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Optimized Particle Swarm Algorithm for Advanced Bi-Level Dispatch in New Energy Power Systems

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Keywords: Improved particle swarm optimization; New energy power system; Output characteristics at the supply side; Demand side load response characteristics; Objective function; Proximity; Bi-level optimal scheduling model

Abstract: In this paper, we presents a novel bi-level optimal scheduling method for new energy power systems, using an enhanced particle swarm optimization algorithm. Addressing the prevalent issues of unclear goals, sub-optimal outcomes, and poor dispatch efficiency, the approach keenly examines the cyclone power generation structure. It uses an equivalent circuit conversion to accurately model key output characteristics, including cyclone turbine power and photovoltaic traits, while defining a suitable index to calculate system electricity levels. The approach also considers response characteristics of the demand side load curve to define the main objective of the nuanced dispatching process. The proposed algorithm, improved by introducing inertia weight, effectively avoids local deadlocks and enhances global search capabilities. This optimization informs the bi-level scheduling objective by calculating the information entropy value and determining particle proximity. The resulting model promises improved scheduling efficiency, cost reduction, and precise photovoltaic output prediction, as substantiated by experimental results.

1. Introduction

The interaction of global economy and the rapid development of social economy have led to the continuous increase of energy consumption worldwide, which has also accelerated the depletion of global energy resources. The emergence of electricity is the key driving force to promote the rapid development of society, and also the main supporting force for social development [1]. It can be said that all social development and progress cannot be separated from electricity, and the industry chain based on electricity is very large. However, the main source of electricity still depends on existing non-renewable resources such as ores. With the increasing scale of power consumption, the massive application of power generation fuels such as ores has seriously affected the normal living environment of human society [2]. At present, the global energy is still dominated by existing coal and other resources, but the application of these fuels cannot guarantee the safety of human living conditions. To this end, the power generation energy mainly based on new energy has been promoted. New energy refers to clean renewable energy mainly based on wind and light [3]. These energy sources are not only easy to obtain, but also contribute to improving human living conditions. For this reason, the emergence of new energy has effectively alleviated the problems in electric power generation, and has been widely concerned and favored by people. With the continuous upgrading of new energy technology, the traditional power system has been replaced by the new energy power system, and has achieved good development space [4]. Compared with the traditional power system, the high penetration rate of wind power in the new energy power system and the environment-friendly type accelerate the progress of society. However, in the application of new energy power system, due to the influence of wind turbine and other factors, its rotor speed, grid frequency and system inertia are likely to cause instability of the new energy power system, leading to the collapse of the entire power chain and other problems, which may seriously cause the collapse of the entire power system [5].

Reference [6] proposed a novel approach for optimal dispatching of multi-source power systems that looks ahead to the next day. By taking into consideration the transient operation characteristics of hydropower systems, a coordinated optimal operation model was conceived for the cascade hydropower system of pumped storage power stations. In order to tackle the output uncertainty of wind and photovoltaic power generation, the chance constrained programming model with prediction error reserve was employed. Furthermore, a joint optimal dispatching model was established for short-term pumped storage wind power, photovoltaic, hydropower, and thermal power systems, with the economy of the system as the primary objective. To assess the influence of renewable energy on thermal power operation, the fluctuation coefficient of thermal power unit operation was proposed. Though this method enhances the precision of the scheduling optimization model, its cost of scheduling optimization remains high. In contrast, reference [7] developed an optimization method of power system grouping dispatching based on minimizing energy loss. In reference to the citation [8], a transient and intermediate convex optimal dispatching methodology for dual-energy complementary power stabilizing systems was presented, whereby a fundamental optimized model of a new energy power system was constructed for the economic cost objective function of thermal power generation. To optimize the arrangement of the new energy power system, given thermal power and other constraints, the multi-objective cuckoo search algorithm and firefly algorithm were combined. Although this approach reasonably arranges the stable operation of new energy power systems and enhances the quality of dispatching, its dispatching optimization performance is comparatively deficient.

Taking into account the advantages and disadvantages of the above optimal scheduling methods, this paper presents a new bi-level optimal scheduling method for new energy power systems based on an improved particle swarm optimization algorithm. In this method, particle swarm optimization is introduced and enhanced to tackle the challenge of new energy power system scheduling, ultimately leading to improved scheduling optimization performance.

