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An Output Power Prediction Method for Multiple Wind Farms under Energy Internet Environment

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Abstract

Traditional wind power prediction is only applicable to a single wind farm. Aim at this isolated prediction method. In this paper, combing with the information sharing and Interconnection mechanism of energy Internet, we propose an output power prediction method for multiple wind farms based on DBPSO-LSSVM model. Firstly, collect SCADA data of multiple wind farms in different areas. Secondly, delete outliers of different farms based on DBSCAN algorithm and select multiple wind fields training samples. And searching the optimal input parameters of LSSVM based on particle swarm algorithm to construct every wind farm model. Thirdly, predict multiple wind fields power combined with numerical weather prediction system. The method we propose can be used to make the scheduling plan in advance to solve a large number of abandoned wind power rationing problem every year. In experiment, the method we propose has the lowest error rate compares to LSSVM and BP-neural network. It's more suitable to predict wind fields in different areas.

Keywords: *Multi-wind farm power prediction; Energy Internet; Least square support vector machine; Particle swarm; Wind power utilization*

1. Introduction

Wind energy, as a kind of high storage capacity, does not consume primary energy, clean and efficient renewable energy, has gained more and more attention from all countries in the world. To develop wind power generation could achieve a series of important strategic measures. Including ease contradiction between energy supply and demand, reduce environmental pollution, adjust the energy's structure and so on. At present, the main generating form of wind power generation is large scale grid connected wind power generation. At the same time, the total generating capacity of wind power generating units and large grid connected wind farms are rapidly increasing. However, the wind power itself has inherent shortcomings such as intermittent and randomness. Due to wind field prediction model is isolated and the capacity of wind power utilization is limited. So every year there are a serious of problems of abandoned wind power rationing in different areas. This will waste a lot of wind power resource.

At present, prediction methods are divided into physical model and statistical model. The physical method to predict power curve of wind turbine based on the weather forecast result of numerical weather forecast and to consider the contour, terrain and obstacles and other factors of the whole wind field region comprehensively. Statistical methods do not need to consider the physical information, but directly to establish a linear or nonlinear mapping relationship between the input and the output. Compared with the physical

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method, the statistical method can be more accurate. At present, the following methods are proposed to predict the output power of wind farm: In paper [1], predict wind farm power based on component Bayesian method. In paper [2], predict wind farm power based on error stack correction. In paper [3], predict wind farm power based on Particle Swarm Optimization for nuclear extreme learning machine model. In paper [4], predict wind farm power based on statistical method. In paper [5], predict wind farm power based on Markoff chain principle and Correlation vector. In paper [6], propose to use (OS-ELS) learning machine to modify the wind speed and achieve the short-term wind prediction. In paper [7], propose to use Tuple vector time warping to predict wind farm power.

However, the current method can only predict a single wind farm. This will result can't share the final prediction information, and then lack of comprehensive and integrated analysis of multiple wind fields prediction. With the rapid development of energy Internet, the efficient and fast data interconnection, information sharing platform has a great impact on the traditional isolated operation mode[8-9]. In order to solve the problems above, in this paper we propose a multiple wind farms output power prediction method based on energy Internet and DBPSO-LSSVM model. Firstly, we introduce the related technologies and features of energy Internet and DBPSO-LSSVM regression theory. Secondly, we introduce the prediction process of multiple wind fields. Finally, the effectiveness of the method we propose is proved by experimental simulation.

2. Related Technologies and Characteristics based on Energy Internet

The important technology of energy Internet include renewable energy power generation technology, high-capacity and long-distance transmission technology, advanced energy storage technology, advanced information technology and micro energy network technology, *etc*. Wind power generation, as one of the main forms of new energy power generation, whether it could be used efficiently is crucial to the construction of future energy Internet. The method of multiple wind farms output prediction we propose in this paper is mainly based on energy Internet related key technologies and features below.

2.1. Related Technologies

(1) Advanced information technology

Advanced information technology is composed of intelligent sensing technology, cloud computing and big data analysis technology [10]. Intelligent sense technology can obtain the operation state parameter includes transmission and distribution grid, electrified transportation network, information and communication network, DG and Microgrid. Cloud computing is a network can be anywhere, anytime, on-demand, convenient and fast access to local computing resources and improve its usability model. Big data refers to the traditional database software tools can't be used in a certain period time to read the contents of the data collection, calculation and management. Then, for this data set requires the use of large data processing methods, such as: Spark memory calculation.

