Research on Wind Speed and Wind Power short term forecasting based on GDSPSO-LSSVR and Low-carbon Dispatching of Grid-connected Wind Power

Abstract: The development and construction of the 21st-Century Maritime Silk Road have an extremely important strategic significance for economic and cultural exchanges between China and the rest of the world. Strengthening the energy interconnection between China and countries along the Maritime Silk Road is an important part of the construction and development of the 21st-Century Maritime Silk Road. Power as a kind of clean energy, is one of the important carrier of energy interconnection. "Internet +" is a sign of the times, is one of the core of the third industrial revolution, is another important developing direction after the smart grid in energy related field. Along with the global energy crisis and environmental pollution problems become increasingly serious, the development and construction of wind power is of great significance for energy conservation and emission reduction, environmental protection and sustainable development of world. Given its unwavering role as one of China's key strategic emerging industries, wind power will for sure see its share in China's national energy mix gradually increase. A key challenge in integrating wind in the electricity grid is to devise approaches that ensure sustainability not only in power system stability, but also from the view point of carbon emissions.

This paper considers two aspects of the wind power prediction and power system operation dispatch. We will then specifically consider short-term generation forecast of wind farm, a low-carbon dispatch model in a wind power integrated system and a smart optimization algorithm for the low-carbon dispatch model. In the 21st-Century Maritime Silk Road context, we study the impacts of electric power system dispatching with wind power integration.

The practical examples of the improved LS-SVR algorithms with common heuristic algorithms and GDSPSO to optimize the LS-SVR parameters, used in multi-step short-term prediction of wind speed and power, are researched. The performance of these methods is analyzed detailed in the comparison of different practical examples. The conclusion is proved by the examples, that the LS-SVR improved by GDSPSO applied in the prediction of wind speed and wind power has good feasibility and performance.

Study optimized dispatching of wind power integrated system on the basis of short-term wind power prediction. Build wind power integrated system low-carbon dispatching model with optimal energy-environmental efficiency and minimized generation resource consumption synthesizing environmental benefit and power generation. Fuzzy optimization method is used to deal with the two contradictory objective functions of optimization dispatch model. The model is solved with tabu search optimization PSO algorithm.

Keywords: Maritime Silk Road; wind power short-term forecasting; LS-SVR; GDSPSO; energy and environmental efficiency; low carbon dispatch

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1 Introduction

1.1 Background and significance of the research

The proposal the Maritime Silk Road in 21st Century was born to upgrade the ASEAN-China relationship, meet the demand of the new round of reform and opening-up in China and build a prerequisite for realizing a modern, global strategic layout[1]. China has made striking achievements in more than 30 years, and is the second largest economy currently in the world. However, under complicated and volatile international political and economic situations, China has had to deepen reforms comprehensively, stimulate change with further opening-up and construct an open economic system in order to become a world power. The proposal of Maritime Silk Road is to build a maritime economic corridor with great development potential. The implementation of this strategy will help enhance economic growth between inland China and coastal areas, and ultimately, resulting in positive interaction between China and the world. Entering the new century, the economic development of maritime countries along the New Silk Road presents a rapid growth. From 2000 to 2012, the GDP growth in the 23 countries along the $ 1,726,500,000,000 to $ 6,626,900,000,000, an average annual growth rate of 11.86%. Wherein the total GDP in 2000, countries in Southeast Asia routes $ 598.039 billion in 2012 to $ 2,257,582,000,000, an average annual growth rate of 11.71%; the total GDP in 2000 (10 countries) South Asia and the Persian Gulf countries to $ 991.809 billion in 2012 it grew to $ 3,991,607,000,000, an average annual growth rate of 12.30%; total GDP 2000 years of red Bay and the Indian Ocean in the West Bank these countries (5 countries) to $ 241.013 billion in the region in 2012 total GDP of $ 761.513 billion, an average annual growth rate of 10.06%. The original data comes from the UN Comrade Database.

Table 1.1 The new silk road on the sea along the representative national GDP growth(unit: us $, %)

Year	Sum	Southeast Asia routes(8 countries)	South Asia and the Persian gulf countries	Red gulf and the Indian Ocean routes
2000	17265.00	5980.39	9918.09	2410.13
2012	66269.00	22575.82	39916.07	615.13
2000~2012	11.86	11.71	12.30	10.06

The strategy will also help the energy flow in various countries, and realized mutual exchange of needed products. [2].Energy is the cornerstone of the development of human society and economy, the safe and effective use of energy is conducive to the development of human civilization. With the rapid development of the global economy, especially since Chinese the rate of Chinese dependence on oil[3].The demand for oil is increasing rapidly and it continues to grow. At the same time, the coal and petroleum based fossil energy accounts for the main structure of a series of problems. Although these fossil fuels have great power in the economic development of the world, it also produced a lot of pollutants, such as carbon dioxide, nitrogen oxide and other pollutants, the deterioration of environmental pollution has seriously affected the sustainable development of human society.

The rapid development of economy will be severely constrained by the supply of energy. In the face of the above challenges, a large number of new energy can reduce the energy consumption, but also reduce the pressure on environmental pollution, produce better economic benefits and environmental benefits, and provide a new impetus for the further development of human society[4].

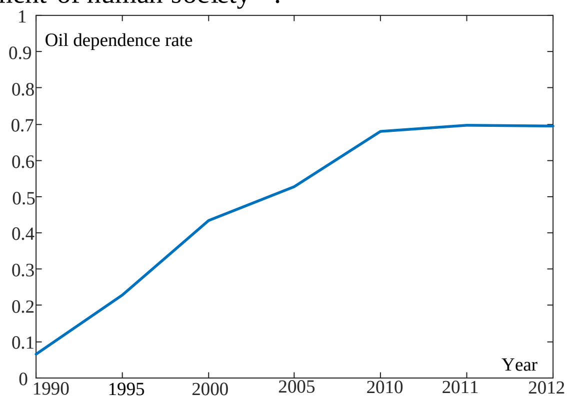


Figure 1.1 The rate of China's dependence on oil

As renewable energy, wind power has the most mature technology, the most widely used, and easy to use, has been developed in many countries in the world. The world's new wind power installed capacity reached a record high of 51477MW in 2014, the total installed capacity has reached 370 million kW.[5].

China has a vast territory and abundant resources. In terms of regional distribution, the area of wind energy resources is mainly concentrated in the northwest region, the southeast coast and some inland regions. The average of wind power density is about 100W/m^2, the national wind energy reserves of about 3.226 billion kW, which has a huge development potential. By the end of 2014, the full year new factory hoisting capacity and installed capacity of 232 million kW and 19 million kW, which is a record high, the total installed capacity of wind power to reach 96 million kW. National total installed capacity of 7% has been occupied by wind power capacity. At the same time, the online power reached 153 billion kWh in 2014, which account for 2.78% of the total consumption of electricity. By the end of February 2015, China's wind power installed capacity has exceeded 100 million kW, showed the rapid development of wind power industry[6].

The State Council on actively promoting the" Internet +" action guidance is published on July 1st Clearly refers to the construction of energy Internet. The maritime Silk Road provides a platform for the energy Internet, based on the integration of energy, each national mutual exchange of needed products and realizes the development of economics[7].

1.2 Mainly works and chapter arrangement in this paper

So, a comprehensive, in-depth, systematic study on the concerned issues above is completed, the primary contents and original contributions of this dissertation are as follows:

1) The first chapter is assigned to analyze the historical background of the proposing of the Maritime Silk Road in 21st Century and the importance of wind speed and wind power short-term forecasting and low-carbon dispatching of grid-connected wind power.
2) The second, this paper studied the main steps and key issues of wind speed and wind power forecast using LS-SVR, and determined the needing parameters of SVM and the significance of parameter selection.
3) In the third chapter, we propose a method based on GDSPSO-LS-SVR algorithm for short-term wind speed and generation forecast of wind farm. Some of the common support vector machine (SVM) algorithms and several prediction instances of the algorithm are furnished in this chapter. Through the extensive simulations, the effectiveness and feasibility of GDSPSO-LS-SVR algorithm is evaluated.
4) This paper studied the wind power integration power system optimization scheduling problem, and focused on considering the requirements of low-carbon electricity production and introduced the "energy and environmental efficiency" concept, constructed the wind power integration power system of low-carbon scheduling model. A numerical example contains a wind farm including 6 units system show that wind power integration power system of low-carbon scheduling model was more reasonable compared to the traditional single objective scheduling model. The resultant scheduling scheme had some reference for the current electricity production and optimal scheduling, wind power integration and low-carbon power system had better practicability after taking the energy efficiency and resource consumption of generation into consideration.

2 The overview of LS-SVR

The literature[8] account of support vector machine (SVM) in detail, here are not tired. SVM model not only considers the complexity of the training sample, but also consider the data curve fitting, and has good generalization ability. But because it requires solving a convex quadratic programming problem, the calculation is more complicated, and need to compute and store the kernel function matrix, so when the sample points is large, need to take up a lot of storage space. For this kind of situation, SVR is proposed on the basis of the least squares support vector machine (LS-SVR) [9].LS-SVR, quadratic loss function is adopted, and the inequality constraints into equality constraints, SVM in the process of solving quadratic optimization problem can be converted into linear KKT (Karush - Kuhn - Tucker) solution of the equations and to solve the complexity is greatly reduced, greatly reduces the computational complexity while guarantee the accuracy, speed up the solution speed[10].

For the training sample set $(x_i, y_i), i = 1, 2 \cdots l$; $i \in R^n$, where $x_{i,}$ is the first input variable and y_i is the corresponding output variable, l is the training sample number. SVM is for the purpose of the nonlinear mapping the input value x mapped to a high-dimensional feature space, in the space to construct linear regression equation for[11]

$$y_i = \omega^T \varphi(x) + b + \varepsilon_i y_i \tag{2.1}$$

where the ω is weight vector with the same dimension and the nuclear space, b for offset constant, $\varphi(x)$ is the mapping function, ε_i is the loss function.

Here need to introduce loss function ε_i [12], the meaning is sample points in the real value of the absolute value of the difference in predicted less than ε, think that the predicted value is equal to the real value of the sample points, namely

$$(y_i - f(x_i))^2 = \varepsilon^2 \tag{2.2}$$

LS-SVR optimization goal uses the squared of loss function ε_i .According to the structural risk minimization principle, the objective function and the constraint functions is

$$\begin{aligned} &\min \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{l}\varepsilon_i^2 \\ &s.t. \quad y_i = \omega^T\varphi(x_i) + b + \varepsilon_i \quad i = 1, ..., l \end{aligned} \tag{2.3}$$

Where C is the regularization parameter used to control the noise effect on the model. The first reflect the LS-SVR largest interval algorithm characteristics, make the fitting function more smoothly, the second is used to reduce the training error, using regularization parameter C control the degree of punishment right or wrong points sample, implementation in the tradeoff between fault samples and the complexity of algorithm, improve the ability in the promotion of the LS-SVR.