2. Analysis and Research on Source Load Characteristics of New Energy Power System

2.1 Research on output characteristics of new energy power system at supply side

In the analysis of the source load characteristics of the new energy power system, the first consideration is the output characteristics of its supply side. According to the endogenous characteristics of the system, effective optimization and dispatching are carried out. The power supply of new energy power system refers to the total amount of power supply on the supply side. The total amount can be divided according to the attribute classification, generally including renewable energy and non-renewable energy. The new energy power system is mainly based on the development of renewable energy, which can be effectively recovered in a short time through wind, tidal energy, solar energy and other renewable resources [10]. The power output characteristics on the supply side of the system are directly related to the resource types of its functions. The power supply structure accounts for a certain proportion in the installed capacity and total amount.

Wind power generation is a key new energy power generation mode in the new energy power system, which converts the collected wind energy into electrical energy through a certain mechanical movement. This resource can realize efficient and economical power conversion and transmission. This resource has been greatly developed in recent years. Under the support of this energy, the units can be divided from different angles. For example, it can be divided into constant speed, limited speed and variable speed according to the difference of speed; According to the difference of transmission chain, it can be divided into gear box drive and direct drive type [11]. It is composed according to different wind turbines and different internal structures. The advanced grid connected fan resistance can be classified according to the function of its power system. The structure of the wind turbine control system of the new energy power system is shown in Figure 1.

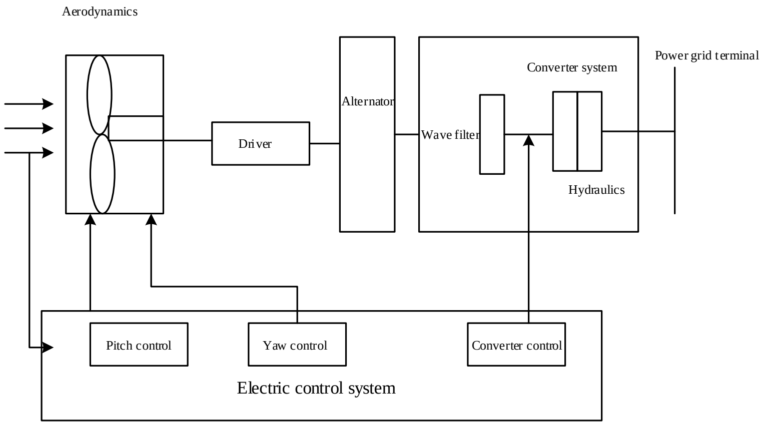

Figure 1: Structure diagram of wind turbine control system of new energy power system

It can be seen from Figure 1 that the composition of wind turbine generator unit in new energy power system mainly includes power system, power generation system and converter. The main electronic control system is relatively complex, including multiple systems and modules. During its power generation process, the yaw control system needs to control the untwisting of the wind turbine based on the engine room; In the pitch control system, it is necessary to achieve effective cooperation among various control systems, so as to complete the power generation of new energy.

In the new energy power system, the treatment characteristics of wind turbine generators are directly related to the natural environment of the site and the appearance of the tower [12]. When the actual wind speed at the generator hub is different from the predicted wind speed, the actual conversion capacity of wind speed shall be determined when determining the output characteristics under this mode, namely:

$$a(t) = a_i \left[\frac{A}{A_i} \right]^{\varepsilon} \tag{1}$$

In formula (1), a_i represents the actual wind speed of the monitoring point at the first time, $a(t)$ represents the actual wind speed of the hub point, A represents the height of the hub, A_i represents the height of the actual measurement point, and ε represents the roughness of the geographical environment.

At this time, the relationship between wind turbine power output and wind speed of new energy power system can be expressed as:

$$
P(k)=\begin{cases} 0 \quad a(t)<a_{\min} \\ p_i \quad a(t)<a_{\min}<a_i \\ p_i \dfrac{a(t)^3-a_{\min}^3}{a_{\min}^3-a_i} \end{cases} \tag{2}
$$

In formula (2), p_i represents the limited output quota, $a_{\min}$ represents the minimum wind speed during the launch, $a_{\max}$ represents the maximum cut-off wind speed, and a_i represents the minimum wind speed value of the limited value power output.

