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A New Strategy for Short-Term Power-Curve Prediction of Wind Turbine Based on PSO-LS-WSVM

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Abstract: Wind turbines are very important and strategic instruments in energy markets. Wind power production is unreliable. Wind power is weather dependent and the extreme wind speed changes make difficult to control of grid voltage and reactive power. Based on these reasons, Wind Power Prediction (WPP) is important for real applications. In this paper, a new short-term WPP method based on Support Vector Machine (SVM) is proposed. In contrast to physical approaches based on very complex differential equations, the proposed method is based on data history. Firstly, data preprocessing and normalization is done. Secondly, formulate the prediction as a regression problem. Thirdly, the prediction model is constructed using the Particle Swarm Optimization (PSO) and Least Square Support Vector Machine (LSSVM). In this paper, instead of using the conventional kernels, such as linear kernel, Polynomial and Radial basis function (RBF), the Wavelet (W) transform is used. The PSO-LS-WSVM accuracy has been tested with industrial wind energy data. This method has been compared with other methods and the experimental results based on practical data illustrate that PSO-LS-WSVM proposed method has better responses than other methods. Statistical results indicate that the predicting error of PSO-LS-WSVM is 2.98% for one look-ahead hour.

Keywords: Wind Turbine, Power Curve, SVM, PSO, Wavelet.

1 Introduction

ENERGY is one of the major challenges of the industry in the world. Quality, reliability and renewability of energy are important [1].The wind has been successful in electrical power generation. The wind turbine as one of the converters of mechanical energy to electrical energy, it is susceptible to various faults [2]. Efficient Wind Power Prediction (WPP) methods are essential for real applications [2-3]. A turbine with a deteriorating performance may be prone to failures [4]. The first signature of faults based on performance can be extracted from power signals. Operational problems are prevented by predicting the wind speed and power output [5]. Various methods of WPP are classified according to time-scales based on Table 1 [1-3]. In this paper, prediction process is based on short-term of time-scale.

WPP methods classified into three groups: physical (deterministic approach), statistical and hybrid methods over different time-scales (long-term and short-term) [1-3]. Physical method is based on the following parameters [1-5]:

a. Numerical weather prediction (NWP) [2]
b. Temperature
c. Pressure
d. Surface roughness
e. Obstacles

Statistical method is based on historical data. Its methods include the following items [2]:

a. Neural Networks (NN) [6-9]
b. Neuro-fuzzy networks [10-11]
c. Support Vector Machine (SVM) [12-13]

Many approaches have been proposed to WPP. The physical method considering NWP data with historical power output [6]. A number of wind power models have been developed in commercial areas [14-18]. Statistical models are known as time-series based models. These models are on data and used for short-term power

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Table 1 WPP based on time-scale.

Time-Scale	Range	Applications
Immediate-short-term	8 hours-ahead	- Real-time grid operations - Regulation actions
Short-term	Day-ahead	- Economic load dispatch planning - Load reasonable decisions - Operational security in electricity market
Long-term	Multiple-days-ahead	- Maintenance planning - Operation management - Optimal operating cost

Table 2 Characteristics of the 2.5 MW MAPNA WT.

WT		DFIG	
Wind speed	11.43m/s	Rated Power	2.5 MW
Power Coefficient	0.43	Number of poles	Three pairs of poles
Air density	1.225 Kg/m3	Speed	750-1310 u/min(50HZ)
Turbine blade radius	53m	Stator rated voltage	690 V
Tip speed ratio	9	Armature resistance	0.0014ohm
Blade surface	8495	Rated frequency	50Hz
Start generation	3.5/4 m/s	Stator Resistance	0.0014ohm
Stop generation	25 m/s	Rotor Resistance	0.0014ohm
Gearbox	Gear with 3 stage by 1:79.6	Stator leakage inductance	9.8e-5H
Back to Back converter		Rotor leakage inductance	8.6e-5H
Switching Frequency of Rotor	2.5KHz	Magnetizing inductance	0.00169H
Switching Frequency of Stator	3KHz	Stator/Rotor turns ratio	0.3
DC-link Capacitor/ DC-link Voltage	22mF/1100 v	Line resistance	0.0001ohm

prediction [19]. In [6] a feed-forward ANN is used to WPP. Back-propagation NN [20] and Radial Basis Function (RBF) NN [8], wavelet NN [9] are other methods that used for WPP. The integration of physical strategy and ANN was suggested in [21]. Other data based methods are SVM and Fuzzy. In [10], a method based on fuzzy for wind power forecasting is provided. In [12] a new kernel based on wavelet for SVM has been used and WPP is based on WSVM and statistic parameters. Another method based on SVM presented in [22], in this reference Genetic Algorithm (GA) is used for optimization SVM parameters. Hybrid methods are studied in [23-25]. In [26], Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary Particle Swarm Optimization (PSO) is introduced. A combination of probabilistic and numeric models in [27] is introduced. In [28], a Kalman filter was employed to improve the wind power forecasting. In this paper, a new WPP method based on SVM is proposed. In contrast to physical approaches based on very complex differential equations, our method is based on history of data. Firstly, data preprocessing and normalization is done. Secondly, formulate the prediction as a regression problem. Thirdly, the prediction model is constructed using the PSO and Least Square SVM (LSSVM). The structure of SVM often encounters with memory and time issues due to nonlinear solution and optimization of the main equations. In order to solve these issues, LS-SVM, which uses linear equations instead of quadratic programming (QP), is utilized. Furthermore, the SVM has parameters that their performances are hugely influenced by the optimized determination of these parameters [28-32].