Constructing the Lagrange function in dual space for solutions of the above optimization problem:

$$L_\alpha = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{l}\varepsilon_i^2 - \sum_{i=1}^{l}\alpha_i\left\{\omega^T\varphi(x_i) + b + \varepsilon_i - y_i\right\} \tag{2.4}$$

Where α_i is the Lagrange multiplier. According to Kuhn - tucker conditions, set the variable partial derivative to 0:

$$\begin{cases} \dfrac{\partial L}{\partial \varepsilon_i} = 0 \rightarrow \alpha_i = C\varepsilon_i \qquad i = 1, 2, 3..., l \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l}\alpha_i = 0 \\ \dfrac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{l}\alpha_i\varphi(x_i) \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \rightarrow y_i = \omega^T\varphi(x_i) + b + \varepsilon_i \quad i = 1, 2, 3, ...l \end{cases} \tag{2.5}$$

Simultaneous equation (2.4)(2.5)on the elimination of ω and ε, getting the following system of linear equations:

$$\begin{bmatrix} I & 0 & 0 & -Z^T \\ 0 & 0 & 0 & -I_l^T \\ 0 & 0 & CI & -I \\ Z & I_l & I & 0 \end{bmatrix} \begin{bmatrix} \omega \\ b \\ \varepsilon \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ y \end{bmatrix} \tag{2.6}$$

Where $y = [y_1, y_2, ..., y_l], I_l = [1,1,...,1],$
$\alpha = [\alpha_1, \alpha_2, ..., \alpha_l], Z = [\varphi(x_1), \varphi(x_2), ..., \varphi(x_l)]$

Using the Mercer conditions $\Omega = \varphi(x_i)^T \varphi(x_j) = K(x_i, x_j), \quad i, j = 1, 2, ..., l$ to elimination item has nothing to do, the equations related to b and α:

$$\begin{bmatrix} 0 & y^T \\ y & H \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ I_l \end{bmatrix} \tag{2.7}$$

The elements in the positive definite matrix H is $h_{ij} = y_i(K(x_i, x_j) + \delta_{ij} C^{-1})$, δ_{ij} for Kronecker Delta function. When $i = j$, $\delta_{ij} = 1$,otherwise, $\delta_{ij} = 0$. According to the formula (2.7) solution to b and αnumerical, using the kernel function can be set for regression function:

$$y = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b \tag{2.8}$$

3 The establishment of prediction model

According to the LS-SVR principle, parameters that need to be determined including the regularization parameter C , the loss function ε and the nuclear parameters σ for the RBF kernel. Based on the principle of KCV, standard particle swarm optimization algorithm for Gauss perturbation algorithm (GDSPSO) is used to optimize the parameters.

3.1 The step of wind speed and wind power prediction based on LS-SVR

LS-SVR is a method based on historical data of wind speed and wind power. The correlation between the data is used to find the inherent function of the historical data, and then forecast the future data. Based on LS-SVR, the wind speed and wind power forecasting are generally divided into two steps: the construction of the forecasting model and the prediction model. The construction of support vector machine prediction model is the key point of the forecast process. It is based on the given data, choosing the appropriate parameters and kernel function to solve the decision-making function.

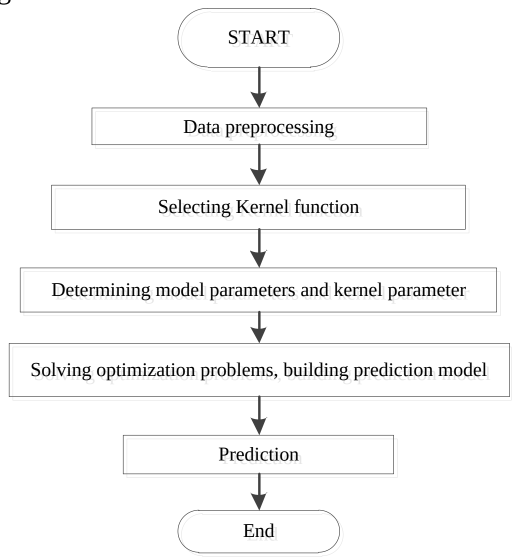


Figure 3.1 The flowchart the basic algorithm of LS-SVR

3.1.1 Data preprocessing

The wind speed and wind power data are influenced by the weather, temperature, air pressure, humidity and other factors, which may lead to the data can't be used directly for the training and prediction of the model.

(1) selection of data

Based on the inherent laws of wind speed and wind power data, the short-term wind power forecasting based on historical data is limited by the correlation of the data. It should be selected as the data of the same season, weather, altitude, and the data are trained and predicted.

(2) normalization of data

Wind speed and wind power have strong fluctuation, and the maximum and minimum values may be very different. In order to avoid the difference between the number of variables, the data is normalized to a given interval before the data is used for training and prediction.

In this paper, the normalized algorithm is that the original data is structured into the range [0,1], and its function is mapped to:

$$f : x \to y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3.1}$$

where, $x, y \in R^n, x_{\min} = \min(x), x_{\max} = \max(x)$

3.1.2 Selection of kernel function

In this paper, the wind speed and wind power short-term forecast is based on the local historical data, these data are in a certain range of fluctuations, and some of the long-term forecasting problems are in the situation of violent fluctuations in different situations. What's more, the short term forecasting needs to track the changes of the data well, and get the accurate prediction of the local in a few hours, so the RBF kernel function is used for the short-term forecasting of wind speed and wind power.

$$K(x, x_i) = \exp(-\|x - x_i\|^2 / \sigma^2) \tag{3.2}$$

where σ is expressed kernel width coefficient

3.1.3 Selection of fitness function

The mean square error (MSE) is used as fitness function[13],the expression is

$$G = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{3.3}$$

where $\hat{y}_i$ is the training output value, y_i is the practical value,G is the fitness function, the smaller the G is, the effect is better.

3.1.4 Determination of parameters

After the kernel function is determined, the key is to determine the parameters of the support vector machine. Parameters in support vector machine, including model parameters and kernel parameters, need to be determined in two categories.

In order to search for the optimal solution , the random particle swarm optimization is used in PSO by iterative operation . The particle is updated by following 2 "extreme" to update its position and speed. One is the optimal solution of the particle itself- $pbest$ and the other is the optimal solution of the whole population- $gbest$.

The mathematical expression of PSO is: in a dimension space m , the number of particles is n , the particle set is $X=(x_1,\ldots x_i \ldots x_{in})$,the position of the particles in space is $x_i=(x_{i,1}, x_{i,2}\ldots x_{i,m})$, the velocity of the particles $v_i=(v_{i,1}, v_{i,2}\ldots v_{i,m})$, the velocity and position of the particle is updated:

$$v_{i,j}(t+1) = w(t)v_{i,j}(t) + c_1\varepsilon_1[pbest_{i,j}(t) - x_{i,j}(t)] + c_2\varepsilon_2[gbest_{g,j}(t) - x_{i,j}(t)] \tag{3.4}$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \tag{3.5}$$

v_{ij} (t) and x_{ij} (t) show that the speed and position of the particle i in the jth dimension of the t iteration; $pbest_{i,j}$ (t) is particle i in the t iteration of the individual extreme value of the jth dimension ;$gbest_{g,j}$ (t) is the particle population in the t iteration of the full value of the jth dimension.; $\varepsilon_1, \varepsilon_2$ is the random numbers in [0 1]; $w(t)$ is the inertia weight of the current iteration.

Inertia weight is mainly to balance the global and local search ability, when w is relatively large, the algorithm has a relatively strong global searching ability, w is relatively small, the algorithm has a strong local searching ability. In order to make the calculation simple, this paper chooses the linear decreasing weight to calculate $w(t)$,the formula is as followed

$$w(t) = w_{\max} - \frac{t \times (w_{\max} - w_{\min})}{t_{\max}} \tag{3.6}$$

where w_{max} is the maximum inertia weight, $w_{\min}$ is the minimum inertia weight, $t_{\max}$ is the maximum number of iterations, t is the current iteration steps. Usually, w_{min}=0.4,w_{max}=0.9 .

Analysis of equation(3.6) ,we can find that the formula is composed of three parts, the first part represents the particle velocity and particle current state reaction; the second part reflects the learning of the particles, so that the particles have strong enough global search ability, and avoid local optimum. The third part reflects the cooperation between particles, which reflects the information sharing among particles. The particle position updating is shown in Figure 3.2.

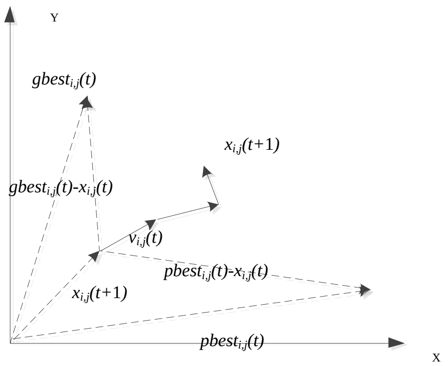


Figure 3.2 Schematic of the particle location update

3.1.5 Standard particle swarm optimization algorithm with Gauss perturbation

Through the analysis of SPSO, the diversity of the particles decreases and the particle is trapped in local optimum to the late iteration. So this paper makes an improvement on SPSO, and introduces the Gauss perturbation operation to make the algorithm jump out of the local optimum, and search the other areas of the solution space to improve the accuracy of calculation. The commonly used disturbance is mainly composed of the following three strategies: 1) joining the disturbance operation in the global optimal position; 2) joining the disturbance in the average location; 3) joining the disturbance in the global optimal position and the average best position. In the literature[14], the simulation results of the standard test functions show that the effect of the perturbation join in the average best position is the best, so the formula of Gauss perturbation term is added to the velocity iteration is followed.

$$v_{i,j}(t+1) = w(t)v_{i,j}(t) + c_1(t)\varepsilon_1[pbest_{i,j}(t) + r_1 gauss_{i,j}(t) - x_{i,j}(t)] + c_2(t)\varepsilon_2[gbest_{g,j}(t) - x_{i,j}(t)] \quad (3.7)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \quad (3.8)$$

$$gauss_{i,j}(t) = r_2 gaussian(\mu, \delta^2) \quad (3.9)$$

$gauss_{i,j}(t)$ is Gauss perturbation of the particle i in the t iterations. μ is mean, δ^2 is variance, r_1, r_2 is random numbers of uniform distribution on [0 1] and the definition of other parameters is the same as the formula(3.4)(3.5).

By the formula(3.9), Gauss disturbance is related with the mean μ and variance δ^2 . Therefore this article selects $\mu = 0$, $\delta^2 = \left| pbest_{i,j}(t) \right|$

$c_1(t)$ and $c_2(t)$ is learning factors and also known as accelerating factors which respects the self - learning ability and the ability to learn from other outstanding particles in the population which is the main means to the best position. Linear decreasing expressions is adopted by $c_1(t)$ and the monotone increasing expression is adopted by $c_2(t)$. In the early iterations, the large $c_1(t)$ ensures the particles to search the best position in the local area, and conducive to the algorithm. With the iteration, large $c_2(t)$ is benefit to jump out of local the most merit, and advantageous for the global search. The expressions of $c_1(t)$ and $c_2(t)$ are

$$\begin{cases} c_1(t) = c_{1i} + (c_{1f} - c_{1i})\dfrac{t}{t_{\max}} \\ c_2(t) = c_{2i} + (c_{2f} - c_{2i})\dfrac{t}{t_{\max}} \end{cases} \quad (3.10)$$

where $c_1(t)$ decreases from the initial c_{1i} to final c_{1f} , $c_2(t)$ increases from the initial c_{2i} to final c_{2f} .

In summary, the algorithm of GDSPSO is the:

1) particle initialization, and the set of the relevant parameters;

2) the evaluation and calculation of the fitness function value of each particle;

3) the calculation of the optimal position of each particle and the optimal position of the population, and the calculation of the value of the Gauss perturbation of the optimal position of the particle at each iteration;

4) adopt the formula (3.7)(3.8)to update the speed and the position of the particle, and calculate the fitness value of the new particle;

5)If the algorithm satisfies the termination condition, then the iteration is stopped, and the global optimal particle position and the fitness value are output, otherwise continue the cycle step (2).

3.1.5 The structuration and solve of optimization problems

The process of constructing and solving the optimization problem requires a large number of sample data. This work can be seen as a support vector machine to extract data from a limited sample of historical data, that is, the learning process.