When the new energy power conversion is carried out, when the cut in wind speed is within the $[a_{\min}, a_{\max}]$ range, it means that the wind turbine is in a limited output state at this time, and the state is close to the predicted state. When the value is out of the range, the wind speed directly affects the change of output power. At this time, the relationship between wind speed and power is shown in Figure 2.

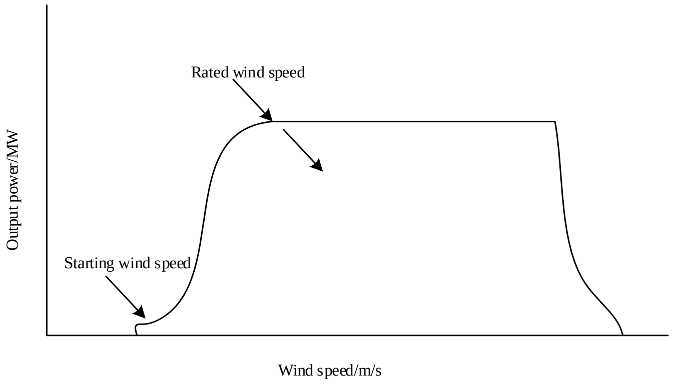

Figure 2: Schematic diagram of the relationship between wind speed and power

In addition to wind energy, photovoltaic characteristics are also the key energy that directly affects the new energy power system. In the output characteristics of photovoltaic modules, they are generally converted into equivalent circuit models, and then their equivalent circuits are effectively classified according to their characteristics and optical basis. When the series resistance of photovoltaic modules is not considered, the problem of resistance is not considered, but this mode is difficult to meet the existing power output; When the internal resistance is ignored in the relatively simplified circuit, the PV array simulation is relatively simple, but there is a certain impact in the complex output; The circuit accuracy is better when series parallel resistance is considered at the same time [13]. At this time, the direction of the set voltage and current is positive, and the determined equivalent circuit model of the photovoltaic module can be expressed as:

$$
U_d = U_i(e^t-1)\frac{akT}{q}\ln(e^t-1) \tag{3}
$$

In formula (3), U_d represents the open-circuit voltage of the cell, U_i represents the current value generated by light radiation, e^t represents the reverse saturation current of the diode in the photovoltaic module, q represents the unit charge value, and a,k,T represents the surface temperature, resistance value and parallel internal resistance value respectively.

Under the influence of existing external factors, the output voltage and current distribution of photovoltaic cells are in the same trend, and the output power will also change with the change of voltage. Among them, the output power of the maximum point is directly related to the voltage and current of the maximum power point in the optimal point of the photovoltaic cell. At this time, the maximum output power of the output area can reflect its processing characteristics, namely:

$$S_i = r\sum_{i=1}^{n} U_i q \frac{ak}{v} b \tag{4}$$

In formula (4), S_i represents the maximum power point, v represents the flow rate, r represents the photovoltaic cell filling factor, and b represents the rectangular area formed.

The analysis of the fundamental structure of power generation is instrumental in determining the output properties of the supply side of the new energy power system. According to the relationship between the power output and wind speed of the wind turbine, and according to the equivalent circuit conversion of photovoltaic characteristics and the relationship between the voltage and current at the maximum power point.

2.2 Analysis of load response characteristics on demand side of new energy power system

Based on the analysis of the output characteristics on the supply side of the new energy power system, the load response characteristics on the demand side should also be considered. In the new energy power system, the total electricity quantity of the transferable load in a certain period is always unchanged, that is to say, the electricity consumption in different stages can be effectively and flexibly adjusted. The power conversion station is one of the transferable load demand response resources. When the resource is a large power storage unit, when the transmission is not running, the power can be provided to the grid through a certain intermediary, and conversely, a certain amount of power can be obtained through the grid. The demand side load in the new energy power system can actually be modeled according to the storage of electricity. However, in the new energy power system dispatching, it is impossible to achieve point-to-point charging and discharging control. Generally, the entire control unit needs to be converted through different levels and levels to complete its load conversion [14]. In the new energy power system, the interaction of this kind of power station exchange is a process in which the capacity is relatively fixed and the remaining power is attenuated. Assume that the remaining electricity in the converter station at a certain time is expressed as:

$$H(t) = H(t-1) + o(t-1)wF(t-1) - \frac{o_d}{\eta_i} \tag{5}$$

In formula (5), $H(t)$ represents the remaining power at a certain time, $o(t-1)$ represents the power output to the grid during that period, o_d represents the power absorption, η_i represents the working efficiency of charge and discharge, F represents the demand for electricity in this period, and w represents the rated capacitor.