(2) Large capacity and long distance transmission technology

Large capacity and long distance transmission are the basic technologies of world to achieve energy Internet. We can develop the construction of UHV power grid and further study high temperature superconducting transmission to achieve the coverage of world's super power grid [11]. And to improve the flexibility, complementarity, security and stability of power supply in China and the world.

(3) Advanced storage technology

In terms of power storage, the energy supply of the Internet in the future mainly comes from renewable energy power generation. However, renewable energy has shortcomings such as intermittent and volatility. Therefore, the future of energy Internet storage technology will be lithium-ion batteries and all vanadium redox flow battery, super capacitor and superconducting magnetic energy storage, pumping energy storage,*etc* [12].

2.2. Related Features[13-15]

(1)Support efficient renewable energy generation access and consumptive.

(2)Energy free transmission and user wide access of Internet architecture.

(3)Promote economic activities in the supply and demand sides to achieve information transparency, data sharing and interconnection.

Firstly, the method proposed in this paper is based on the characteristics of renewable energy sources, information sharing, interconnection and so on. And combined with the advanced information processing technology of energy Internet can achieve predict the output power data of multiple wind fields[16]. Secondly, the significance of method in this paper is that: because the method is to predict the output of a number of wind farms, scheduling personnel can be comprehensive, overall analysis the wind power forecast results in different regions. So, based on the characteristics of energy free transmission, large capacity long distance transmission and advanced storage technology. Can make the scheduling personnel to develop the wind power scheduling plan in advance, to resolve the energy waste caused by areas that capacity of wind power utilization is limited.

3. DBPSO-LSSVM Regression Prediction Method

3.1. DBSCAN Basic Principle

In 1996, DBSCAN algorithm [17] is a well-known clustering algorithm based on density proposed by Ester Martin *et al*. The algorithm that according to the given density threshold to identify a cluster, and the density threshold determined by Eps and MinPts two parameters. Among them, Eps represents the radius of the cluster and MinPts indicates the number of data points that should be included in the Eps radius within the cluster core point. The advantage of algorithm is that it can identify clusters and isolated points of any shape, and is not sensitive to noise data.

The parameter Eps of DBSCAN algorithm with the classical Euclidean distance calculation:

$$d_{i,j} = \left| x_i - x_j \right| \tag{1}$$

The center of the cluster is to calculate the mean of each element, as shown below:

$$w_j = \frac{1}{m} \sum_{i=1}^{m} x_i \tag{2}$$

In the formula: m is the number of data objects that are included in the j-th cluster.

3.2. Sample Selection based on DBSCAN

Due to the fact that the real data noise is very large, it will affect the accuracy of prediction model. And to establish a prediction model for the multiple wind fields need to eliminate the difference of the sparse data distribution on the edge of the different wind fields. So the method proposed in this paper firstly based on DBSCAN algorithm to remove outliers and the remaining data are as input training samples. Specific steps are as follows:

(1) Due to the establishment of the wind farm output power prediction model should be exclude human factors, so the initial sample data less than 0 are deleted;
(2) Set the parameters Eps and MinPts of DBSCAN algorithm and to cluster wind power data handled by last step;

(3) Among the output clusters, the number of data points in the Eps radius are larger than the MinPts labeled as the training sample data; others are labeled as outliers;
(4) Remove outliers, and the remaining data are as the training sample.

3.3 The Basic Theory of LSSVM Regression Prediction

LSSVM [18] is an improvement of SVM, it transform the traditional SVM inequality constraints into equality constraints and transform the solution of quadratic program problem into solving linear equations. So as to improve the calculation speed and convergence precision. LSSVM maps the training sample data to high dimensional feature space by a nonlinear mapping. In this high dimensional feature space, the optimal decision function is constructed as follows:

$$y(x)=\omega\varphi(x)+b \tag{3}$$

In the formula: φ(x) is a nonlinear mapping from the original space to the high dimensional feature space; ω is the characteristic space weight coefficient vector; b is the offset.