The learning process is affected by the quality of forecast sample data. If the sample data is too large, it will increase the complexity of the optimization problem, reduce the computation efficiency, and there may be some strong external factors leading to the change trend of the front and back. There may be some errors in the measurement, the sample point is missing, which will make the prediction accuracy.

Through the training of a large number of samples, we can determine the optimal solution of the optimization problem, and then determine the decision function, that is to get the prediction model, and predict.

3.1.6 Forecast analysis

The wind speed is random and fluctuating, which is affected by many uncertain factors. Therefore, the short-term wind speed and the wind power forecast based on historical data have some errors between the forecast and the actual value. The analysis and forecast error is an important method to study the forecast method and the forecast model. In this paper, the measures expressions are followed

(1) Absolute Error：

$$AE = \hat{y} - y \tag{3.11}$$

(2) Relative Error：

$$RE = \left| \frac{\hat{y} - y}{\hat{y}} \right| \times 100\% \tag{3.12}$$

(3) Mean Absolute Error：

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \hat{y}_i - y_i \right| \tag{3.13}$$

(4) Mean Relative Error：

$$MRE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{\hat{y}_i} \right| \times 100\% \tag{3.14}$$

(5) Mean Squared Error：

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{3.15}$$

(6) Root of the Mean Squared Error：

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{3.16}$$

where $\hat{y}$ and $\hat{y}_i$ for the real value, y and y_i for the forecast value.

In summary, the steps to build LS-SVR prediction model based on GDSPSO is shown in figure 3.3.

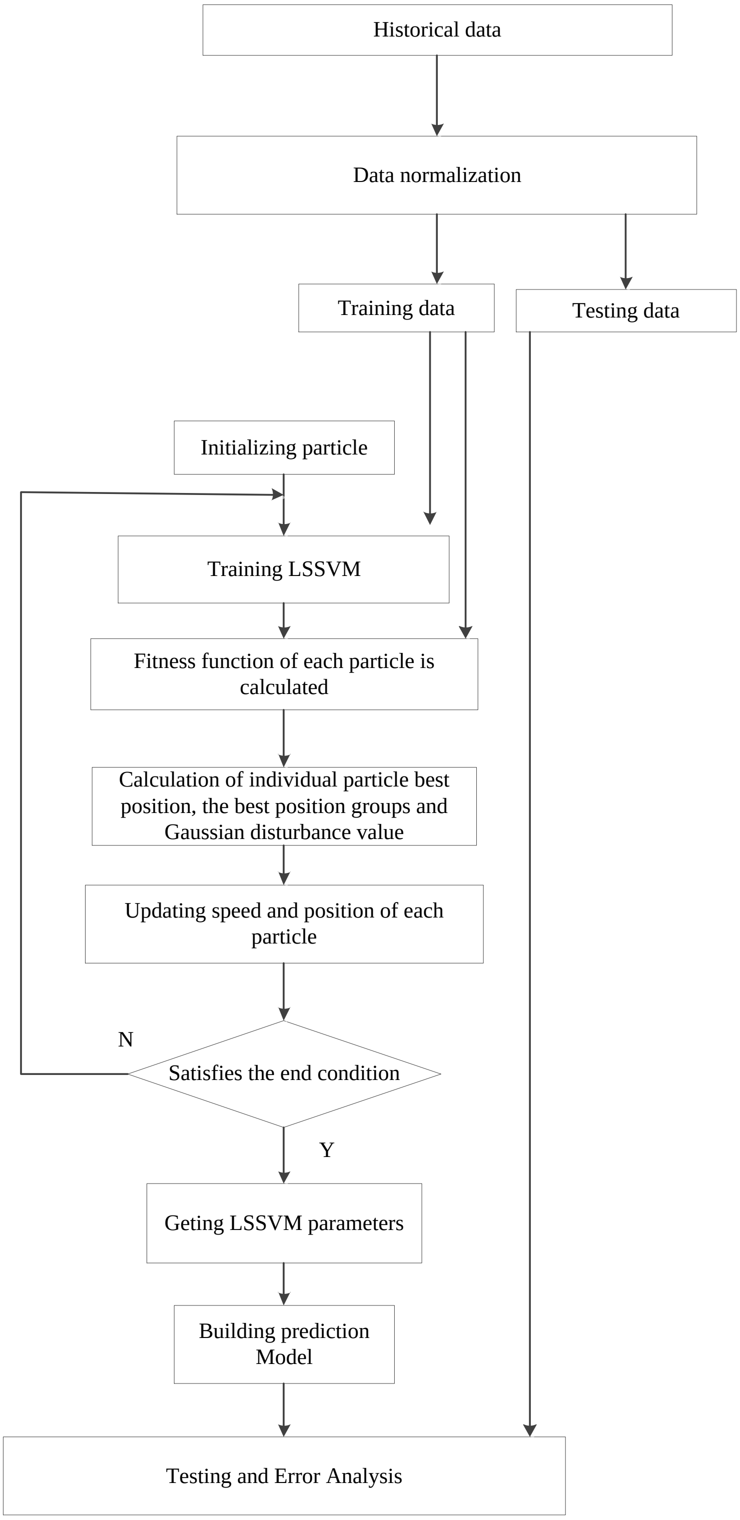


Fig. 3.3 the prediction step of least squares support vector regression

3.2 Case analysis

3.2.1 Multi-step prediction of wind speed

There are two kinds of multi-step forecasting methods, namely, rolling multi-step method and direct multi-step prediction method. Suppose that the number of training sample data is m, that is, the number of true value is m, and taking advance of k step prediction as an example. Rolling prediction method use single step prediction method to calculate the value of the m+1 point using 1 to m sample data points, and get the m+2 point forecast using 2 to *m*+1 points, double counting k times, achieving k ahead prediction. Direct prediction method use the *i*+*k* sample point as the training target of the point of i, and the obtain the prediction model. Then the prediction value of m+1 to $m+k$ is obtained by this model. The defects of the rolling prediction method is that the error of the prediction will be accumulated to the next one, so that the prediction error will continue to increase, and the prediction effect is poor. In this paper, the direct prediction method is used to predict the wind speed and wind power.

Taking the daily wind speed with time variation into account, that is, the wind speed of 24h can be divided into four periods, the trend of wind speed change in each period is roughly the same, therefore, this paper mainly studies the wind speed and wind power prediction advanced 6 steps.

3.2.2 The forecast of wind speed

Comparison of the three methods of wind speed forecasting results are followed in Table 3.1 to Table 3.3:

Table 3.1 Parameters optimization of wind speed forecasting of three forecasting methods

algorithm	C	σ	ε	cross validation error	time consuming in optimization (s)
GA	2.0256	0.4385	0.1253	1.7657×10^{-3}	21.93
PSO	48.4345	0.3492	0.1651	1.7777×10^{-3}	25.25
GDSPSO	30.6416	0.6887	0.1229	1.7922×10^{-3}	16.22

Table 3.2 wind speed forecasting data of three forecasting methods

Time (h)	measured wind speed (m/s)	GA-LS-SVR		PSO-LS-SVR		GDSPSO-LS-SVR	
		Forecast wind speed (m/s)	relative error (%)	Forecast wind speed (m/s)	relative error (%)	Forecast wind speed (m/s)	relative error (%)
1	10.8209	10.8440	0.21	11.2912	4.35	10.8405	0.18
2	10.3103	10.5783	2.60	10.6198	3.00	10.6043	2.85
3	11.0474	10.8649	1.65	11.3405	2.65	10.8588	1.71
4	10.6041	10.6022	0.02	10.6766	0.68	10.6262	0.21
5	10.0053	10.3846	3.79	10.2374	2.32	10.4221	4.17
6	10.5071	10.7136	1.97	10.9578	4.29	10.7259	2.08
7	10.4083	10.4964	0.85	10.4400	0.30	10.5286	1.16
8	10.1310	10.2984	1.65	10.1178	0.13	10.3375	2.04
9	10.5287	10.5796	0.48	10.6229	0.89	10.6056	0.73
10	10.0026	10.4140	4.11	10.2856	2.83	10.4505	4.48
11	9.7466	10.1731	4.38	9.9986	2.59	10.2109	4.76
12	9.8364	10.3764	5.49	10.2246	3.95	10.4141	5.87
13	10.2369	10.3375	0.98	10.1681	0.67	10.3761	1.36
14	10.0032	10.2254	2.22	10.0411	0.38	10.2643	2.61
15	10.8430	10.3848	4.23	10.2377	5.58	10.4223	3.88
16	10.6467	10.1720	4.46	9.9978	6.10	10.2098	4.10
17	10.3492	10.0620	2.78	9.9378	3.98	10.0958	2.45
18	10.7429	10.1011	5.97	9.9552	7.33	10.1366	5.64
19	11.0393	10.2688	6.98	10.0840	8.65	10.3079	6.63
20	10.8257	10.1722	6.04	9.9979	7.65	10.2100	5.69
21	11.3089	10.5046	7.11	10.4570	7.53	10.5363	6.83
22	11.4199	10.4304	8.66	10.3141	9.68	10.4662	8.35
23	10.7067	10.3140	3.67	10.1371	5.32	10.3529	3.30
24	11.2015	10.4671	6.56	10.3818	7.32	10.5010	6.25

Table 3.3 Prediction error of wind speed of three kinds of forecasting methods

algorithm	MAE(m/s)	MRE(%)	MSE(m/s)	RMSE(m/s)	number of RE<1%	number of RE<5%	number of RE<10%
GA	0.3865	3.62	0.2210	0.4701	5	17	24
PSO	0.4409	4.09	0.2956	0.5437	6	15	24
GDSPSO	0.3874	3.64	0.2117	0.4601	3	17	24

In the case of parameter optimization, the cross validation error of the three algorithms is quite different, the algorithm parameters are the same, the calculation speed of GDSPSO-LS-SVR is fast. Compared with these three methods, the effect of GA-LS-SVR and GDSPSO-LS-SVR is better, and the average absolute error and average relative error of the former is smaller, the mean square error and the mean square error of the latter are smaller. And the distribution of errors in the GA-LS-SVR prediction results is wide, while the error distribution of GDSPSO-LS-SVR prediction results is relatively compact, the errors of small data points exceed the maximum error level of GDSPSO-LS-SVR prediction results.

Combined three methods of wind speed forecasting results, the three methods of optimization and prediction results can meet certain requirements, in which the prediction of GA-LS-SVR and GDSPSO-LS-SVR prediction is better. And GDSPSO algorithm has obvious advantages.

3.2.3 The forecast of wind power

Prediction of wind power can be predicted by two methods: one is directly on the wind field measurement data based on wind power forecasting method to get wind power forecasting data, which is called the direct power prediction method; the other one is based on the relationship between the wind power curve or the wind speed and wind power function of the wind turbine, calculating the wind power forecasting data based on wind speed forecast data which is called the wind speed conversion method. In accordance with the idea of direct multi-step forecasting method, the 6h prediction of the future 24 *h* is realized.

1 direct prediction of wind power

For the use of power direct prediction method to forecast the wind power, as mentioned above, this paper carries on 10 experiments to investigate the performance of the algorithm, the detailed experimental data are shown in Table 3.4.