There are three common solutions for this purpose: using grid search, GA [29] and PSO [28]. In this paper, instead of using the conventional kernels, such as linear kernel, Polynomial, RBF and MLP, the wavelet transform kernel is used. Therefore, the method used in this paper has three characteristics that make it different from the conventional SVMs; that is:

a. Using the Least squares (LS) type of SVM algorithm instead of nonlinear QP type.
b. Using wavelet transform kernel function instead of the conventional RBF kernel.
c. Optimized determination of kernel and SVM parameters using the PSO method.

The practical 5-minute average data of wind power generation in Ghazvin-Iran is used to test of the proposed method. Commercial turbine studied in this paper is a 2.5 MW wind turbine.

WPP is an industry-wide problem, with presenting this paper; we are able to share the progress of different methods structure of WPP. We also hope that PSO-LS-WSVM proposed method as statistically based approach is attractive for WT industry technicians.

This paper is organized as follows. In Section 2, WPP proposed structure is introduced. Section 3, a detailed proposed method based on PSO-LS-WSVM is presented. Section 4 is the experimental result. Discuss is drawn in Section 5. Finally concluding remark is given in Section 6.

2 WPP Proposed Structure

Fig. 1 presents the flowchart of the proposed structure.

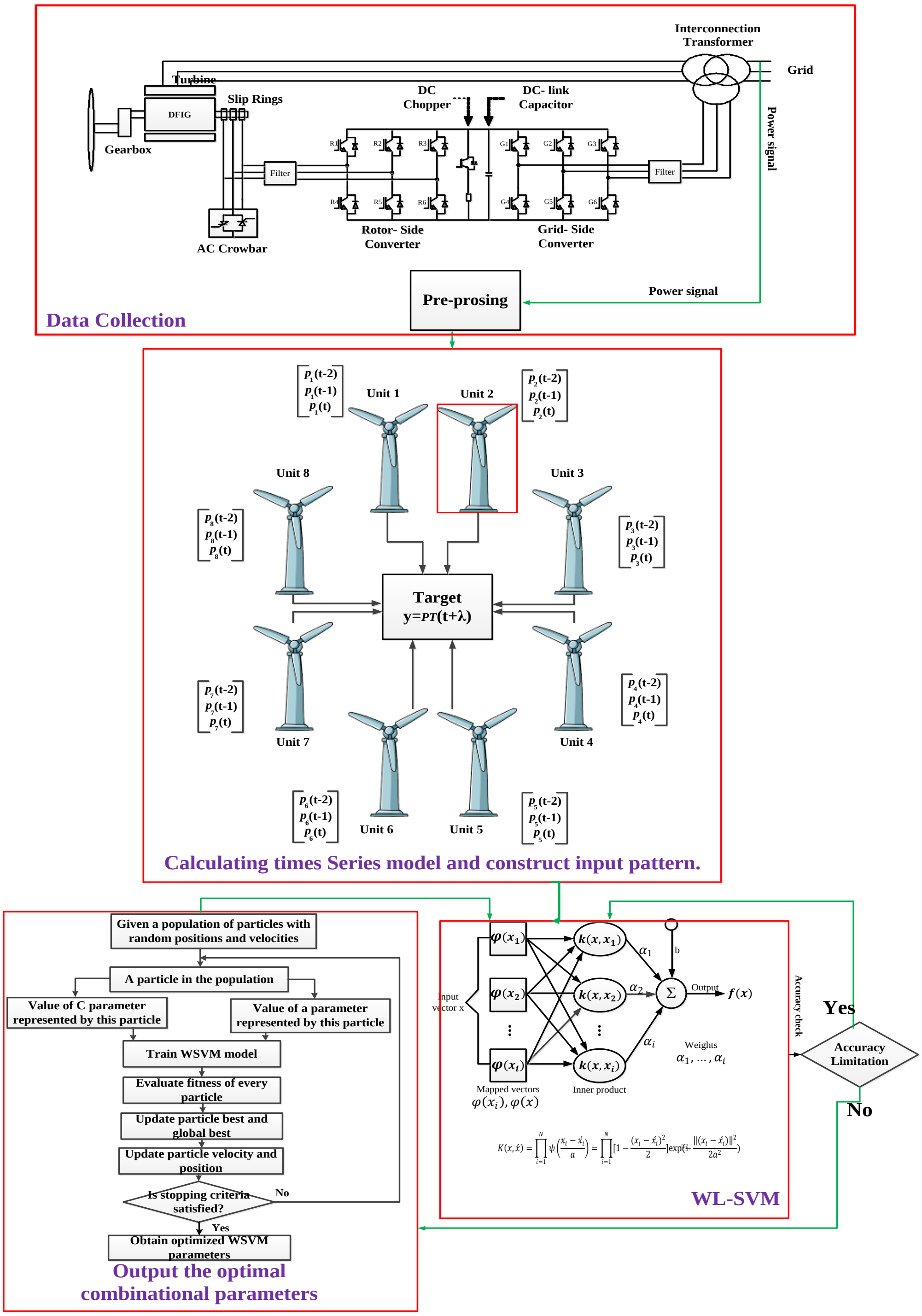

Fig. 1 Main structure of WPP.

The description of the different parts of the proposed structure is as follows:

2.1 Data Collection

According to Fig. 1, the case study turbine is based on a doubly-fed induction generator (DFIG). In this kind of turbines, the generator is directly connected to the grid from the stator side, while from the rotor side; it is connected to the grid via a back-to-back converter. This turbine is a variable speed turbine, and it can generate power from low wind speeds to high wind speeds. The characteristics of this turbine are presented in Table 2.

Supervisory control and Data Acquisition (SCADA) is a five-minute average of the signals which are collected by the control system hardware. In this paper, SCADA data is accessed using Gateway software. The data includes 91 signals, from which power signal is selected for WPP. In Fig. 2, the wind speed data received from SCADA (5-min AV. LOG) are shown. The power-curve