If the replaced battery does not need to be involved, the maximum charging and discharging power in the station can be expressed as:

$$G_{\max} = n(v_s - o(t-1)) \tag{6}$$

In formula (6), v_s represents the power of charge and discharge, and n represents the number of power changing points in the station.

Considering that the capacity of the battery pack in the exchange station in the new energy power system is consistent, the time required for each battery pack to be fully charged is t_i. At this time, the minimum power constraint can be considered, and the maximum power constraint cannot exceed the total rated capacity of the battery in the station, namely:

$$H_{\min}(t)=\sum_{t=1}^{m}D_t\frac{T}{t_i}\phi_d w(o_d-n) \tag{7}$$

In formula (7), ϕ_d represents the number of spare cells and D_t represents the maximum discharge depth.

Under different user demands, the load response characteristics of the demand side change in real time. When the correlation threshold value of the high correlation degree of the curves of both the supplier and the demander is determined, its changes are also similar. At this time, you need to define the correlation matching index to get the following:

$$\sum_{t=1}^{\psi}y_t=l\frac{1}{n}\sum_{k=1}^{n}e_k \tag{8}$$

In formula (8), y_t represents the entropy weight of the multi-target association in this period, k represents the resolution coefficient, e_k represents the curve dimension, ψ represents the curve mean, and l represents the best combination scheme.

In accordance with the designated correlation indicators, discern the pertinent features of the load on the demand side of the new energy power system, and formulate the corresponding characteristic model of demand by considering the shift in demand elasticity:

$$L_i=L_i^0(1+\vartheta_i)+\sum_{i=1}^{24}{q_i}/{p_i} \tag{9}$$

In formula (9), L_i^0 represents the price elasticity at a certain time, q_i, p_i represents the power load and power price of demand response respectively, and ϑ_i represents the demand load change and price change after demand response.

3. Improvement of particle swarm optimization algorithm and design of bi-level highly reinforced, sophisticated and nuanced dispatching model for new energy power system

3.1 Research on Improvement of Particle Swarm Optimization

Particle swarm optimization (PSO) is a form of evolutionary algorithm that falls within the realm of artificial intelligence algorithms. PSO operates through dynamic interaction by means of continuous evolution of individual particles and local particle optimization. The algorithm accomplishes its objective by seeking out the optimal solution via continuous social learning of particles during the calculation process, ultimately resulting in the attainment of goal locking [15].

The fundamental algorithm of PSO is designed on the premise of minimizing the objective function of the optimization problem. The algorithm begins by assembling a group consisting of multiple particles, with each particle being represented by a one-dimensional vector (x_i, w_i, v_i, z_i), in a particular space, as expressed by the equation:

$$x_i = (x_{i1}, x_{i2}, ..., x_{in}) \tag{10}$$

In the above equation, each particle is identified by its distinct characteristics.

The running speed of the particles within the D-dimensional space is conveyed through the expression:

$$v_i = (v_{i1}, v_{i2}, ..., v_{in}) \tag{11}$$

In the above equation, represents the velocity of each particle.

When the particle reaches its best position in the space, it is expressed as:

$$\beta_i = (\beta_{i1}, \beta_{i2}, ..., \beta_{in}), \beta_i = \arg\min f(x_i) \tag{12}$$

In formula (12), β_{in} denotes the optimal position of the particle.

Building upon the aforementioned, the iterative evolution equation of the basic algorithm is defined as:

$$\alpha_i(t+1) = Vc_1 rand(\beta_{in} - x_i) + c_2 rand(\beta_{in} - x_i) \tag{13}$$

In formula (13), c_1, c_2 represent two positive acceleration coefficients, while signifies the maximum velocity of the particle.