Table 3.4 Three parameters optimization data of forecasting methods for wind power forecasting

algorithm	C	σ	ε	cross validation error	time consuming in optimization (s)
GA	0.3834	0.2439	0.1349	2.0100×10^{-2}	46.97
PSO	1000	7.0711	0.1888	2.1085×10^{-2}	231.49
GDSPSO	9.6312	1.7393	0.001	2.0790×10^{-2}	25.34

Table 3.5 Prediction of wind power

time (h)	measured power (kW)	GA-LS-SVR		PSO-LS-SVR		GDSPSO-LS-SVR	
		predictive power (kW)	relative error (%)	predictive power (kW)	relative error (%)	predictive power (kW)	relative error (%)
1	12167	13684	12.47	13520	11.12	13345	9.68
2	10458	12224	16.89	12002	14.77	12071	15.42
3	13880	13711	1.21	13711	1.21	13484	2.85
4	11964	12659	5.82	12347	3.20	12382	3.49
5	9875	11020	11.60	10995	11.35	11110	12.51
6	11125	13298	19.54	12919	16.13	12872	15.71
7	10986	11700	6.50	11586	5.47	11682	6.34
8	10106	10721	6.08	10701	5.88	10817	7.04
9	11421	12730	11.46	12404	8.61	12433	8.85
10	9809	11576	18.02	11484	17.08	11585	18.11
11	8978	10426	16.12	10383	15.65	10496	16.91
12	9127	11084	21.43	11054	21.11	11168	22.36
13	10534	11006	4.48	10982	4.25	11096	5.34
14	9975	10541	5.67	10510	5.37	10625	6.52
15	12347	11254	8.85	11208	9.22	11319	8.32
16	11674	10393	10.97	10347	11.37	10459	10.40
17	10787	10002	7.28	9879	8.41	9978	7.50
18	12046	10071	16.40	9965	17.28	10066	16.43
19	12456	10761	13.60	10742	13.76	10858	12.82
20	12156	10475	13.82	10438	14.13	10552	13.19
21	12844	11810	8.05	11675	9.10	11767	8.39
22	12983	11402	12.17	11338	12.67	11444	11.85
23	11528	10896	5.48	10876	5.65	10992	4.65

time (h)	measured power (kW)	GA-LS-SVR		PSO-LS-SVR		GDSPSO-LS-SVR	
		predictive power (kW)	relative error (%)	predictive power (kW)	relative error (%)	predictive power (kW)	relative error (%)
24	12151	11626	4.32	11526	5.14	11625	4.33

Table 3.6 Prediction error of wind power

algorithm	MAE(10^3kW)	MRE(%)	MSE(10^3kW)^2	RMSE(10^3kW)	number of RE<1%	number of RE<10%	number of RE<20%
GA	1.1913	10.76	1.7269	1.3141	3	11	23
PSO	1.1461	10.37	1.6046	1.2667	3	12	23
GDSPSO	1.1443	10.38	1.5665	1.2516	4	13	23

From the above data we can see, all the three methods can find the solution to a certain accuracy requirements. But it is found that PSO-LS-SVR and GDSPSO-LS-SVR algorithm is better than other methods, and the latter is better than the other two algorithms. The average relative of GDSPSO-LS-SVR algorithm error is slightly higher than the other algorithms, but the mean square error, the root mean square error is smaller, and the error distribution of each time point is better.

Comprehensive analysis, the GDSPSO-LS-SVR parameters optimization and prediction effect is good, has a good computational stability, and has obvious advantages in the calculation speed.

2 forecast of wind power based on wind speed conversion

The output active power of a single unit is mainly determined by the size of the wind speed of the hub height of the wind turbine, and the relationship between the output and the is represented by the piecewise function [46]:

$$P_s = \begin{cases} 0 & (v_s \le v_{CI} \;\; or \; v_s \ge v_{CO}) \\ \dfrac{v_s^{\,3} - v_{CI}^3}{v_R^3 - v_{CI}^3} P_R & (v_{CI} < v_s < v_R) \\ P_R & (v_R \le v_s < v_{CO}) \end{cases} \tag{3.17}$$

where P_R is rated output power for the wind turbine, V_R is the wind turbine running the rated wind speed, V_{CI} is the cut in wind speed, V_{CO} the output wind speed. The wind speed power characteristic curve is shown in Figure 3.4.

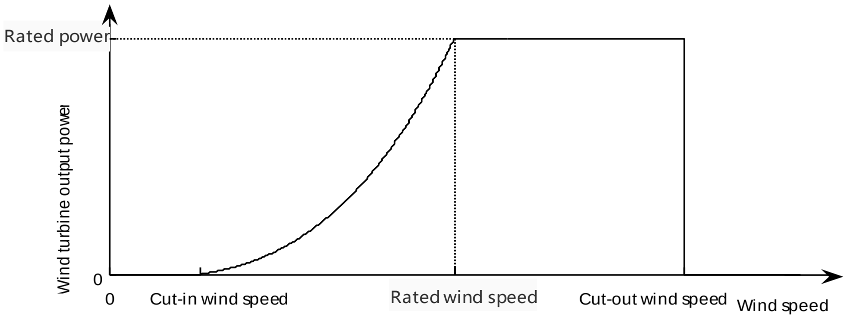


Figure 3.4 The wind speed power characteristic curve

It is considered that the wind speed of each wheel hub in the wind farm is the same, and the average wind speed of the wind farm is the wind speed, the wind speed value is predicted by the above.

$$P = n \times P_s \tag{3.18}$$

where n is the number of wind power units; P_s Output power of single unit, the previously predicted wind speed values v is used to replace the v_s in equation.

Table 3.7-3.8 is comparison for three algorithms through the wind speed conversion forecasting method.

Table 3.7 prediction of wind power for three kinds of forecasting methods

time (h)	measured power (kW)	GA-LS-SVR		PSO-LS-SVR		GDSPSO-LS-SVR	
		predictive power(kW)	relative error(%)	predictive power (kW)	relative error (%)	predictive power(kW)	relative error (%)
1	12167	11405	6.26	12926	6.24	11394	6.36

time (h)	measured power (kW)	GA-LS-SVR		PSO-LS-SVR		GDSPSO-LS-SVR	
		predictive power(kW)	relative error(%)	predictive power (kW)	relative error (%)	predictive power(kW)	relative error (%)
2	10458	10559	0.97	10688	2.20	10640	1.74
3	13880	11474	17.33	13102	5.60	11454	17.48
4	11964	10633	11.12	10867	9.17	10708	10.49
5	9875	9968	0.95	9534	3.45	10081	2.09
6	11125	10985	1.26	11781	5.90	11024	0.90
7	10986	10306	6.18	10135	7.75	10405	5.28
8	10106	9712	3.90	9190	9.07	9828	2.76
9	11421	10563	7.52	10698	6.33	10644	6.81
10	9809	10056	2.53	9674	1.37	10167	3.65
11	8978	9348	4.11	8855	1.38	9457	5.33
12	9127	9943	8.94	9496	4.04	10057	10.18
13	10534	9828	6.71	9333	11.40	9943	5.62
14	9975	9499	4.77	8973	10.04	9612	3.64
15	12347	9969	19.26	9534	22.78	10081	18.35
16	11674	9344	19.95	8852	24.17	9453	19.02
17	10787	9032	16.27	8687	19.47	9127	15.38
18	12046	9142	24.10	8735	27.49	9243	23.27
19	12456	9625	22.72	9094	26.99	9740	21.80
20	12156	9345	23.12	8853	27.17	9454	22.22
21	12844	10332	19.56	10186	20.69	10429	18.81
22	12983	10106	22.16	9758	24.84	10214	21.32
23	11528	9758	15.35	9244	19.81	9874	14.35
24	12151	10217	15.91	9960	18.03	10321	15.06

Table 3.8 prediction error of wind power for three kinds of forecasting methods

algorithm	MAE(10^3kW)	MRE(%)	MSE(10^3kW)^2	RMSE(10^3kW)	number of RE<10%	number of RE<1%	number of RE<20%
GA	1.3950	11.71	2.9618	1.7210	12	7	20
PSO	1.5519	13.14	3.6921	1.9215	12	5	17
GDSPSO	1.3472	11.33	2.7413	1.6557	11	6	20

Compared with the above data, it can be seen that the prediction method of wind speed change has a big difference, and the four error indicators have a more obvious difference, and the prediction error distribution of each time point is not as ideal as direct power prediction.

To sum up the above analysis, it is concluded that there is a certain gap of the forecast effect between wind power prediction using the wind speed conversion and the direct use of wind power, and it's more prominent in the multi - step prediction. This is mainly because the wind power is related with wind direction, air temperature, air pressure, unit loss and other conditions of the work conditions and other conditions, not simply controlled by the wind speed. Therefore, It's not recommended to use wind speed conversion method in the prediction of wind power.

In addition, compared the prediction accuracy of wind power and wind power ,it is found that the former is better than that of the latter. This is because the wind power not only influenced by the impact of wind speed, but also by the wind direction, the operation of the unit itself, and other uncertain factors. These factors make the variation regularity of wind power is weaker than the wind speed. The prediction method based on historical data is realized by searching the inherent law of historical data. Therefore, the effect of wind power is worse than that of wind power. The conclusion is also found in other prediction methods of wind speed and wind power.

4 Low carbon scheduling model of wind power system considering the environmental benefits of energy

On January 1, 2006, China implemented the "renewable energy law" that clearly identified the wind power and other renewable energy policy of full access to the power grid. With the rapid development of wind power in the world in recent years, wind power is now no longer is "alternative". Chinese power system is faced with very serious pressure to reduce emissions. Under the premise of more and more serious environment pollution, energy depletion and the development of large-scale wind power grid, for the sustainable development of the whole electric power system, how to make the power industry optimizing the scheduling of CO_2 emissions effectively, realize power production of "low carbon", has important theoretical significance and practical significance.

This chapter has a further study optimized dispatching of wind power integrated system on the basis of short-term wind power prediction. Build wind power integrated system low-carbon dispatching model with optimal energy-environmental efficiency and minimized generation resource consumption synthesizing environmental benefit and power generation. Fuzzy optimization method is used to deal with the two contradictory objective functions of optimization dispatch model. The model is solved with tabu search(TS) optimization PSO algorithm.

4.1 Wind power integrated system low-carbon dispatching model

We consider the "low carbon" requirements of the electric power production in low-carbon dispatching model, in view of the protection of ecological environment and improve the efficiency of energy utilization, introduce the "energy environmental benefits" concept, build wind power integrated system low-carbon dispatching model with optimal energy-environmental efficiency and minimized generation resource consumption synthesizing environmental benefit and power generation.

4.1.1 Optimization objective function of energy and environment

The ecological environment pollution problem resulted from CO_2、SO_2、NO_x and dust in a large number of pollutants that traditional thermal power unit during fuel combustion produces has already caused severely restricts the sustainable development of the national energy economy. Many countries have introduced the corresponding laws and regulations limit power plant emissions of pollutants. As a result, we consider power production effects on ecological environment firstly in wind power integrated system low-carbon dispatching model.

The low-carbon dispatching model was constructed according to the thermal power unit discharge of different pollutants to the severity of the ecological environment impact, consider mainly CO_2、SO_2 and NO_x three gas pollution.

Three kinds of pollution gas in the working environment of maximum allowable emission concentration data from[15], as shown in Table 4.1.

Table4.1 Three kinds of pollution gas in the working environment of the highest emission concentration

Pollution of the gas	The average /(mg/m^3)	The highest emission concentration /(mg/m^3)
CO_2	7 000	10 000
SO_2	10	15
NO_x	—	10

The data in Table 4.1 show that SO_2 pollution to the environment is about 700 times of CO_2 and NO_x pollution is about 1, 000 times of CO_2. Therefore, in order to put the SO_2 and NO_x are expressed as carbon emissions calculation, SO_2 and NO_x can be converted into equivalent CO_2, after conversion of equivalent CO_2 expression is:

$$(C_{\mathrm{CO_2}})_e = (C_{\mathrm{CO_2}}) + 700(C_{\mathrm{SO_2}}) + 1\,000(C_{\mathrm{NO}_x}) \tag{4.1}$$

where $(C_{\mathrm{CO_2}})_e$ represents equivalent CO_2 concentration after the conversion, the unit kg/m^3.