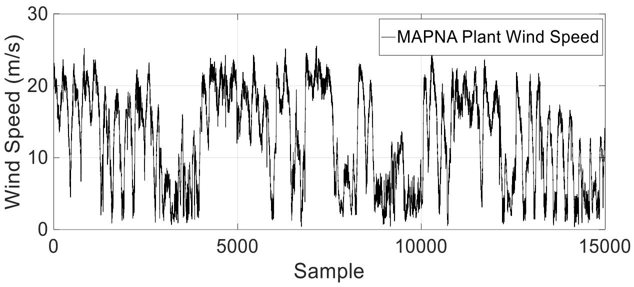

Fig. 2 Wind speed data.

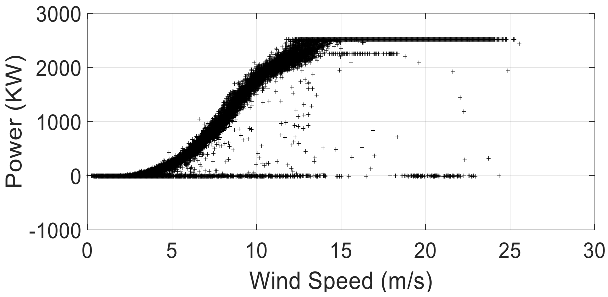

Fig. 3 Power curve of wind turbine.

of the turbine under study (Unit 2) is illustrated in Fig. 3. As can be seen from the figure, the turbine had been operating at varying wind speeds.

2.2 Preprocessing

The data preprocessing tasks such as:

1. Validity check: For a smoother network generalization it may sometimes be necessary to remove some of the data outliers.
2. Data scaling
3. Missing data processing: Unknown or missing values are particularly harmful during training. This will increase the generalization error of the network.
4. Lag removal: Wind turbine signals usually do not respond immediately to changes in operational conditions. It was found that neglecting the signal lags led to an increase in prediction error.
5. Convert data to hourly format: Data is in minute format and it is essential to convert to hourly format.

2.3 Wind Farm and Construction of Times Series

MAPNA wind farm includes 22 wind turbine, we use data of eight turbines in this paper. The proposed prediction method based on past wind power measurements. This method yields better prediction if more information of the time series will be used. Thus past measurements are used from 1 to $\beta = 2, 3, \ldots$ and data of other turbines, target turbine is unit 2 and other turbines are subsidiary. Formulation of the times series is as follows.

$$\text{pattern: } X = P(t) \tag{1}$$

$$\text{Output: } y = p(t+\gamma) \tag{2}$$

Input of algorithm #1:

$$p(t-1)_{target\ turbine}, p(t-2)_{target}, \ldots, p(t-\beta)_{target} \text{ and } \left(p(t)-p(t-1)\right)_{target\ turbine}, \ldots, \left(p(t-(\beta-1)-p(t-\beta)\right)_{target\ turbine} \tag{3}$$

Input of algorithm #2:

$$\text{above equation for unit } \#1, \#3, \ldots, \#8 \tag{4}$$

The experimental setup architect with seven neighboring turbines and the target turbine itself was shown in Fig. 1. For each turbine, the current and two past measurements are considered, resulting in a (7 + 1) × 3 = 24-dimensional input vector.

