curve.

The specific experimental parameters set according to the characteristics of the study area and the actual situation of renewable energy consumption and dispatching project are shown in Table 1:

Table 1 Experimental parameter design

Project	Single Machine Capacity/kw	Operation Management Coefficient	Service Life
Photovoltaic cells	0.055	0.0095	20
Photovoltaic cells	6	0.0269	10
storage battery	4	0.009	10
Renewable energy consumption system	0.21	0.035	10
power rating	275	–	–

According to the experimental parameters designed above, the experiment mainly tests the use of renewable energy in this area. Taking the renewable energy consumption rate, renewable energy consumption scheduling error and the stability of input parameters of quantitative feedback controller in scheduling as the research object, the experimental analysis is carried out by comparing the methods of reference [6] and reference [7].

4.2 Analysis of Experimental Results

In the experiment, firstly, the methods of reference [6], reference [7] and this paper are analyzed. The experimental analysis is carried out for the consumption rate of renewable energy in the sample area. The higher the consumption rate, the better the consumption capacity of renewable energy. Therefore, the experiment analyzes the absorption rate of renewable energy in the sample area by three methods, and the experimental results are shown in Figure 8:

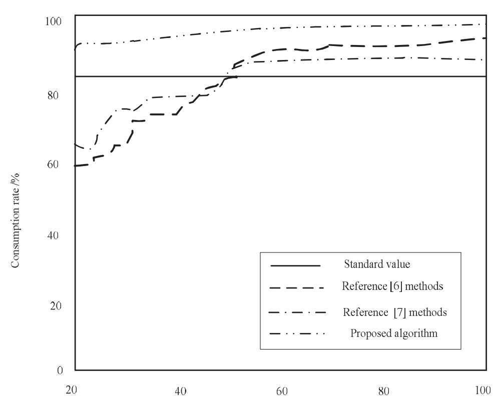

Figure 8 Comparison results of renewable energy consumption rate of different methods.

According to the research results in Figure 8, there are some differences in the consumption rate of renewable energy in the sample area by using the methods of reference [6], reference [7] and this paper. When the number of iterations is changing, the absorption rate of the three methods is also changing. From the example of curve trend, the three methods show a rising trend. Among them, the absorption rate of the methods in reference [6] and reference [7] did not reach the standard value in the first iteration. When the number of iterations exceeded 40, the absorption rate of the two methods rose above the standard value and always increased. In contrast, the proposed method is always higher than the standard value, and always higher than 90%, and higher than the other two methods. This is because the proposed method considers the output of different energy sources in renewable energy in the design and scheduling model, and makes a detailed calculation, which improves the consumption rate of renewable energy and the feasibility of the proposed model.

Renewable energy consumption scheduling error refers to the defect of renewable energy consumption surplus scheduling due to the interference of many factors. This index directly reflects the functionality of the design model. Therefore, in the experiment, the errors of reference [6], reference [7] and this method on renewable energy consumption scheduling in the sample area are tested respectively. The results are shown in Figure 9:

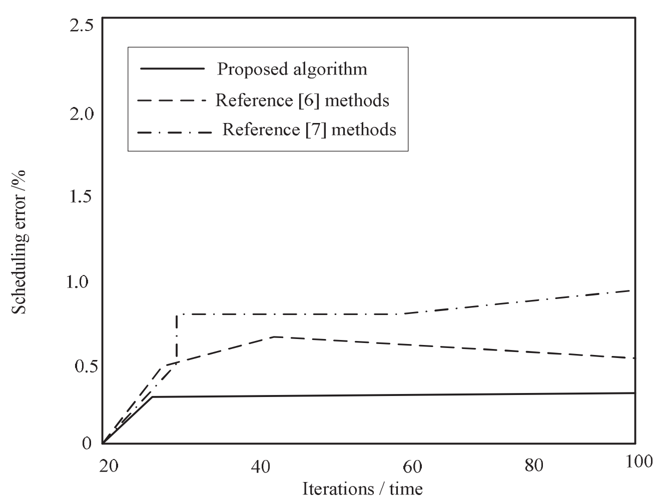

Figure 9 Comparison results of renewable energy consumption scheduling errors of different methods.

It can be seen from Figure 9 that with the continuous change of the number of experiments, the error of renewable energy consumption scheduling in the sample area by the methods of reference [6], reference [7] and this paper changes to some extent. From the curve trend in the figure, it can be seen that in the first three methods, the scheduling error gap is small and the trend is relatively close, but with the continuous increase of consumption, the scheduling error gap of the three methods is gradually obvious. From the later curve trend, it can be seen that the scheduling error of this model is always low, and less than 0.5%. Therefore, it can be seen that the scheduling model of this method is more reliable.