By expression (4.1) can be further expression of equivalent CO_2 emissions proportion:

$$E_{\mathrm{C}} = \frac{(C_{\mathrm{CO_2}})_e \times V}{M} \tag{4.2}$$

Where E_{C} is equivalent proportion of CO_2 emissions, specific to a constant, related to use of the characteristics of fuel for thermal power unit; M is unit mass of fuel, the unit is kg; V is pollution gas volume of unit mass fuel combustion, the unit is m^3.

From the view point of engineering thermodynamics, the heat generated by the unit mass fuel is related to the efficiency of the thermal power unit and operating conditions. In addition, the different thermal power unit power generation efficiency is different, different unit that using the same kind of fuel resources is different. In order to conform to the actual working condition, the energy-environmental efficiency indicator need to consider the influence of the efficiency of thermal power generating units. The efficiency of the thermal power η_e expression is:

$$\eta_e = \frac{The\ output\ of\ the\ thermal\ power\ unit\ electricity(kW)}{Heat\ from\ the\ burning\ of\ fuel\ per\ unit\ time(kJ/s)} \tag{4.3}$$

For thermal power unit that use of unit mass of fuel, burning the useful heat can approximate calculation by equation(4.4).

$$Q_u = \eta_e \times q_a \tag{4.4}$$

Where Q_u is a useful heat of unit mass quality fuel combustion, unit is kJ/kg; θ_a is low calorific value of thermal power unit using unit fuel, unit is kJ/kg.

In addition to the power generation efficiency, the operating mode of thermal power unit is impact to the energy-environmental efficiency and the unit resource utilization, therefore, building the energy-environmental efficiency indicators need to consider the thermal power unit active power and the relationship between the power generation efficiency η_e. Specific function is as follows:

$$h_r(P_i) = \gamma_i + \beta_i P_i + \alpha_i P_i^2 \tag{4.5}$$

Where P_i is thermal power unit i active output, unit is MW; $\eta_r(P_i)$ is a function relation between P_i and η_e, α_i、β_i and γ_i to the function coefficient and the specific values determined by the model of thermal power unit.

Reference relevant research results in[16], we can obtain the energy-environmental efficiency of specific expression is:

$$e = \frac{\eta_{ie}\eta_r(P_i)\theta_a}{\eta_{ie}\eta_r(P_i)\theta_a + vE_C} \tag{4.6}$$

Where η_{ie} is generating efficiency of the thermal power generating unit I; v is heat loss coefficient that is mainly due to the heat loss caused by pollution emissions, comparing the combustion process of the coal and hydrogen by fire test solution to the heat loss coefficient of unit mass of standard coal combustion in full approximation of 2.

By expression (4.6), the energy-environmental efficiency indicator e is a dimensionless quantity that value between 0 ~ 1, the greater value shows that the higher the energy efficiency of the unit, the energy-environmental efficiency is better.

The energy-environmental efficiency optimization model based the energy-environmental efficiency indicator used to evaluate different units of energy efficiency and carbon emissions to the degree of ecological environmental impact.

The expression of the energy-environmental efficiency optimization model is as follows:

$$E = \max \sum_{t=1}^{T}\sum_{i=1}^{G}\left[\frac{\eta_{ie}\eta_r(P_{it})\theta_{ia}}{\eta_{ie}\eta_r(P_{it})\theta_{ia} + vE_{iC}} \times I_{it}\right] \tag{4.7}$$

Where G is the number of thermal power unit operating in power system; T is the number of hours in a scheduling cycle, unit is h, in this paper, T=24; I_{it} is operation state of the unit i in period of time t, I_{it}=1 represents operation，I_{it}=0 is downtime.

The energy-environmental efficiency optimization model represents the sum of all operating generators energy-environmental efficiency indicators in a scheduling cycle used to illustrate carbide produced by generate electricity in unit time causes the degree of pollution to the ecological environment, the greater value shows that the scheduling time better energy-environmental efficiency, and the higher energy utilization[17]

4.1.2 The objective of resource to generate electricity consumption minimizing function

Resource to generate electricity consumption is one of the most important economic indicators to measure generating set production cost. It is the core of the traditional ED problem, but also is considered as a sub-objective function in the EED model. The low carbon dispatching model building in this chapter are paying attention to ecological environment protection and promote "low carbon", at the same time, take into account the efficiency of power production, minimize the resource to generate electricity consumption as a target function.

In the premise of the reasonable arrangement of unit start-stop and satisfy the economic load distribution, the objective of resource to generate electricity consumption minimizing function, make the whole system the total resource consumption to a minimum in a scheduling cycle. specific expression is as follows:

$$F = \min \sum_{t=1}^{T} \sum_{i=1}^{G} \left\{ \left[f_{it}(P_{it}) + (1 - I_{i(t-1)}) S_{it} \right] \times I_{it} \right\} \tag{4.8}$$

Where S_{it} represents the energy dissipation in start of the unit i in period of time t, unit is$;

$f_{it}(P_{it})$ is energy dissipation function in operation of the unit i in period of time t, specific expression is as follows:

$$f_{it}(P_{it}) = a_i + b_i P_{it} + c_i (P_{it})^2 \tag{4.9}$$

Where a_i、b_i and c_i are operation energy consumption coefficient of unit i

Power system traditional ED problem regard expression (4.8) as the single objective model, only consider the efficiency of generate electricity. As the society increasingly attention for environmental protection and large-scale clean energy represented by wind combined to the grid, EED model of considering pollutant discharge is more used commonly. EED model increased CO2 emissions function to research generating electricity to the destruction of the ecological environment, specific expression is as follows:

$$E_{\mathrm{c}} = \min \sum_{t=1}^{T} \sum_{i=1}^{G} \left\{ \left[(a_{\mathrm{c}i} + b_{\mathrm{c}i} P_{it} + c_{\mathrm{c}i} (P_{it})^2) \right] \times I_{it} \right\} \tag{4.10}$$

Where a_i、b_i and c_i are coefficient of CO_2 emissions function.

The energy-environment efficiency optimization function is the core of the low-carbon dispatching model. The energy-environmental efficiency optimization showed by (4.7)(4.7) compared to CO_2 emissions function showed by (4.10), can better evaluate "environmental benefits" and energy efficiency between primary energy, show generating electricity to the destruction of the ecological environment, make the optimization scheduling results more objective and reasonable.

4.1.3 Constraint condition of low-carbon dispatching model

Constraint condition of low-carbon dispatching model includes static restriction and dynamic constraint mainly, static restriction is system restriction primarily and dynamic restriction is set restriction.

1) System restriction

① Power balance constraints, ignore the grid loss

$$\sum_{i=1}^{G} P_{it} + \bar{W}_t = P_{\mathrm{D}t}, \quad t \in T \tag{4.11}$$

Where $P_{\mathrm{D}t}$ is the system load demand forecast in period of time t, unit is MW; $\bar{W}_t$ is the predicted value active power output of wind farms in period of time t, unit is MW.

②Spinning reserve capacity constraints

Assuming that wind power only provide the energy, and does not provide spare capacity, therefore, system spinning reserve capacity for thermal power unit is spare capacity

$$\sum_{i=1}^{G} (P_{it}^{\max} - P_{it}) \ge u_1 P_{\mathrm{D}t}^{\mathrm{up}}, \quad t \in T \tag{4.12}$$

$$\sum_{i=1}^{G} (P_{it} - P_{it}^{\min}) \ge u_2 P_{\mathrm{D}t}^{\mathrm{down}}, \quad t \in T \tag{4.13}$$

Where $P_{\mathrm{D}t}^{\mathrm{up}}$ and $P_{\mathrm{D}t}^{\mathrm{down}}$ are load demand when the upper and lower rotating standby respectively, unit is MW; $P_{it}^{\max}$ and $P_{it}^{\min}$ are upper limit and lower limit of thermal power generating unit i active power output in period of time t, unit is MW. u_1 and u_2 are upper limit and lower limit of the spinning reserve rate.

2) Set restriction

① Thermal power unit output constraint

$$P_i^{min} \le P_{it} P_i^{max}, ? \in G \ t \in T \tag{4.14}$$

Where $P_i^{\max}$ and $P_i^{\min}$ are upper limit and lower limit of thermal power generating unit i power output, unit is MW.

② Thermal power unit creep speed constraints

$$r_i^{down} \Delta T \le P_{it} - P_{i(t-1)} \le r_i^{up} \Delta T, ? \in G \ t \in T \tag{4.15}$$

Where r_i^{up} and r_i^{down} are the maximum permissible creep speed and creep speed of thermal power generating unit i active power output per hour respectively, unit is MW/h; ΔT is a period of time of thermal power unit operation, in this chapter, $\Delta T = 1$ h.

③ Thermal power unit start-stop time constraints

$$(I_{it} - I_{i(t-1)}) \times \sum_{j=t-T_{i\min}^{\text{off}}}^{t-1} (1 - I_{ij}) \geq T_{i\min}^{\text{off}}, \quad t \in T \tag{4.16}$$

$$(I_{i(t-1)} - I_{it}) \times \sum_{j=t-T_{i\min}^{\text{on}}}^{t-1} (1 - I_{ij}) \geq T_{i\min}^{\text{on}}, \quad t \in T \tag{4.17}$$

Where T_{it}^{off} is shutdown time thermal power generating unit *i* in period of time *t*, unit is h； $T_{i\min}^{\text{off}}$ and $T_{i\min}^{\text{on}}$ are minimum continuous stoppage time and minimum continuous operating time of unit *i* respectively, unit is h.

4.1.4 Mathematical expression of low carbon scheduling model

By the former mathematical expression of the low carbon scheduling model for the wind power grid connected power system is showed as:

$$\begin{cases} \min \ [F(\mathbf{P}), -E(\mathbf{P})] \\ \text{s.t.} \quad h_d(\mathbf{P}) \leq 0, \qquad d = 1, 2, \cdots, q \\ \qquad P_i^{\min} \leq P_i \leq P_i^{\max}, \qquad i = 1, 2, \cdots G \end{cases} \tag{4.18}$$

where P is the control vector of active power generation in thermal power units; H is inequality constraints composed of the number of *q* non-control variables in the model .

The low carbon scheduling model of the wind power system shown in the type (4.18) is MOPs, and the 2 sub objective functions are conflict with each other. So this paper uses the fuzzy optimization technology and interactive decision-making method to deal with.

4.2 Method for solving the low carbon scheduling model of wind power grid connected power system

4.2.1 The overview of multi objective optimization problem

In general, the problem of multi-objective optimization is a contradiction, and the improvement of a sub objective function may cause the reduction of other target performance, that is, the multi-objective problem can't get a global optimal solution as a single objective problem, and can only be a compromise between multiple objectives to make the best of all sub objectives as far as possible. The essential difference between multi-objective optimization problem and single objective optimization problem is that its solution is not unique, but there is a non-inferior solution set.