2.4 Prediction Model

This part includes two sub-parts as PSO and LS-WSVM. PSO is for determination of SVM and wavelet kernel parameters. This technique is fully described in the next section.

3. PSO-LS-WSVM

This section of the paper is based on Ref [29-32]. Structure of prediction model is of great importance in implementing an SVM model with proper prediction capability. In recent years, using SVM model for predicting time series has been increased. Modeling nonlinear relations and solving complicated problems are some of the SVM model's capabilities. However, this model has some limitations. In fact, this model includes some free parameters that must be determined by the user. The good performance of this algorithm depends on the proper adjustment of SVM factors and kernel parameters. Therefore, it is necessary to use a fast and automatic approach for optimizing SVM parameters and decreasing generalization error of this model.

3.1 LS-WSVM

The SVM is a machine learning algorithm which was proposed by Vapnic and Cortes in 1993. In the beginning, this technique was used for solving classification problems but later it was also used for solving regression problem. The regression problem in SVM is a linear function in the form of $f(x) = \langle w.x \rangle + b$ [34]. Where x is the value of input vector. Also, w and b are the control parameters of function f and $\langle w.x \rangle$ represents the inner product.

The training set is in the form of (5):

$$\left\{(x_1, y_1), \ldots, (x_k, y_k)\right\} \subseteq R^N \times R \tag{5}$$

In Eq. (5), x is the vector of input values. The regression model is constructed by (6):

$$y = w^T.\varphi(x) + b \quad \forall w \in R^N, b \in R, \quad \varphi \in R^N \to R^M, M \to \infty \tag{6}$$

where w is the weight vector and b is the bias and φ is a nonlinear mapping function. Based on SRM, regression problem becomes a minimization problem by (8):

$$\sum_{w,b,e} \min J(w,e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{l} e_i^2 \tag{7}$$

Subject to

$$y_i w^T \Phi(x_i) + b + e_i \qquad (i = 1, 2, \ldots, l) \tag{8}$$

where γ is the margin parameter and e_i the slack variable for x_i. To solve the optimization problem with the help of Lagrange theory:

$$L(w,b,e,\alpha) = J(w,e) - \sum_{k=1}^{N} \alpha_i \left\{ w^T \varphi(x_i) + b + e_i - y_i \right\} \tag{9}$$

Based on optimal solution of Karush-Kuhn-Tucker (KKT):

$$\begin{aligned} & w = \sum_{i=1}^{l} \alpha_i \Phi(x_i), \sum_{i=1}^{l} \alpha_i = 0, \quad \alpha_i = \gamma e_i \\ & w^T \Phi(x_i) + b + e - y_i = 0 \end{aligned} \tag{10}$$

A Linear solution of Eq. (7) is performed according to the following equation:

$$\begin{bmatrix} 0 & \mathrm{y}^{\mathrm{T}} \\ \mathrm{y} & \mathrm{ZZ}^{\mathrm{T}} + \gamma^{-1}\mathrm{I} \end{bmatrix} \begin{bmatrix} \mathrm{b} \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \tag{11}$$

where $Z = [\Phi(x_1) y_1, \ldots, \Phi(x_N) y_N]^T$, $y = [y_1, y_2, \ldots, y_N]^T$, $\vec{1} = [1, 1, \ldots, 1]$, $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_N]$. LS solution reduces computation time and cost. Finally, after solving (14), the LS-SVM for estimation will be obtained as follows:

$$y(x) = \sum_{i=1}^{N} \alpha_k K(X, X_i) + b \tag{12}$$

The type of kernel function is important. As a general rule, if a function satisfies the mercer condition, it can be used as a kernel function; it has been proven that the wavelet transform satisfies this condition. The mother of wavelet functions is defined by the following equation:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right) \tag{13}$$

where a, b ∈ R; a is the dilation factor, and it is always larger than zero. Moreover, b is the translation factor. A multidimensional wavelet function is constructed based on a one-dimensional wavelet function.

$$\psi(x) = \prod_{i=1}^{N} \psi(x_i) \tag{14}$$

The wavelet function that is inserted into SVM is according to (15).

$$\begin{aligned} K(x, \dot{x}) &= \prod_{i=1}^{N} \psi\left(\frac{x_i - \dot{x}_i}{a}\right) \\ &= \prod_{i=1}^{N} \left[1 - \frac{(x_i - \dot{x}_i)^2}{2}\right] \exp\left(-\frac{(x_i - \dot{x}_i)^2}{2a^2}\right) \end{aligned} \tag{15}$$