However, as the basic PSO algorithm tends to exhibit issues related to local optimization, there is a need to improve the existing algorithm to better enable particles to enhance their search ability. Thus, this paper introduces an inertial weight value to the improved algorithm in order to address this problem. The modified equation for particle velocity is presented as:

$$\alpha_i(t+1)' = Vc_1 rand(\beta_{in} - x_i) w_{\max} + c_2 rand(\beta_{in} - x_i) n_{\max} \tag{14}$$

In formula (14), $w_{\max}$ in the above equation, represents the largest inertia weight, while signifies the maximum number of iterations.

The incorporation of inertia weight in the enhanced algorithm plays a pivotal role in determining the initial velocity of particles, as well as governing their velocity modifications throughout the algorithm's course, thus significantly augmenting the algorithm's global detection capacity.

In this study's PSO algorithm refinement, the fundamental principles of the original PSO algorithm are meticulously examined, and various factors impacting the algorithm's core particles' operation are carefully scrutinized. An inertia weight value is then introduced to bolster the algorithm's search efficacy, circumventing local deadlocks and empowering particle exploration on a global scale. Subsequently, the upgraded PSO algorithm is applied to the bi-level scheduling optimization of the new energy power system in this research paper.

3.2 Design of bi-level highly reinforced, sophisticated and nuanced dispatching model for new energy power system

On the basis of the above improved algorithm, the bi-level highly reinforced, sophisticated and nuanced dispatching model of new energy power system is designed using the optimized algorithm to achieve the key objective of this paper. In the two-layer dispatching of new energy power system, the load response of the supply side and the demand side is taken as the goal of its two-layer optimization, that is, the output of the supply side is taken as a layer for optimization. On this basis, the demand side load response is again optimized in the second layer, and the design of the dispatching model in this paper is completed.

In the context of optimizing the new energy power system, we first determines the objective function in the bi-level highly reinforced, sophisticated, and nuanced dispatching model. That is, we set the load response on the supply side and demand side as the objective layer, and convert it into the objective function of optimal dispatching according to the modeling optimization analysis. Its expression form is:

$$\min R = \min(b_1 + b_2 + ...b_n) \tag{15}$$

In formula (15), b_n represents the peak load cost value of load response on the supply and demand sides.

After setting this limiting condition, in order to remove the difference in dimensions in the objective function, the original objective function needs to be normalized to obtain:

$$R' = f' \tag{16}$$

In formula (16), f' represents the dimensionless decision objective function matrix.

Then, according to the determined optimization objective function of bi-level dispatching, the information entropy value of the bi-level objective function is calculated, and the weight of the objective information entropy of the bi-level highly reinforced, sophisticated and nuanced dispatching of the new energy power system is obtained as follows:

$$\mu_i = W(\sum_{i=1}^{n} \mu_i) / \sum_{i=1}^{n} (1 + \mu_i) \tag{17}$$

In formula (17), μ_i represents the target information value and W represents the weight coefficient.

Thirdly, we determines the closeness of the objective function in the bi-level highly reinforced, sophisticated and nuanced dispatching of the new energy power system, that is, the distance value of the optimal solution determined by the particles in the search process, namely:

$$D_i = \sqrt{\sum_{i=1}^{n} (Q_i - f')^2} \tag{18}$$

In formula (18), D_i represents the optimal solution vector value, and Q_i represents the particle residence point of the non-inferior solution.

Finally, a bi-level highly reinforced, sophisticated and nuanced dispatching model of new energy power system is constructed, and the specific setting steps are as follows:

Step 1: Our team sets out to determine the control parameters of the bi-level scheduling optimization of the new energy power system in the improved particle swarm optimization algorithm. That is, we identify the objective parameters of the optimization, such as the distribution parameters of wind turbines, direct cost coefficients, penalty costs, and other characteristic data.

Step 2: We then determine the target particles for initial optimization. Our team sets the position matrix of particle optimization as:

$$X = \left[X_1, X_2, ..., X_n\right]^{\mathrm{T}} \tag{19}$$

The i th position vector in the optimization is expressed as:

$$X_i = \left\lfloor X_{i1}, X_{i2}, ... X_{i(n)} \right\rfloor \tag{20}$$

Among them, $X_{i(n)}$ represents the unit output random factor.

Step 3: Next, we analyze the operation effect and economic cost in the initial particle optimal scheduling. Our team conducts continuous iteration to determine the optimal population and particles in the optimal scheduling.