In this way, the nonlinear estimation function is transformed into the linear estimation function in high dimensional feature space. Based on the structural risk minimization principle and Lagrange method, the regression problem can be formulated as the following constraints:

$$\mathrm{L}(\omega,\mathrm{b},\xi,\mathrm{a})=\frac{1}{2}\omega\omega+\mathrm{c}\sum_{\mathrm{i}=1}^{\mathrm{l}}\xi_{\mathrm{i}}^{2}-\sum_{\mathrm{i}=1}^{\mathrm{l}}\mathrm{a}_{\mathrm{i}}(\varphi(\mathrm{x}_{\mathrm{i}})\omega+\mathrm{b}+\xi-\mathrm{y}_{\mathrm{i}}) \tag{4}$$

In formula: ξ_i is the relaxation factor, a_i (i=1, 2⋯.l) is the Lagrange multipliers, c as constant. According to the optimization conditions could obtain formula (5)

$$\begin{cases} \dfrac{\partial L}{\partial \omega}=0\Rightarrow \omega=\sum_{i=1}^{l}\alpha_i\varphi(x_i) \\ \dfrac{\partial L}{\partial b}=0\Rightarrow \sum_{i=1}^{l}\alpha_i=0 \\ \dfrac{\partial L}{\partial \xi}=0\Rightarrow \alpha_i=\gamma\xi_i \\ \dfrac{\partial L}{\partial \alpha}=0\Rightarrow \omega\varphi(x_i)+b+\xi_i-y_i=0 \end{cases} \tag{5}$$

Eliminate ξ and ω in formula (5) and can be obtained formula (6)

$$\begin{bmatrix} 0 & I^T \\ 1 & ZZ^T+\gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix} \tag{6}$$

In formula:y=[y1,y2, ⋯ yl]^T,a=[a1,a2, ⋯ al]T,z=[φ(x1),φ(x2), ⋯ φ(xl)]^T,ZZ^T is a l × l square matrix.

The increase of dimension will lead the computational complexity and complexity increasingly. So, according to the theory of universal function, the LSSVM regression function is obtained as follows:

$$f(x)=\sum_{i=1}^{l}a_iK(x,x_i)+b \tag{7}$$

As mentioned above, quadratic programming problem of solving SVM is transformed into the problem of solving equations based on LSSVM method.

3.4 Selection of Kernel Function and Kernel Parameter

Due to the wind power SCADA data distribution relationship is nonlinear, so the kernel function selection of LSSVM is very important. Gauss radial kernel function is the most widely used and has good smoothness, it can directly reflect the distance between the two data. So select Gauss function as the LSSVM kernel function. The formula as follows:

$$k\left(x, x^*\right) = e^{-\left|x-x^*\right| / 2\sigma^2} \tag{8}$$

In formula: σ is the variance for Gauss's function; x* is the center for the Gauss function.

The Mercer condition of kernel function ensures that the two programming problem of LSSVM training is a convex optimization problem, namely, the optimal solution is the global optimal solution.

Then, after determining the kernel function, LSSVM needs to select two nuclear parameters, which are super parameter γ and kernel parameter σ^2. Because the particle swarm optimization algorithm (PSO) [19] has the advantages of simple structure, easy implementation, fast convergence speed, strong search ability and no need to adjust many parameters. So in this paper, particle swarm optimization algorithm is used to determine the parameters of LSSVM kernel. Specific steps are as follows:

(1) Initial accelerate constant, inertia weight, population size ,maximum number of evolution, parameters γ and σ^2. And the parameters are mapped into random particles.

(2) According to current position to calculate optimal position of current point and group .Update the speed, position of each particle and generate new population.

(3) Calculate new location and adaptive value of each particle, compare its best position and optimal location of population in history. If better, replace it, otherwise, not change.

(4) Check whether to meet the end of optimization conditions, if satisfy, output the best nuclear parameters of LSSVM, otherwise, turn to step (2).