3.2 PSO

Performance of SVM model depends on two parameters C and γ. PSO undertook the optimum selection of wavelet and SVM parameters. If the selected value for C is not correct, the balance between ERM and SRM will be interrupted, moreover, using the incorrect value of kernel parameter will reduce the flexibility of model in solving complicated problems. There are three common solutions for determination of these parameters: grid search, GA and PSO. Compared to PSO, GA needs more operators for adjusting and computational complexity of it is high. The population size of PSO is nearly half of the population size of GA. The CPU time of PSO is less than that of GA and PSO is proper choices for automatic and optimum determination of the SVM parameters [29]. PSO is an optimization approach inspired by the social behavior of birds and fish in search for food [32]. In this technique, each candidate solution of the problem which is called a particle is considered as a bird searching for food. In PSO approach, a position, y_i, and a velocity, v_i, is considered for each particle, i. If 'n' is the dimension of the optimization problem, the position and velocity vectors are defined as follows:

$$y_i = [y_{i1}, y_{i2}, \ldots, y_{in}] \tag{16}$$

$$V_i = [v_{i1}, v_{i2}, \ldots, v_{in}] \tag{17}$$

where, y_{id} and vid are the spatial position and velocity of the d-th dimension of the particle i, respectively. The velocity and position of this dimension of the particle in (t+1)th iteration are given by Eqs. (18) and (19), respectively [32].

$$\begin{aligned} v_{id}(t+1) &= \omega v_{id}(t) \\ &+ c_1.rand\left(P_{id}(t) - y_{id}(t)\right) \\ &+ c_2 rand\left(P_d(t) - y_{id}(t)\right) \end{aligned} \tag{18}$$

$$y_{id}(t+1) = y_{id}(t) + v_{id}(t+1) \tag{19}$$

In equations above, w is the inertia weight within the interval of [0, 1], c_1 and c_2 are the learning coefficients or the accelerations within the interval of [1, 2]. C_1 is called the social parameter and C_2 is called the cognitive parameter and usually, these parameters are equal. Rand is a random number with a uniform distribution within the interval of [0, 1], P_{id} is the best position of the particle in the d-th dimension obtained so far and, P_d is the best position among all particles for the d-th dimension obtained so far. Parameter ω has been entered the equation above to create a balance between finding the global solution and finding the local solution. A linear w is proposed as follows.

$$w = w_{\max} \frac{w_{\max} - w_{\min}}{k_{\max}} k \tag{20}$$

The architecture of PSO algorithm is illuminated by Fig. 1 [29, 32].

3.3 Implementation of PSO-LS-WSVM

The proposed structure in this paper implementation as following steps:

Step 1: The data acquisition is carried out through real wind turbines (8 unit of MAPNA wind farm).
Step 2: Preprocessing is conducted based on reduction, noise cancellation, normalization, remove out-line and convert of data.
Step 3: Selection and calculation of input data.
Step 4: Calculating times series model and construct input pattern.
Step 5: Building dataset and partition into a training set and testing set.
Step 6: Choosing a kernel function.
Step 7: Go to PSO algorithm, and obtain the optimal parameters.
Step 8: Create a prediction model based on PSO-LS-WSVM.
Step 9: Calculating evaluation parameters of proposed method.
Step 10: Plot of WPP output, prediction error and regression diagram.

4 Experimental Results

In order to verify the validity of PSO-LS-WSVM prediction method, a sampled data of wind power is simulated and analyzed. This paper uses the data of a wind farm in Ghazvin, Iran. We collect data for the three months of 2016. The practical hourly data of power data in Kahak-MAPNA plant is used to test this predictor. The 5-min wind power output data sets' hourly averages are applied for the analysis. The goal is predicting the wind power for the next 24 hours with 1-hour time interval. In this paper, we use data from 8 turbines to construct an input time series. The target turbine is turbine of Unit 2, the power output of this turbine is predicted. The 5 min average wind power series of unit 2 is illustrated in Fig. 4. Fig. 5 also shows sample data of one-day after preprocessing.

To verify the effectiveness of the PSO-LS-WSVM predicting model, this method is compared with other method in different types: Type 1: Evaluation of optimization algorithm, PSO-LS-WSVM is compared with GA-LS-WSVM. Type 2: Evaluation of solution and optimization of the main equations of SVM, PSO-LS-WSVM is compared with PSO-QP-WSVM. Type 3: Evaluation of kernel function, PSO-LS-WSVM is compared with PSO-LS-RBFSVM. The comparative criteria are the normalized root mean square error (nRMSE) and the normalized mean absolute error (nMAE), which are defined as:

$$nRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \times 100\% \tag{21}$$

$$nMAE = \frac{1}{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad \forall i = 0,1,\ldots,n \tag{22}$$

4.1 Type 1: Evaluation of Optimization Algorithm

The performance evaluation that uses nMAE and nRMSE for the different predicting models is illustrated in Fig. 6, and also shown in Table 3. It can be seen from Fig. 6(a) that the nMAE of PSO-LS-WSVM and GA-LS-WSVM decrease slowly with the increasing of look-ahead time. However, PSO-LS-WSVM decreases more slowly than GA-LS-WSVM. The result indicates that the proposed method has a probability larger than 90% to predict wind power at 24 look-ahead hours, with a 3.5% error. The probability can even reach about 100% for 24 look-ahead hours with a 4% error. Furthermore, the nRMSE of PSO-LS-WSVM can be shown to decrease the slowest with the increasing of look-ahead time. The performance evaluation using nMAE and nRMSE all show that PSO-LS-WSVM is the best predicting method compared with other method.