Step 4: We then accelerate the particle search speed through inertia weight and gravity constant. We determine the particle speed and position of the updated bi-level optimization target and establish the bi-level optimization dispatching model of the new energy power system as follows:

$$\gamma_i(t+1) = wc_1 \sum_{i=1}^{n} r_i(t) \frac{w}{v_{id}} \tag{21}$$

In formula (21), v_{id} represents the two-layer optimization target constraint condition, $r_i(t)$ represents the interference coefficient in the particle traveling, and γ_i represents the final optimization result output.

Step 5: Correct the error in the optimization to achieve the final optimal scheduling.

In the design of bi-level highly reinforced, sophisticated and nuanced dispatching model of new energy power system, the objective function in bi-level highly reinforced, sophisticated and nuanced dispatching is determined, the information entropy value of the bi-level objective function is calculated, the objective information entropy weight value is obtained, and the particle closeness is calculated.

4. Experimental analysis

4.1 Design of experimental protocol

In order to verify the feasibility of the research model in this paper, experimental analysis is carried out. In this experiment, 24 hours a day is taken as the peak shaving period of the new energy power system, and the dispatching of the new energy power system of an electric power enterprise is studied. There are 10 traditional generators, a wind farm and a photovoltaic power station in the study. The rated power of wind farm and photovoltaic power station is 200MW, and the experimental parameters are shown in Table 1.

Table 1: Details of Experimental Parameters

Parameter	Value
Number of units / individual	10
Minimum start stop time/h	1
Wind farm power / MW	200
Photovoltaic power station power / MW	200
Load forecast point / each	100
Wind power load blur number	[0,1]
Scheduling times / times	100

Based on the above experimental parameters, the accuracy of the wind power and photovoltaic output of the sample new energy power system is tested in the experiment, and the cost of bi-level scheduling optimization and the error generated in the final optimal scheduling are determined. In the experiment, in order to ensure the accuracy of the experiment, the interference factors of the sample test system are excluded, and other interference factors are not considered. Only the current results are taken as the research objective.

4.2 Analysis of experimental results

In the experiment, we first analyzed the model in this paper to predict the wind power and photovoltaic output in the double-layer scheduling optimization. In order to verify the effectiveness of the method in this paper, introduced the reference [9] method and the reference [7] method for comparison in the experiment, and used the prediction accuracy to reflect the tuning optimization performance of different methods. The results are shown in Figure 3 and Figure 4.

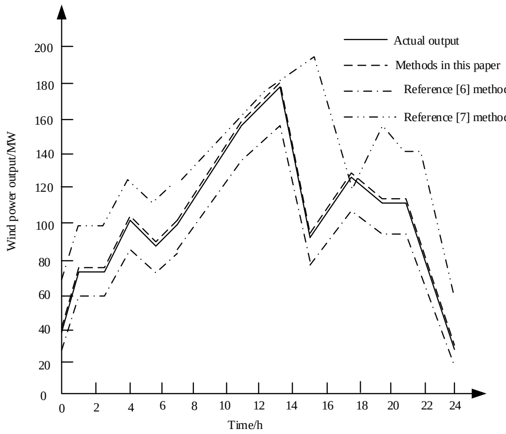

Figure 3: Comparison of power prediction results of wind power output by different scheduling optimization methods

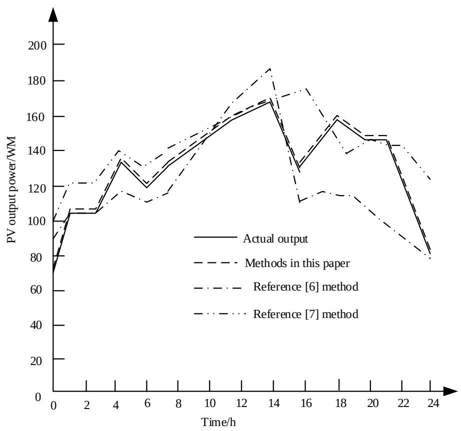

Figure 4: Comparison of PV output power prediction results in different scheduling optimization methods

By analyzing the experimental results in Figure 3, it can be seen that under the same experimental conditions, there is a certain difference between the power prediction results of the three selected methods and the actual output power results.