The mathematical expression of multi-objective optimization problem can be described as followed:

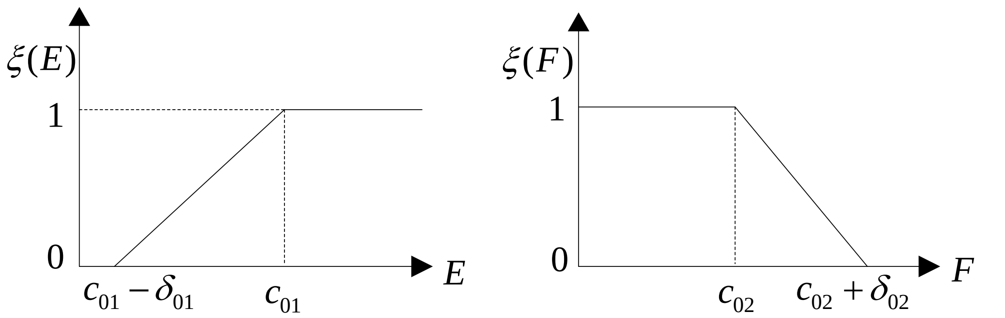
$$\begin{cases} \boldsymbol{y} = \min \boldsymbol{f}(\boldsymbol{x}) = \min(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \cdots, f_m(\boldsymbol{x})) \\ \text{s.t.} \quad g_r(\boldsymbol{x}) \leq 0, \quad (r = 1, 2, \ldots, p) \\ \qquad h_k(\boldsymbol{x}) = 0, \quad (k = 1, 2, \ldots, l) \end{cases} \tag{4.19}$$

where *x* is a decision variable; *y* is the target vector; $f_m(x)$ is the mth objective function; $g_r(\boldsymbol{x})$ is the *rth* inequality constraints, the number of inequality constraints is *p*; $h_k(\boldsymbol{x})$ is the *kth* equality constraints, and the number of constraints is *l*.

4.2.2 Method for solving the multi-objective optimization problem

In the real world, there is a part of things that cannot be clearly defined, and the decision maker can't make the judgment of right and wrong. This characteristic is called "ambiguity", the thing is called "fuzzy thing". Fuzziness is the uncertainty of things, and is the degree of object qualification.

In this paper, a fuzzy optimization method is used to deal with the low carbon scheduling model of the wind connected power grid. The double objective function is converted into a single objective function, and the multi objective problem is converted into a single objective problem. The key to use the fuzzy optimization method is to determine the membership function of each sub objective. Optimization of energy environment benefit in a low-carbon dispatch model which is the bigger the better; power resource consumption minimization is a cost function, which is the smaller, the better. Therefore, according to the characteristics of low carbon scheduling model, the membership function of the optimization objective function of the energy environment benefit is selected as the half rise linear shape; the membership function of the objective function of minimizing the consumption of the power generation resource is selected as half reduced line. The curves of 2membership functions are shown in Figure 4.2, the mathematical expression are as (4.20)(4.21) described.



(a) Maximizing membership function

(b) Minimizing membership function

Figure 4.1 The curve of membership function

$$\xi(E)=\begin{cases}1 & E>c_{01}\\ \dfrac{E-c_{01}+\delta_{01}}{\delta_{01}} & c_{01}-\delta_{01}<E\le c_{01}\\ 0 & E\le c_{01}-\delta_{01}\end{cases} \tag{4.20}$$

$$\xi(F)=\begin{cases}1 & F\le c_{02}\\ \dfrac{c_{02}+\delta_{02}-F}{\delta_{02}} & c_{02}<F\le c_{02}+\delta_{02}\\ 0 & F>c_{02}+\delta_{02}\end{cases} \tag{4.21}$$

where $\xi(E)$ and $\xi(F)$ is the membership function of energy and environmental benefit optimization objectives and generation resource consumption minimization objective; c_{01} is the target value of the single objective optimization for the energy environment benefit optimization; c_{02} is the objective value of the minimum amount of power generation resource consumption as the single objective optimization; δ_{01} is the loss value of the energy environment benefit the decision which maker can accept; δ_{02} is the increase in the amount of power consumed by the power generation which the decision maker can accept.

The definition of ξ^* is to describe the satisfaction of the membership function of the formula (4.20) and (4.21), the equation is followed:

$$\xi^* = min\{\xi(E),\xi(F)\} \tag{4.22}$$

Based on the maximum and minimum rule theory of the fuzzy set, formula (4.22) can be transformed into the maximum of the satisfaction ξ^*, namely maxξ^*, also known as the maximum satisfaction method. From this, the multi-objective optimization problem can transform into a single objective problem and the concrete expression is as followed:

$$\begin{cases}\max\xi^*\\ \text{s.t. } \xi(E)\ge\xi^*\\ \quad\ \xi(F)\ge\xi^*\\ \quad\ 0\le\xi^*\le 1\\ \quad\ h_d(\mathbf{P})\le 0, & d=1,2,\cdots,q\\ \quad\ P_i^{\min}\le P_i\le P_i^{\max}, & i=1,2,\cdots G\end{cases} \tag{4.23}$$

Respectively by substitutions $\xi(E)$and $\xi(F)$ in the formula (4.20) and (4.21) then into formula (4.23), and the further mathematical expressions are as followed:

$$
\begin{cases}
\max \xi^* \\
\text{s.t. } E + \xi^* \delta_{01} \le c_{01} + \delta_{01} \\
\quad F - \xi^* \delta_{02} \ge c_{02} - \delta_{02} \\
\quad 0 \le \xi^* \le 1 \\
\quad h_d(\mathbf{P}) \le 0, \qquad d = 1, 2, \cdots, q \\
\quad P_i^{\min} \le P_i \le P_i^{\max}, \qquad i = 1, 2, \cdots G
\end{cases} \tag{4.24}
$$

The single objective programming problem is shown in the formula (4.24), which can be solved by using the Intelligent Heuristic Algorithm. The concrete steps are as followed[18]:

1) input raw data, apply the optimization algorithm to optimize the single target model of the energy environment benefit, then obtain the energy environment benefit value c_{01} the power consumption of $\hat{c}_{02}$ and the combination of the unit and the unit output;

2) input raw data, apply the optimization algorithm to optimize the single target model of the power consumption benefit the energy environment benefit value c_{01}, then obtain the power consumption of $\hat{c}_{02}$, the combination of the unit and the unit output ;

3)On the basis of the step 1) and 2, the value of each single target is expanded in a degree, which is to determine the value of δ_{01} and δ_{02}, to make the deterministic problem be fuzzy. The method of determining the δ_{01} andδ_{02} is 0<δ_{01}< (c01- $\hat{c}_{01}$), 0<δ_{02} <($\hat{c}_{02}$- c_{02}). According to different decision makers for the environmental benefits and economic preferences, δ_{01} andδ_{02} can be expanded in different degrees. But in theory, δ_{01}, δ_{02} is the smaller the better, but the difficulty will increase;

4)By substitution c_{01}、δ_{01}、c_{02} andδ_{02} respectively into equation (4.20) and (4.21), and the fuzzy membership function model of the objective function is constructed;

5)The multi objective of low carbon scheduling model in (4.18) is transformed into the single objective optimization problem in (4.39) by using the maximum satisfaction method;

6) the single objective optimization problem is solved by the intelligent optimization algorithm in (4.24), and provide satisfactory solution for the decision maker.

4.2.3An improved particle swarm optimization algorithm based on comprehensive tabu search

PSO algorithm has the advantages of less control parameters, fast convergence rate and high computational deficiency[19]. However, its essence is to use the particle's own information, individual best position information and the global best position information of the 3 information, to guide the next step of the particle, which is actually a positive feedback process. This is actually a positive feedback process, when the particle's own information and the individual best position information, that is, once a particle finds the best position, other particles will be through the information sharing mechanism quickly move closer, it is likely to gather in the position. If this point is the best position in local, the group will not be able to search the other regions. Then the algorithm is trapped into local optimum, and the convergence of the algorithm is premature.

Therefore, in order to improve the local search performance of PSO algorithm and avoid the occurrence of "premature" phenomenon, this paper is to improve the PSO algorithm by using the idea of tabu search, and to form an improved particle swarm optimization (PSO-TS) algorithm.

The main idea of PSO-TS algorithm is: record the current global best position information base on the PSO algorithm, and write in the tabu list; in the next iteration, it is better to determine whether individual particles in the group are better than the taboo object. If it si, the best position of the individual is updated, and the global best position is written into the tabu list. If not, the best solution to is selected from the best position of a non-tabu particle, which is used as the global best position, and write in the tabu list; update the speed and position information of the particles, and carry out the next iteration.

4.4.4 The steps of PSO-TS algorithm

The low carbon scheduling of wind power grid connected power system is based on the comprehensive consideration of the environmental benefits and economic benefits of electric power production, the tradeoff between the optimal environmental benefit and economic benefit can get through the reasonable starting, stopping group and optimization the load distribution with the established units.

1) encode method of the particle

The encoding method of the particle is the first problem to be solved when using the PSO algorithm, and the reasonable way of the encoding is benefit to solve the problem. Select the active power output of each scheduling period as the decision-making variables, real encoding is used by the individual, specific encoding form is:

$$\boldsymbol{U}_j = \begin{bmatrix} P_{1t}^1 & P_{1t}^2 & P_{1t}^3 & \cdots & P_{1T}^Q \\ P_{2t}^1 & P_{2t}^2 & P_{2t}^3 & \cdots & P_{2T}^Q \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{Gt}^1 & P_{Gt}^2 & P_{Gt}^3 & \cdots & P_{GT}^Q \end{bmatrix} \tag{4.25}$$

where U_j is the jth individual in the group, j=1,2,... , Q, is the size of the group; $P_{GT}{}^Q$ is row G column T element in matrix U_j, indicates the output of active power of the Gth in the Tth period .The element of in the matrix U_j, can initialize randomly.

2) The treatment of constraint conditions

In the process of particle updating, the system's rotation, the output of the thermal power plant, the of the climbing rate and the starting and stopping time are considered as constraint conditions, so that the search space can be reduced and the calculation efficiency is improved. The specific method is that ensure that all the particles meet the above 4 constraints in the initial population $\boldsymbol{U}_j$, and then the updated particles must meet the 4 constraints after each iteration.

3) fitness function

The fitness function is used to evaluate the quality of the PSO-TS algorithm. The fitness function for optimization problem in the equation (4.39) is as followed:

$$\xi_j = min\left\{\xi\left(E_j\right), \xi\left(F_j\right)\right\} \tag{4.26}$$

where ξ_j is the fitness function of candidate solutions $\boldsymbol{U}_j$.

For all the candidate solutions $\boldsymbol{U}_j$ (j=1,2,... Q), the greater the fitness value ξ_j is ,the better the quality of $\boldsymbol{U}_j$ corresponding to the candidate solution is.

4) PSO-TS algorithm flow chart

The PSO-TS algorithm is applied to solve the problem of low carbon scheduling in the wind power system. The flow chart of the algorithm is shown in Figure 4-3, the concrete steps are as followed:

①Initialization, input system and unit parameters, set the particle swarm size Q, the maximum number of iterations k_{max}, inertia weight e_0, learning factor e_1 and e_2, the maximum speed of flight V_{max} and Tabu list length L;

②The initial position and velocity of the particle swarm are formed under the condition of equitation (4.11) ~ (4.17);

③According to formula (4.26), the fitness value of each particle is calculated, and the current position of the particle is the best position of the particle, take the minimum value of the individual best position as the global best position of the current group, and join the global best position into the tabu list, the taboo length is L;

④The speed and position of the particle is updated, and the fitness value of each particle is calculated through formula (3.4) and (3.5);

⑤Determine whether the particles are taboo, if it is, formula (3.4)is used to calculate each particle speed, and formula (3.7) is used to update the position of the particles, turn to step3 ; and if not, to step 6.

⑥The particle velocity and position is updated, and ach particle's fitness value is calculated after updating, the individual best position and the global best position of the group are updated, and the global best position is to join the tabu list;

⑦Judge if the number of current iteration k meets the maximum number k_{max}, if it is, the global best position is output, and the algorithm ends; if not, then set the number of iterations k=k+1, turn to the steps②.