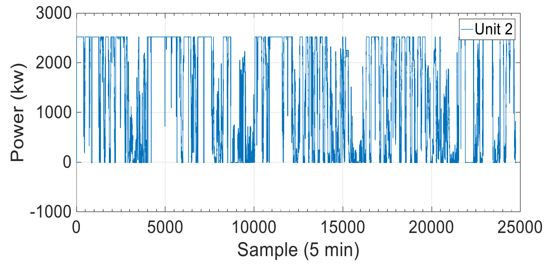

Fig. 4 Five min average wind power series of total samples.

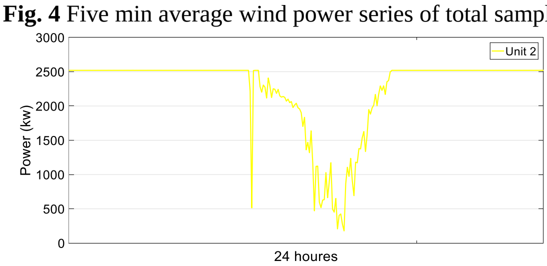

Fig. 5 Sample data of one-day.

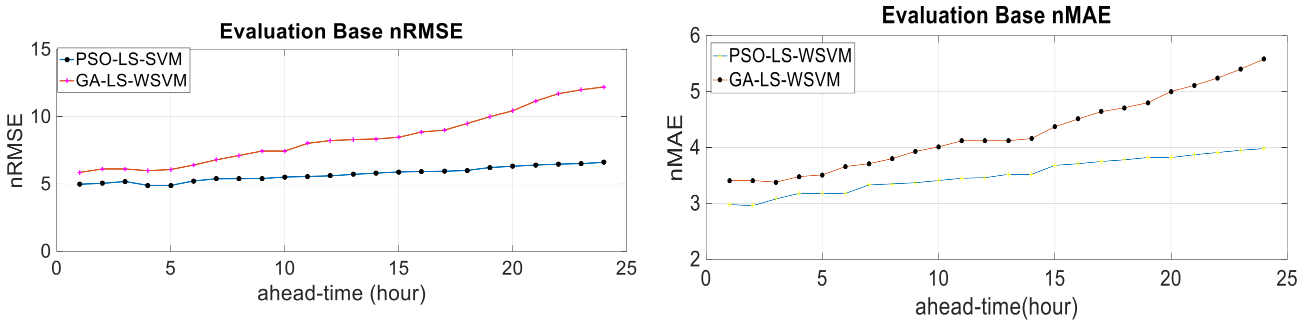

Fig. 6 Evaluation of PSO-LS-WSVM and GA-LS-WSVM based on nMAE and nRMSE.

Table 3 Wind power predicting error for PSO-LS-WSVM and GA-LS-WSVM.

Predicting Lead Hour	PSO-LS-WSVM		GA-LS-WSVM	
	nMAE (%)	nRMSE(%)	nMAE(%)	nRMSE(%)
One lead hour	2.98	4.99	3.41	5.86
4 lead hour	3.18	4.90	3.48	5.99
8 lead hour	3.35	5.40	3.80	7.12
16 lead hour	3.71	5.93	4.51	8.87
24 lead hour	3.95	6.52	5.58	12.21
Average of 24 lead hour	3.50	5.71	4.25	8.40

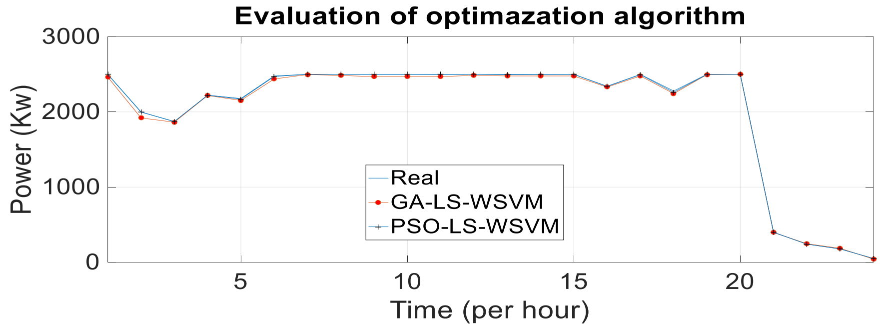

Fig. 7 Comparison of real and predicted value of the power for the next 24-houres using PSO-LS-WSVM and GA-LS-WSVM.