The accuracy of the input parameters of the quantitative feedback controller is the key index affecting the consumption scheduling. In the experiment, the stability of the input parameters of the quantitative feedback controller designed by this method is tested to improve the scheduling effect of the proposed model. The results are shown in Figure 10:

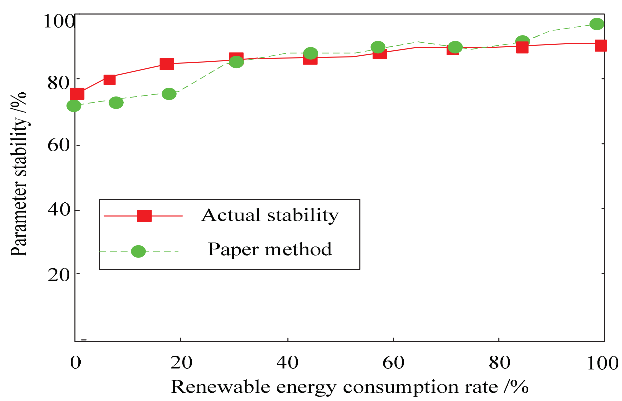

Figure 10 Stability analysis of input parameters of this model quantitative feedback controller.

It can be seen from the experimental results in Figure 10 that the stability of the input parameters of the model quantitative feedback controller in this paper is close to the curve trend of the actual stability. However, in the initial absorption rate, there is a large gap between the stability of the input parameters of the quantitative feedback controller of this model and the actual value. This is because there is no global optimization in the initial parameter input. After the optimization by particle swarm optimization algorithm, the stability of the input parameters of the quantitative feedback controller of this model is improved.

Table 2 Power supply cost after renewable energy consumption and dispatching

Power Supply Area/m^2	Power Supply Cost After Renewable Energy Consumption and Dispatching/10000 Yuan		
	Reference [6] Method	Reference [7] Method	Method in This Paper
10000	12.62	9.33	0.91
30000	19.39	15.87	1.26
50000	25.26	18.60	2.58
100000	30.13	26.06	3.06

In order to verify the renewable energy consumption scheduling effect of this method, this paper uses the power supply cost before and after renewable energy consumption scheduling to analyze, and the results are shown in Table 2.

According to the analysis of Table 2, when the renewable energy power supply area is 10000 m^2, the power supply cost after renewable energy consumption and scheduling of reference [6] method is 126200 yuan, the power supply cost after renewable energy consumption and scheduling of reference [7] method is 93300 yuan, and the power supply cost after renewable energy consumption and scheduling of this method is 9100 yuan; When the renewable energy power supply area is 100000 m^2, the power supply cost after renewable energy consumption and scheduling of reference [6] method is 301300 yuan, the power supply cost after renewable energy consumption and scheduling of reference [7] method is 260600 yuan, and the power supply cost after renewable energy consumption and scheduling of this method is 30600 yuan; The reason why the power supply cost of this method is lower than that of other methods shows that after the treatment of this method, the power supply cost has been effectively reduced and the economic benefits of renewable energy power supply have been improved.

5 Conclusion

Aiming at the problems of low consumption rate and large scheduling error in renewable energy consumption scheduling, a renewable energy consumption scheduling model based on quantitative feedback theory is designed. Build the objective function of renewable energy consumption, determine the constraint range of renewable energy consumption capacity according to the current constraint, voltage constraint and other static constraints, design the quantitative feedback theoretical controller, build the renewable energy consumption scheduling model, use the particle swarm optimization algorithm to solve the renewable energy consumption scheduling model, and complete the renewable energy consumption scheduling. The results show that:

(1) The scheduling error of this model is always low, and less than 0.5%, which shows that the scheduling model of this method is more reliable.
(2) The renewable energy consumption rate of the proposed method is always higher than 90%, which improves the renewable energy consumption rate and the feasibility of the proposed model.
(3) The power supply cost of renewable energy consumption scheduling in this method is only 30600 yuan; After the treatment of this method, the power supply cost is effectively reduced, and the economic benefits of renewable energy power supply are improved.

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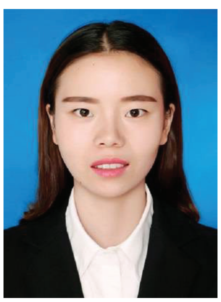

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