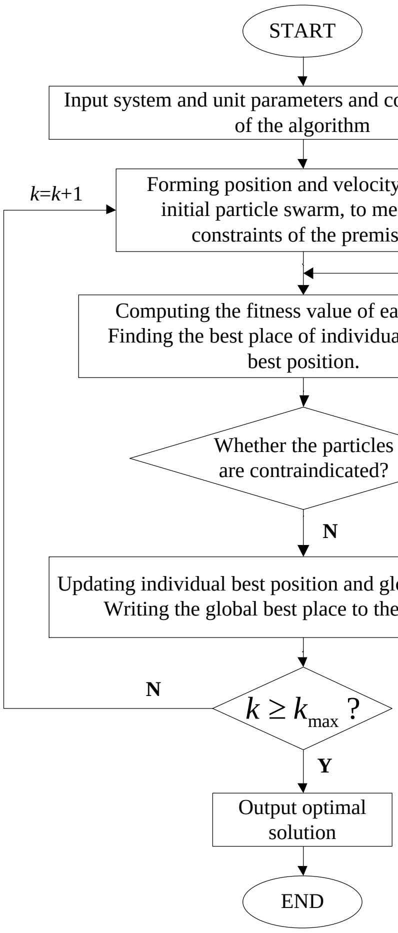


Figure 4.2 Algorithm flowchart of PSO-TS

4.3 Case analysis

4.3.1 Parameters of the case

In order to verify the rationality of the low carbon scheduling model and the effectiveness of PSO-TS algorithm, the simulation analysis is carried out with 6 units systems including one wind farms connected grid, and the scheduling period is 24 *h* (each scheduling interval is 1 *h*). The grid connected wind farm consists of 60 wind turbines with a nominal power of 750 kW. In the simulation analysis, the optimized variables are calculated by using the standard value, and the power base value is 100 MVA, rotate spare is 5% value of the system load. PSO-TS algorithm control parameters are as follows: population size is 40, the maximum number of iterations is 500, the learning factor e_1=e_2=2.0, the length of the tabu list is 10. The system of thermal generators parameters are shown in Table 4.2, the data of the system load for forecast are shown in Table 4.3, fuel characteristic parameters of power plant are shown in Table 4.4, the curve of grid connected wind power prediction as shown in Figure 4.3 with the use of the direct multi-step prediction.

Table 4.2 thermal generators parameters

parameters	G1	G2	G_3	G_4	G_5	G_6
P_i^{max}/pu	4.00	1.30	1.30	0.80	0.55	0.55
P_i^{min}/pu	1.20	0.20	0.20	0.20	0.10	0.10
a_i/($/h)	663.3562	932.6582	876.7851	1235.2237	1332.3704	1658.1029
b_i/(10^{-2}·$/(MW·h))	36.1938	45.6024	42.5818	38.2607	39.9277	35.2756
c_i/(10^{-4}·$/(MW·$h^2$))	0.2048	0.1332	0.1298	0.0640	0.0254	0.0128
r_i^{up}/(pu/h)	0.8	0.3	0.3	0.25	0.15	0.15
r_i^{down}/(pu/h)	0.8	0.3	0.3	0.25	0.15	0.15
η_{ie}	0.75	0.50	0.55	0.40	0.35	0.30
γ i	0.8300	0.7466	0.7795	0.7496	0.7472	0.7520
β i/(10-2 (MW)-1)	0.1375	0.4017	0.3775	0.3228	0.5301	0.4866
α_i/(10^{-4} (MW)$^{-2}$)	-0.0313	-0.2495	-0.1875	-0.1210	-0.7503	-0.6714

S_i/$	4000	800	860	600	550	550
$T_{i\min}^{\text{on}}$ /h	8	5	5	3	1	1
$T_{i\min}^{\text{off}}$ /h	8	5	5	3	1	1

Table 4.3 the data of the system load for forecast

time /h	load /pu	time /h	load /pu	time /h	load /pu	time /h	load/pu
1	2.305	7	2.650	13	3.412	19	3.977
2	1.963	8	3.041	14	3.613	20	3.756
3	1.958	9	3.685	15	3.592	21	3.486
4	1.909	10	3.736	16	3.636	22	3.093
5	2.047	11	3.782	17	3.875	23	2.608
6	2.359	12	3.548	18	3.932	24	2.706

Table 4.3fuel characteristic parameters of power plant

parameters	G_1	G_2	G3	G4	G_5	G_6
E_C	23.933	38.953	34.212	40.593	42.015	44.128
θ_a/(kJ/kg)	25.8627	14.873	13.071	12.288	11.192	10.530

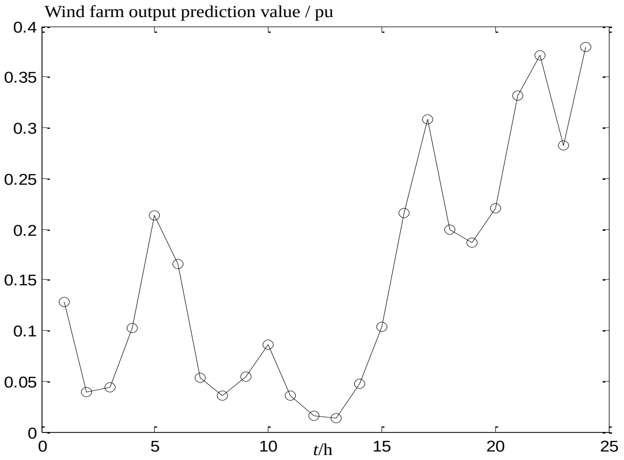


Figure 4.3 Wind power prediction curve of wind farm

4.3.2 Performance analysis of PSO-TS algorithm

In order to verify the effectiveness of the proposed PSO-TS algorithm, PSO-TS algorithm and PSO algorithm are used to calculate the effectiveness of the optimization of the energy and environmental benefits. Among them, the parameters of PSO algorithm and the PSO-TS algorithm are consistent. Considering the randomness of the operation of the algorithm, the 2 algorithms are run independently 10 times, and the results are shown in Table 4.5. "—" in the Table indicated the algorithm does not converge to the global optimal solution.

From Table 4.5 we can see, in the 10 independent operations, the PSO-TS algorithm has a total of 9 times to converge to the global optimal solution, and the PSO algorithm is only 7 times which shows that PSO-TS algorithm can effectively improve the algorithm's global optimization ability, and avoid the algorithm into local optimal solution when compared with the PSO algorithm.

A comparative analysis of the 10 test results of the PSO-TS algorithm and the PSO algorithm is given Table 4.4,which shows that The optimal value and average value of the energy environment benefit obtained by PSO-TS are 0.0656 and 0.0706 higher than that of the PSO algorithm, while the difference is 0.3869% lower than the PSO algorithm.

Table 4.4 Test results for 2 algorithms

algorithm	1	2	3	4	5	6	7	8	9	10
PSO-TS	11.0182	10.8771	10.9033	—	10.6913	10.7845	11.0374	10.9901	10.8820	11.0172
PSO	10.8200	10.9718	—	—	10.9142	10.9039	10.7318	10.6501	—	10.8922

Table 4.5 Comparison of test results of 2 algorithms

algorithm	optimal value	the worse value	mean value
PSO-TS	11.0374	10.6913	10.9112
PSO	10.9718	10.6501	10.8406

The comparison of Table 4.5 and 4.6 shows that the PSO-TS algorithm can effectively avoid the premature convergence of the algorithm compared with the PSO algorithm, which can improve the probability of the algorithm to jump out of the local optimal solution and improve the global search ability of the algorithm. The results show that the PSO-TS algorithm can provide higher precision for the decision maker, and meet the need of the DLCD model for the wind power system.

4.3.3 Analysis of low carbon scheduling model of wind power grid connected power system

The prediction of wind farm power under the output full consumptive, the use of PSO-TS algorithm respectively for energy environmental benefit optimization of single target schedule, power resource consumption minimization of single objective schedule and multi-objective low carbon schedule, and results of 3 schedule model are shown in Table 4.6, the results of multi-objective fuzzy optimization of low carbon scheduling model are given Table 4.7.

Comparison the data in Table 4.6 and Table 4.7 shows that when the multi-objective and low carbon scheduling model is used to optimize the scheduling ,the global optimal time maximum satisfaction ξ^*=0.8135in Table 4.8, the value of the energy environment is 10.8021, and compared with the energy and environment benefit value, which is the best single objective, the optimization of energy and environmental benefit is reduced by 0.2353, however, compared with the energy consumption of power consumption which is minimized as a single target of the energy efficiency of the environment compared is increased by 0.2355. At this time the power consumption is 96755.5805 $.Compared with the power consumption of power consumption which is minimized the amount of resource consumption the single target is increased 3087.3468 $, but the same as the optimization of the energy environment for the single objective of resource consumption compared to a decrease of 3102.7798.

Table 4.6 Comparison of the optimization results of multi objective low carbon scheduling connected wind power grid and single objective scheduling

Optimal scheduling results	Optimization of energy environment benefit	Power consumption minimization scheduling	Low carbon scheduling
Energy environment benefit	11.0374	10.5666	10.8021
Power consumption /$	99858.3603	93668.2337	96755.5805

Table 4.7 Fuzzy optimization of multi objective low carbon scheduling connected with wind power grid

ξ*	ξ(E)	ξ(F)	E	F/($)	ξ*	ξ(E)	ξ(F)	E	F/($)
0.643	0.643	0.907	10.572	94372.654	0.762	0.762	0.834	10.750	95817.052
0.651	0.651	0.897	10.595	94580.794	0.793	0.79	0.830	10.775	96120.437
0.6708	0.6708	0.8755	10.6334	94901.128	0.807	0.80	0.821	10.789	96501.455
0.6866	0.6866	0.8672	10.6902	95120.5275	0.811	0.81	0.810	10.795	96684.187
0.7150	0.7150	0.8591	10.7280	95576.386	0.813	0.81	0.81	10.80	96755.58

From Table 4.6, the power consumption of the power generation is greater than the single target with the minimum power consumption, while it is less than the single objective of the optimization of the energy environment. It can be considered that the low carbon scheduling model of the wind power system takes the economic and environmental factors of the electric power production into account, while the power consumption model of the power consumption only considers a pure economic factor, and the optimization model of the energy environment benefits considers a pure environment factor. From the above analysis, it can be seen that, in the comprehensive consideration of environmental and economic, this chapter puts forward the consideration of the energy and environmental benefits of wind power system low carbon scheduling model can better take the power production of environmental benefits and economic requirements into account; in the preferred consumptive wind power at the same time, it more accurately reflect the actual operation of the thermal power units, evaluate of primary energy utilization rate of different units ,achieve a satisfactory compromise in environmental and compare with the traditional single objective optimal scheduling results is reasonable .

From Table 4.7, with the increase of the degree of satisfaction of fuzzy optimization with multi-objective low carbon scheduling model, the corresponding power consumption has increased, however, the value of energy environment benefit is greatly increased. In the electricity production, in order to achieve energy-saving and emission-reduction, the purpose of significantly reduced CO2 emissions, will add decarburization, desulfurization and dust removal equipment, and increase the cost of the system. This is also a further explanation of the low carbon scheduling model is necessary and effective to improve the system's energy efficiency and reduce carbon emissions.