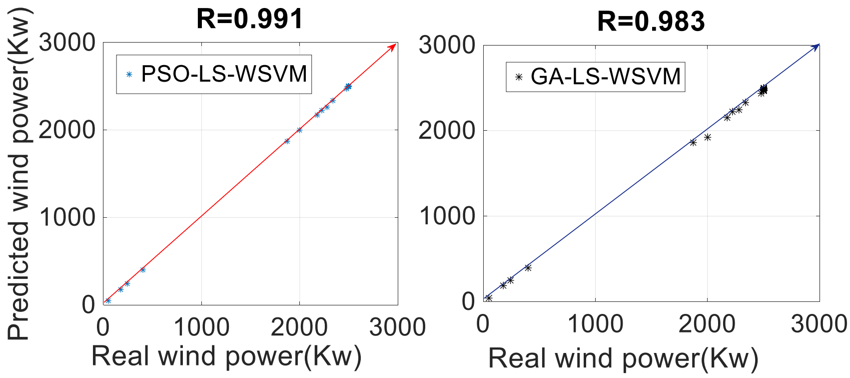

Fig. 8 Regression diagram: a) PSO-LS-WSVM and b) GA-LS-WSVM.

It can be observed from Table 3 that the average nMAE value of PSO-LS-WSVM is 3.5% for 24 look-ahead times over the whole evaluation period, which is well below the 4.25% error of the GA-LS-WSVM.

In order to more clearly illustrate the predicting results, we also intercept part of the predicted curve (as Fig. 7) to show in partially enlarged way, it can be seen that in the test procedure the difference between the real and predicted value while using PSO algorithm is less than the case where GA is used as optimization algorithm for SVM.

Regression diagram in Fig. 8 is correspondent to the proposed method of this paper. It can be seen that the PSO-LS-WSVM algorithm is more accurate in comparison with the GA-LS-WSVM.

4.2 Type 2: Evaluation of Solution and Optimization of the Main Equations of SVM, PSO-LS-WSVM Compared with PSO-QP-WSVM

The proposed solution and optimization of the main equations of SVM effectiveness is evaluated using numerical experiments. In order to verify the effectiveness of the linear solution, PSO-LS-WSVM and PSO-QP-WSVM are used for prediction of wind power. Performance evaluation of different predicting models using nMAE and nRMSE is shown in Fig. 9. It can be seen from Fig. 9(a) and (b) that the nMAE and nRMSE of PSO-LS-WSVM decrease slowly with the increase in look-ahead time. Fig. 9 illustrates that the nMAE and nRMSE of PSO-LS-WSVM are also the smallest in all two models. These results also show that SVM solution by LS can obtain higher precision compared to QP. The predicting accuracy of PSO-QP-WSVM is at a low level at the beginning of the predicting period, while the predicting accuracy of PSO-LS-WSVM sharply decreases at the end of the predicting period. Table 4 lists the nMAE, nRMSE and the predicting time of two models for one hour lead time. It can be seen that the proposed PSO-LS-WSVM has the lowest wind prediction errors. In Fig. 10 the regression value of the predicted data for the next 24-houres in case of using PSO-LS-WSVM and PSO-QP-WSVM as testing algorithm are calculated 0.993 and 0.954 respectively that shows the efficiency of the proposed method. In Fig. 11, the PSO-LS-WSVM predicts model has been able to properly estimate the actual values and the closet of the actual points. The error of predict model which is the difference between the actual values of power and its predicted values are very low.

Table 4 Wind power predicting error for PSO-LS-WSVM and GA-QP-WSVM.

Predicting lead hour	PSO-LS-WSVM		PSO-QP-WSVM	
	nMAE	nRMSE	nMAE	nRMSE
One lead hour	3.00	4.86	9.12	15.16
4 lead hour	3.89	4.76	10.00	16.45
8 lead hour	3.35	5.40	11.79	18.33
16 lead hour	3.99	5.93	15.28	20.98
24 lead hour	3.98	6.61	20.00	23.00
Average of 24 lead hour	3.70	5.64	13.94	19.56

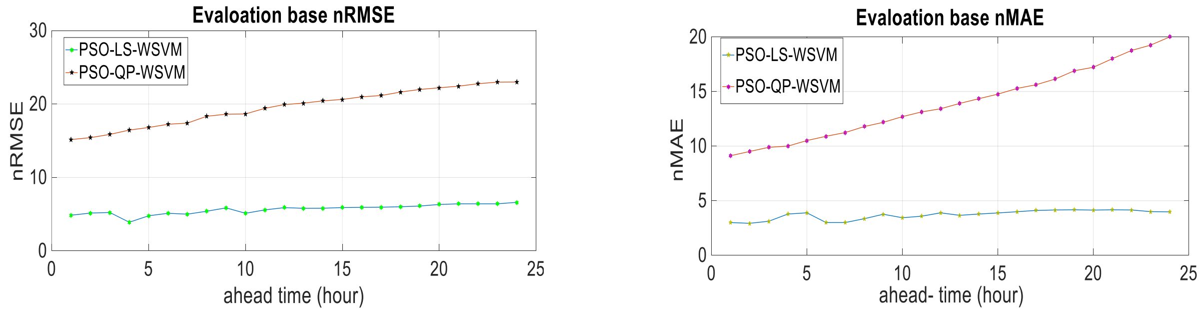

Fig. 9 Evaluation of PSO-LS-WSVM and PSO-QP-WSVM based on nMAE and nRMSE.