In the experiment, the cost of the method in this paper, the reference [6] method and the reference [7] method in scheduling optimization are further tested. The calculation and prediction of the cost are also critical, which is related to the feasibility of the new energy power system. For this purpose, the cost is compared, and the results are shown in Figure 5.

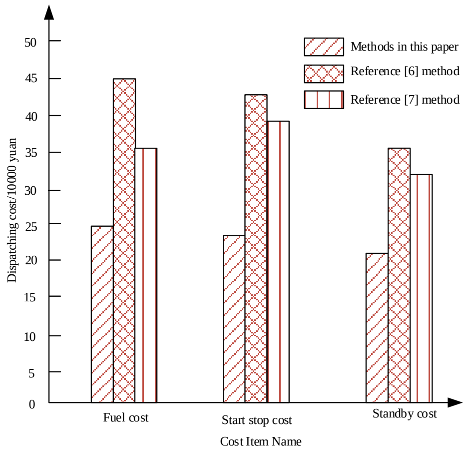

Figure 5: Cost results analysis of scheduling optimization by different methods

By analyzing the experimental results in Figure 5, we can see that there is a certain difference in the cost of scheduling optimization between the method in this paper, the reference [6] method and the reference [7] method. Among them, the reference [6] method has the highest fuel cost, followed by the reference [13] method, and the method in this paper has the lowest fuel cost; The reference [15] method has the highest startup and shutdown cost, the method in this paper has the lowest startup and shutdown cost, and the method in this paper also has the lowest standby cost. It can be seen from Figure 5 that the scheduling cost of this method is controlled below 250000 yuan in this scheduling. It can be seen that the scheduling optimization cost of this method is lower and more suitable for practical application.

In order to verify the performance of the bi-level scheduling optimization method in this paper, the experiment further tested the scheduling error of the three methods on the scheduling target in scheduling to verify the feasibility of the method in this paper. The results are shown in Figure 6.

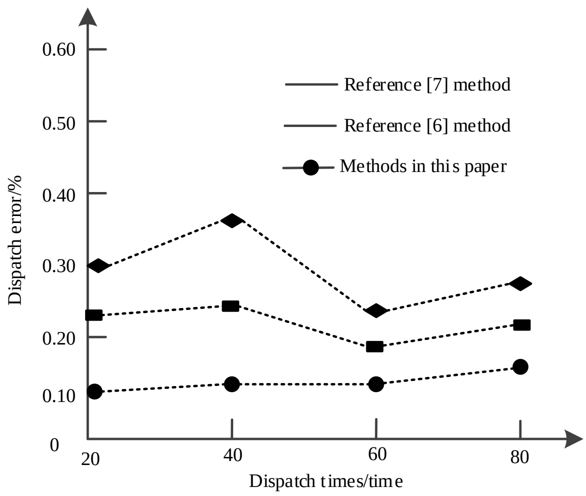

Figure 6: Analysis of scheduling optimization error results by different methods

It can be seen from the analysis of the results in Figure 6 that the dispatching error results of the three methods are different when dispatching the new energy power system. Among them, the method in this paper has the smallest error. The error of this method is less than 0.2%, while the error of other methods is higher than the method in this paper. It can be seen that the method in this paper has better effect.

5. Conclusion

By examining the various factors impacting the operation of the algorithm's core particle, the introduction of inertia weight improves the particle swarm algorithm's search capacity, while simultaneously circumventing the algorithm from getting stuck in local deadlock. Furthermore, the objective function for the two-layer optimization scheduling is determined, whereby the information entropy value of the objective function is calculated. In order to fully and comprehensively assess and analyze the fundamental structure of wind power generation, as well as the photovoltaic characteristics of equivalent circuit conversion, a correlation matching index is rigorously established and implemented, taking into account the intricate and multifaceted relationships between the wind turbine power output, the wind speed, the maximum power point voltage and current, and the dynamic load response characteristic curve. This multifarious and sophisticated approach establishes a bi-level dispatching goal that is agile, adaptable, and in tune with the evolving and dynamic demand of the load response curve. The experimental results demonstrate that the proposed methodology has yielded significant improvements in scheduling cost and accuracy, exhibiting lower errors than previous methods employed in the industry.

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