4. Multiple Wind Farms Output Power Prediction based on Energy Internet and DBPSO-LSSVM

4.1 Basic Concept

The method proposed in this paper is to share the multiple wind fields SCADA data information in different regions under the environment of energy Internet. Based on the DBPSO-LSSVM model, the output power of multiple wind farms can be predicted accurate and integrate. And the predict results can be used to analysis by scheduling personnel. Compared to the traditional wind farm prediction model, the method we propose has the following advantages:

(1) Integration: Based on energy Internet technology, this paper proposes a method that can be used to share the SCADA data information of multiple wind fields and to forecast multiple wind farms output integrated;

(2) Dynamic: For different data distribution of different wind field, the method will choose different training samples and search different input parameters, and then establish different prediction models. So this method is the process of dynamic building prediction model;

(3) Reference: The prediction results of multiple wind fields can be used to analysis specific needs by scheduling staff. And to provide a reference for developing scheduling plans.
The overall process is as follows:

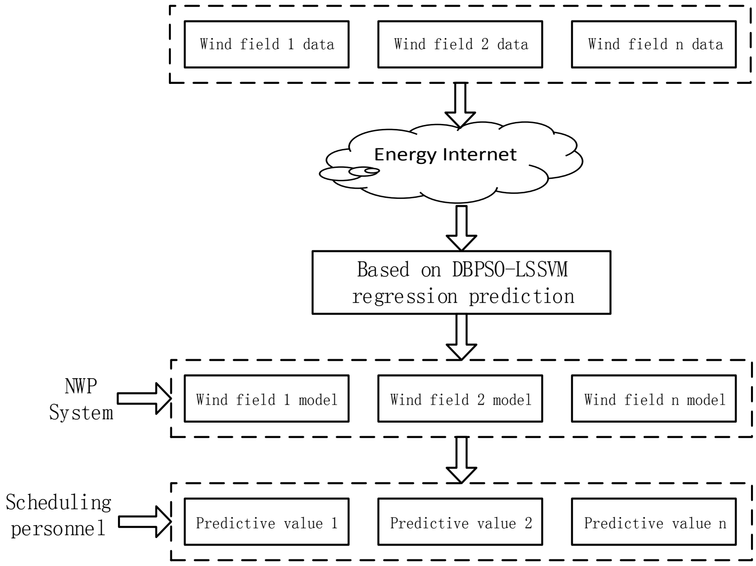


Figure 1. Method Integrated Process

4.2 Selection and Normalization of Input Parameters

The capture power of wind turbines can be expressed by the following formula [20]:

$$P_w = \frac{1}{2} C_p A \rho v^3 \tag{9}$$

In formula: P_w is the output power of wind turbine; v is the wind speed; ρ is the air density; A is the fan wheel swept area; C_p is the wind wheel coefficient.

From formula (9), power is proportional to the angstroms cube of the wind speed, so wind speed is the most important parameter that affects the output of the wind turbine generator. Therefore, the wind speed is used as the input variable of the training sample data.

Air density is determined by the pressure, temperature and humidity:

$$\rho = 3.48 \frac{P}{T}\left(1 - 0.378 \frac{\varphi P_b}{P}\right) \tag{10}$$

In formula: P is the standard atmospheric pressure; T is the thermodynamic temperature; P_b is the Vapor pressure of saturated water; φ is the air relative humidity.

By the formula (10), it can be seen that the air density is also a parameter which has a great influence on output power of wind turbine. The change of air temperature, air pressure and humidity can be indirectly reflected by the air density, which has little effect on output power of wind turbine. Therefore, the air density as another input variable of training data. In addition, the effect of wind direction on output power is relatively large.So the wind direction is also used as an input variable [21].

In this paper, the input vector matrix is defined as $\{P^T, W^T, D^T, \rho^T\}$, P is power, W is wind speed, D is wind direction and ρ is air density. The data corresponding to the four attributes are used as input initial training sample data in this paper. As the input training sample data are vector of classes and will affect analysis the result. In order to eliminate the influence of the volume, the input data are normalized to the [0, 1] range. The normalization formula is as follows:

$$x^* = \frac{x - \mu}{\sigma} \tag{11}$$

In formula: x* is normalized initial training sample data; u is mean of all sample data; σ is Standard deviation of all sample data.