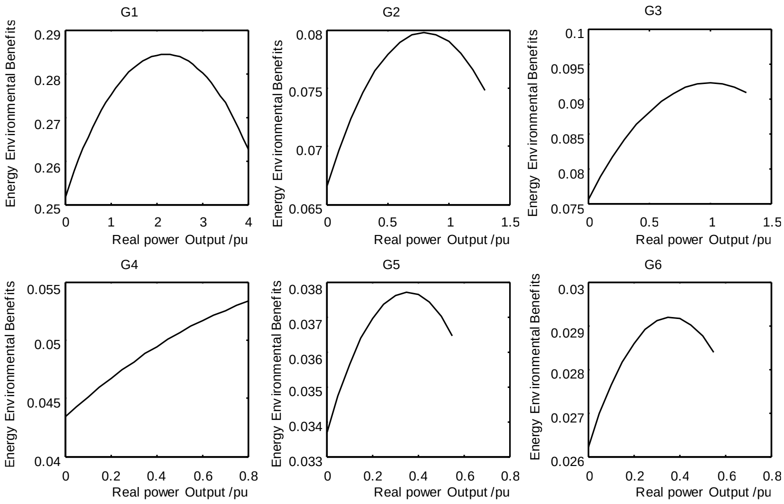


Figure 4.4 Thermal power energy and environmental efficiency curve of G1 ~ G6

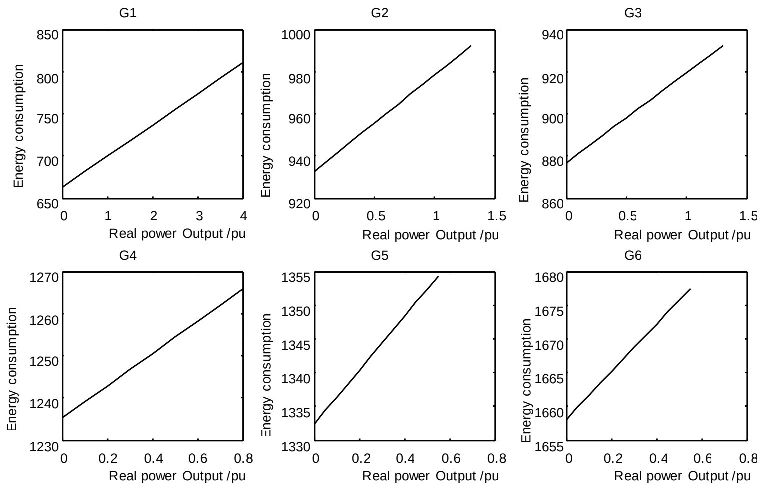


Figure 4.5 Thermal power generation resource consumption curve of G1 ~ G6

Figure 4.5 and figure 4.6, respectively, are energy efficiency curve and the power consumption curve for the thermal power unit of G1~G6. It can be seen from figure 4.5, in addition to the unit G4, the other 5 units of the energy and environment benefit value was not accompanied by a unit output increases monotonously, but shows a type of top point upward. Therefore, when the wind power system is used to optimize the scheduling model of the power system, the characteristics of the load distribution between different units will have a major impact due to the consideration of the energy environment benefit. For the same unit, the active power output of different scheduling periods is close to the level of active power output as much as possible; In addition, the active power output characteristics of the same unit, the better the energy and environmental benefits will give priority to load. Figure 4.6 shows curve of the power consumption and energy efficiency of the 6 units of power generation. It can be seen from the figure, the power consumption of all 6 units of thermal power generation increases with the increase of the output of the unit. Therefore, when using the power consumption to minimize the single objective optimization scheduling, the above characteristics will cause all units in different scheduling time of the active power output are as much as possible to the active power output level corresponding to the power consumption of the smaller space In addition, the rated capacity of the same unit, at the same time, the distribution of the same load, the power consumption of power generation is small, and it will be a priority to load.

The energy efficiency characteristics of the thermal power units and the characteristics of power consumption in Figure 4.6 and figure 4.5 can be further verified in Table 4.8, 4.9 and 4.10 with the unit output data to. No matter the optimization of the efficiency of energy and environment or the optimization of the single objective or multi-objective low carbon scheduling model, the active power output of G1~G6 in most of the scheduling time is near the level of active power, which is corresponding to the optimal value of the energy environment. When the load is low, the relatively poor energy efficiency of the unit will be shut down which can ensure the value of the energy environment to run in the energy and environmental benefits, and improve the energy efficiency of the whole system.

Table 4.8 Output data of thermal power generating units in multi objective and low carbon scheduling

period	G_1/pu	G_2/pu	G_3/pu	G_4/pu	G_5/pu	G_6/pu
1	1.87	0	0	0	0.34	0
2	1.61	0	0	0	0.21	0
3	1.56	0	0	0	0.35	0
4	1.5	0	0	0	0.22	0
5	1.6	0	0	0	0.17	0
6	1.88	0	0.22	0	0	0
7	1.90	0.26	0.42	0	0	0
8	1.56	0.41	0.69	0.25	0	0
9	1.86	0.58	0.86	0.31	0	0
10	1. 35	0.69	0.76	0.43	0	0
11	1.73	0.64	0.70	0.43	0.12	0
12	1. 10	0.53	0.61	0.53	0.2155	0
13	1.67	0.47	0.67	0.45	0.2	0
14	1.99	0.48	0.58	0.30	0.32	0
15	1.67	0.45	0.58	0.4543	0.26	0
16	1.50	0.57	0.66	0.5019	0.13	0
17	1. 47	0.65	0.59	0.6070	0	0.12
18	1. 09	0.51	0.60	0.4363	0	0.28
19	2.23	0.21	0.718	0.2366	0	0.33
20	2.73	0	0.54	0	0	0.3003
21	1.95	0	0.781	0	0	0.38
22	1.71	0	0.66	0	0	0.34
23	1.53	0	0.43	0	0.18	0.26
24	1.74	0	0.23	0	0.29	0.12

Table 4.9 The output data of the thermal power units in the optimization of the energy environment benefit

period	G_1/pu	G_2/pu	G_3/pu	G_4/pu	G_5/pu	G_6/pu
1	1.93	0	0.2511	0	0	0
2	1.72	0	0	0	0.2	0
3	1.63	0	0	0	0.34	0
4	1.52	0	0	0	0.28	0
5	1.57	0	0	0	0.27	0
6	1.60	0	0.28	0	0.31	0
7	1.51	0.21	0.21	0.24	0.26	0.20
8	1.73	0.22	0.30	0.36	0.25	0.15
9	1.80	0.40	0.53	0.48	0.28	0.17
10	1.67	0.34	0.53	0.64	0.32	0.20
11	1.48	0.41	0.62	0.70	0.26	0.20
12	1.57	0.50	0.62	0.61	0.14	0.12
13	1.68	0.52	0.60	0.58	0	0
14	1.78	0.56	0.87	0.45	0	0
15	1.71	0.62	0.78	0.40	0	0
16	1.72	0.61	0.80	0.33	0	0
17	1.90	0.67	0.89	0.21	0	0
18	2.11	0.71	0.85	0	0	0
19	2.23	0.73	0.77	0	0	0
20	2.17	0.71	0.66	0	0	0
21	1.75	0.50	0.70	0	0	0.15
22	1.81	0.23	0.4	0	0	0.30
23	1.77	0	0.3	0	0	0.24
24	1.9	0	0.33	0	0	0.11

Table 4.10 Output data of thermal power units with generation resource consumption minimization single objective scheduling

period	G_1/pu	G_2/pu	G_3/pu	G_4/pu	G_5/pu	G_6/pu
1	1.645	0	0	0	0.28	0.27
2	1.498	0	0	0	0.234	0.231
3	1.59	0	0	0	0.377	0.1882
4	1.345	0	0	0	0.345	0.1451
5	1.47	0	0	0	0.38	0
6	1.86	0	0	0	0.39	0
7	2.07	0	0	0.1400	0.40	0
8	2.05	0.23	0	0.3824	0.45	0
9	2.50	0.41	0	0.462	0.21	0
10	2.51	0.53	0	0.482	0.13	0
11	2.6088	0.55	0.25	0.364	0	0
12	2.39	0.58	0.36	0.273	0	0
13	2.02	0.56	0.50	0.253	0	0
14	2.177	0.52	0.46	0.315	0	0
15	2.10	0.55	0.46	0.41	0	0
16	2.34	0.581	0.44	0.367	0	0
17	2.40	0.62	0.30	0.20	0	0
18	2.87	0.61	0.32	0	0	0
19	2.87	0.43	0.47	0	0	0
20	2.77	0.37	0.28	0	0.18	0
21	2. 49	0.37	0.32	0	0.253	0
22	1.58	0.67	0.38	0	0.245	0
23	1.24	0.38	0.32	0	0.234	0.130
24	1.38	0.30	0.2900	0	0.180	0.213

When minimize the power consumption of power consumption, in order to reduce the cost of generating electricity, G1~G6 in the low load period ,the active power output is lower, the corresponding energy environment is also poor. At this point, although the reduction of the system's power consumption, but it has intensified the destruction of the ecological environment, and contrary to the requirements of low carbon development .On the other hand, the same active power output characteristics of units, the energy and environmental benefits better will be a priority to take load. However, it can be seen that after taking into account energy and environmental efficiency, G3 running at boot time and active output both were significantly better than the G2 form Table 4.8 and 4.9, G5 and G6 output data also proved the same problem. The curve of the energy environment benefit value curve of the unit G4 increases monotonically with the increase of the active power. By comparing the data of the 4.8, 4.9 and 4.10 of G4, the active power output data can be seen, when the energy environment benefit optimization as a single objective, G4 has the maximum active power in the entire scheduling period of active power. When using multi-objective scheduling model of low-carbon, the active output G4 has decreased, but still much larger than the active output power resource consumption when a single goal. From the above comparison can be drawn, after considering the energy and environmental benefits, the original unit commitment and load distribution of cases there has been a big change, energy and environmental benefits of optimum value of the unit got the chance to priority scheduling, the corresponding power consumption of system resources have also been increased. When using multi-objective scheduling model of low-carbon, environmental benefits and a better economy are taken into account, which enhance the system energy and environmental efficiency, and promote low-carbon scheduling to reduce resource consumption in power generation has also achieved satisfactory results, which reflects the requirements of the development of low-carbon electricity.

Energy Environmental benefits can’t be measured as consumption of resources like thermal power generation through specific value, it is more in the form of an "invisible capital" to show. By contrast the foregoing analysis, the wind power integration scheduling model of low-carbon power system resource consumption slightly increases in thermal power generation after considering energy and environmental benefits, but at the same time it greatly enhance the energy and environmental efficiency of the whole system, reducing the production of electricity pollution and destruction of the ecological environment. Energy Environmental benefits have a very clear practical significance for the power system optimization scheduling. Wind power and low-carbon power system dispatch network has a wider application space in the background of developing wind power as the representative of the green clean energy in the global efforts and promoting low-carbon economy.

5 Conclusion

With the energy crisis and environmental problems continue to emerge, the world has started a new clean energy power generation mode research. As the most common type of clean energy, wind power has received wide attention. The Silk Road on the sea provides a reliable and convenient channel for the transmission of energy.

A LS-SVR method for short-term wind speed and generation forecast of wind farm is proposed in this paper. To improve the prediction precision, we use heuristic algorithm to optimize the LS-SVR parameters. By incorporating the LS-SVR parameters optimizing, the proposed LS-SVR method for short-term wind speed and generation forecast of wind based on GDSPSO is better. Through the extensive simulations, the effectiveness and feasibility of GDSPSO-LS-SVR algorithm is evaluated.

This paper studied the wind power integration power system optimization scheduling problem, and focused on considering the requirements of low-carbon electricity production and introduced the "energy and environmental efficiency" concept, constructed the wind power integration power system of low-carbon scheduling model. A numerical example contains a wind farm including 6 units system show that wind power integration power system of low-carbon scheduling model was more reasonable compared to the traditional single objective scheduling model. The resultant scheduling scheme had some reference for the current electricity production and optimal scheduling, wind power integration and low-carbon power system had better practicability after taking the energy efficiency and resource consumption of generation into consideration.

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