4.3 Establishment of Prediction Model based on Energy Internet and DBPSO-LSSVM

The prediction method proposed in this paper is a process of multiple prediction models are established for multiple wind farms. Specific steps are as follows:

(1) Collect multiple wind field SCADA data sets under energy Internet environment, the historical data corresponding to the input vector matrix are used as the initial data set and normalization.

(2) Multiple wind field initial sample data sets are input DBSCAN algorithm. Based on the 3.2 step to delete outliers, select the training sample data set.

(3) To established LS-SVM objective function.

(4) Based on the 3.4 step, the particle swarm optimization algorithm is used to search the optimal kernel parameters of LS-SVM.

(5) At last, multiple wind farm prediction models are established and combined with NWP system to predict.

The specific process of the method are shown in Figure 2:

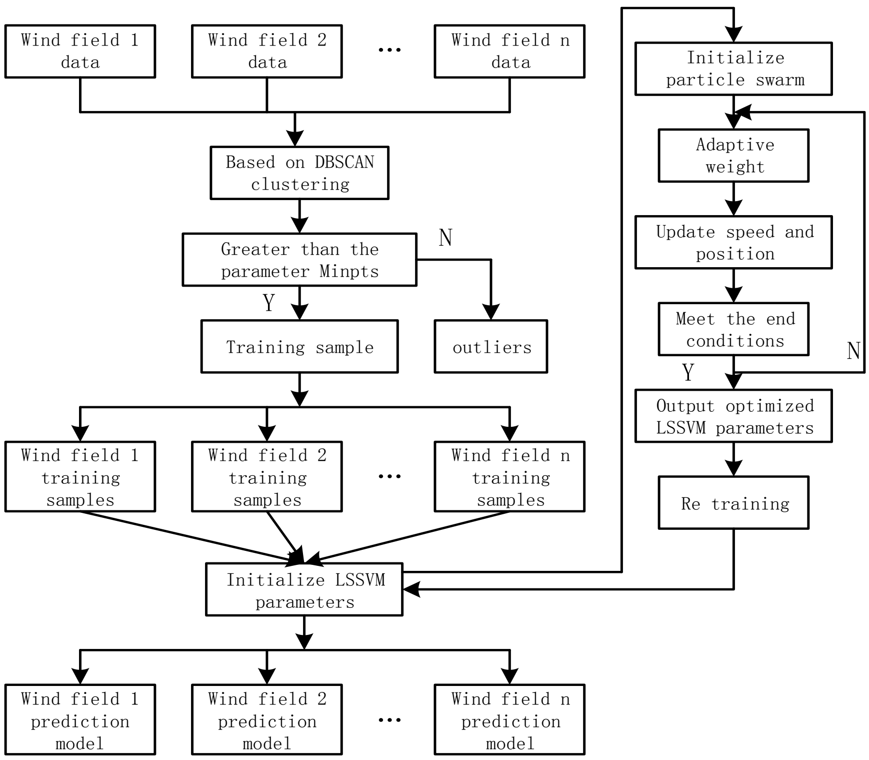


Figure 2. Integrated Prediction

As can be seen from Figure 2, the method we propose to share the multiple wind farms SCADA data in different regions under the environment of energy Internet.And when the SCADA data of n wind fields are input, the n regression models will be output. This is due to the method will be selected different training samples and different optimal input parameters among different wind fields. At last, it will be output different prediction models aim at different data distribution of wind farms.

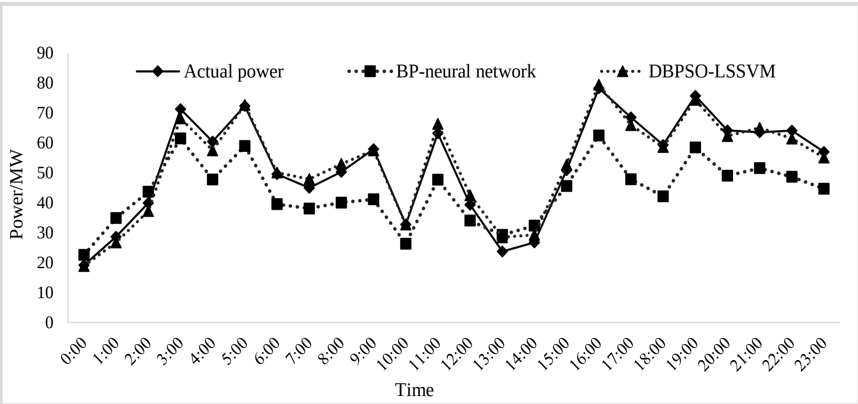
5. Example Analysis

In experiment, we predict two wind farms in North and South China(hereinafter referred to as A, B wind field)based on the method we propose with MATLAB simulation technology.The value of wind speed, wind direction and air density are as the input data based on numerical weather prediction system provided. The output data are predict values of each wind field.

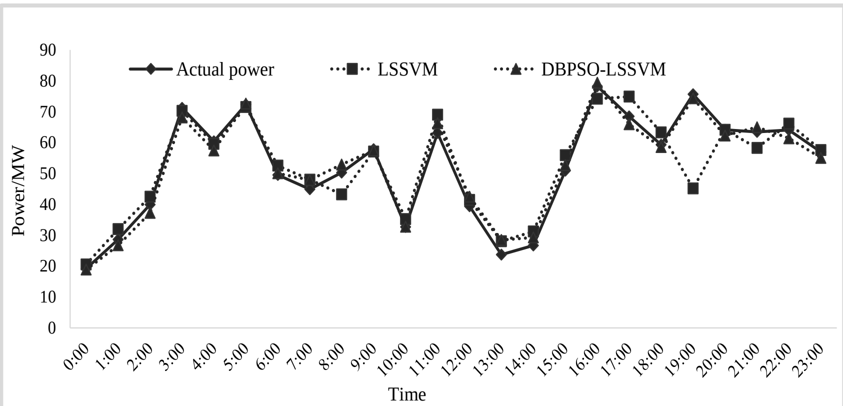
5.1 Comparison of Prediction Results of Wind Power

The wind farm of A installed a total of 35 variable pitch wind turbines, stand-alone capacity of 2500kw. The total installed capacity of the wind farm is 87.5MW, and the hub height is 68 meters. The wind farm of B installed a total of 50 variable pitch wind turbines, stand-alone capacity of 2500kw.The total installed capacity of the wind farm is 125MW, and the hub height is 70 meters.

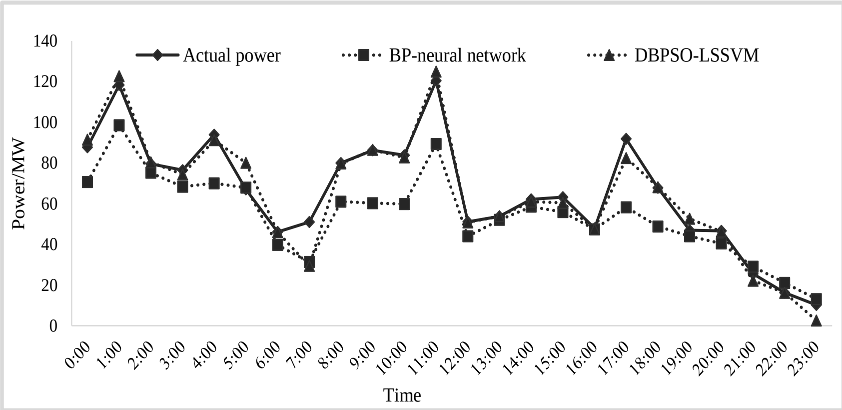
Based on the method we propose in this paper, BP-neural network and LSSVM to predict two wind farms power, the result as shown in Figure 3. The above two are the experimental results of the wind field of A and the bottom two are the wind farm of B.



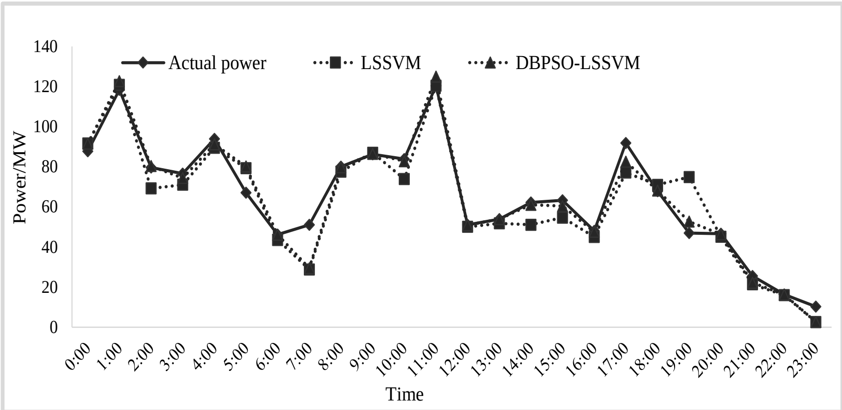
(a)



(b)



(c)



(d)

Figure 3. Comparison of DBPSO-LSSVM, LSSVM, BP Neural Network, Actual 0utput Power

As can be seen from Fet. aligure 3, the method we propose in this paper has the highest prediction accuracy and the predict values close to actual power mostly between two wind farms in different areas compare to LSSVM and BP-neural models. It can illustrative that the method we propose not only has a good adaptability to different data distribution but also the process of select optimal input parameters and training samples can improve accuracy. The experimental results show that the proposed method has the characteristics of dynamic and accuracy. So the method can establish the best prediction model for different data distribution.

5.2 Comparison of Output Power Prediction Error

In this paper, the mean square error (MSE) and the mean absolute percentage error (MAPE) are used to evaluate the prediction results.

$$E_{MSE} = \frac{1}{n}\sqrt{\sum_{t=1}^{n}\left(P_t - P_t^{\wedge}\right)^2} \tag{12}$$

$$E_{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_t - P_t^{\wedge}}{P_t}\right| \tag{13}$$

In formula: P is the real value of the forecast; P^ is the predictive value of prediction; n is the data quantity.

The prediction error comparison of two wind farms as shown in table 1 and table 2:

Table.1 Main Error Indicators of the Prediction Models of Wind Field of A

Algorithm type	MSE	MAPE
BP neural network	7.24	0.1724
LSSVM	2.0	0.1396
DBPSO-LSSVM	0.4151	0.0790

Table 2. Main Error Indicators of the Prediction Models of Wind Field of B

Algorithm type	MSE	MAPE
BP neural network	4.98	0.1582
LSSVM	1.93	0.1297
DBPSO-LSSVM	0.3782	0.0694

As can be seen from table 1 and table 2: through the mean square error (MSE) and the mean absolute error (MAPE) two common error indicators calculated, based on the method proposed in this paper to predict the output power of wind field has a small error index compare to BP neural network and LSSVM. So the method proposed in this paper has high precision.

Comprehensive analysis table 1 and table 2, the mean square error (MSE) of the proposed method is maintained at 0.4 up and down, and the mean absolute error (MAPE) is maintained at 0.07.The fluctuation range of two wind fields is very small. However, the prediction error of BP neural network about the wind field of A is obviously higher than the wind field of B, and the fluctuation range of error index is higher. The fluctuation range of error index of LS-SVM for two wind fields is lower than BP neural network, but it is still higher than the method proposed in this paper. It shows that the two methods can't apply to predict the wind field with different data distribution. So the proposed method is more suitable than the two methods to predict the output power of different wind fields.

5. Conclusion

In this paper, based on the operation mechanism of information sharing and Interconnection of energy Internet, we propose a multiple wind farms output power prediction method based on energy Internet and DBPSO-LSSVM model. This method takes into account the characteristic of different wind farm data distribution to establish the best forecasting models for different wind fields. And combined with scheduling personnel's analysis about regional wind power consumptive, ahead of schedule, could solve the problem of a large number of abandoned wind power rationing every year.

In this paper, the method based on the DBSCAN algorithm to select the training samples. At the same time, establish the LS-SVM with Gauss radial basis function as the kernel function and search the optimal input parameters by PSO algorithm. The method takes account into data distribution of wind farm in different areas to establish best predict model. It has the smallest error compared to LSSVM, BP neural network and the fluctuation range of MSE and MAPE between two wind fields are smallest. It is stable.So the method provides a basic research for future to realize multiple wind farms prediction under the energy Internet environment.

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