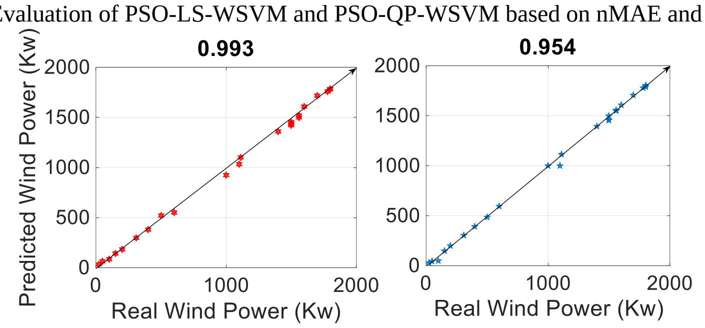

Fig. 10 Regression diagram: a) PSO-LS-WSVM and b) PSO-QP-WSVM.

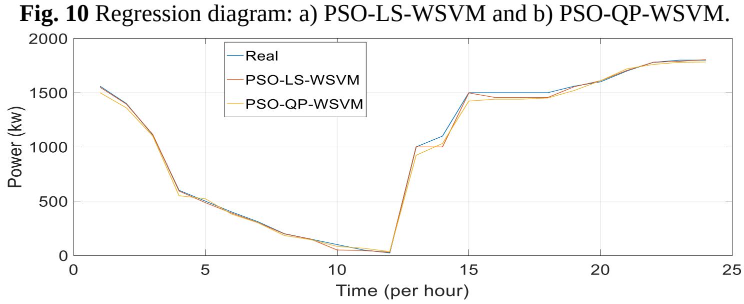

Fig. 11 Comparison of real and predicted value of the power for the next 24-houres using PSO-LS-WSVM and PSO-QP-WSVM.

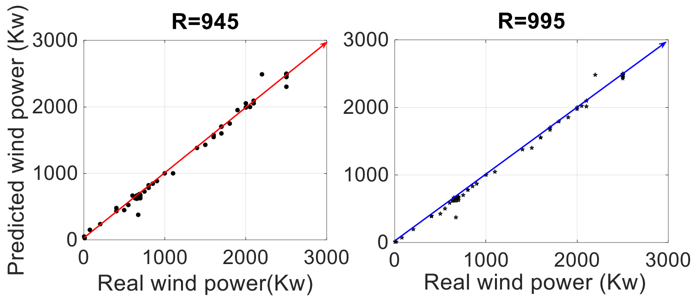

Fig. 12 Regression diagram: a) PSO-LS-WSVM and b) PSO-LS-RBF-SVM.

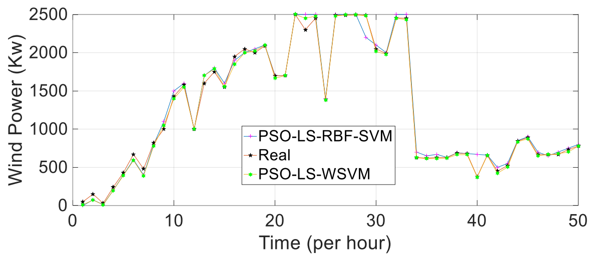

Fig. 13 Comparison of real and predicted value of the power for the next 50-houres using PSO-LS-WSVM and PSO-LS-RBF-SVM.

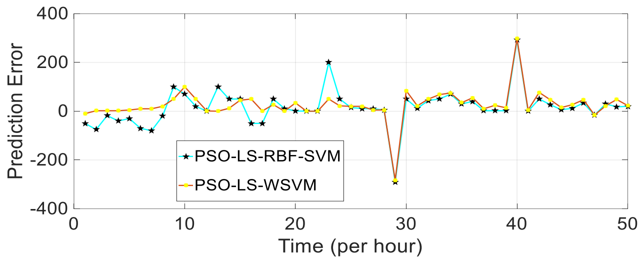

Fig. 14 Error of predicting algorithms (Difference between real value and predicted value).

Table 5 Wind power predicting error for PSO-LS-WSVM and GA-LS-WSVM.

Predicting lead hour	PSO-LS-WSVM		PSO-LS-RBF-SVM	
	nMAE	nRMSE	nMAE	nRMSE
One lead hour	3.01	4.66	10.18	17.12
10 lead hour	3.41	5.61	20.12	27.45
20 lead hour	4.12	6.78	24.66	31.26
30 lead hour	4.56	7.93	26.28	33.98
40 lead hour	4.98	9.12	29.78	36.55
50 lead hour	5.32	11.64	30.94	37.56
Average of 50 lead hour	3.83	5.70	15.01	21.12

4.3 Type 3: Evaluation of Kernel Function, PSO-LS-WSVM is Compared with PSO-LS-RBFSVM

A key issue for illustrating the effectiveness of a predict method is comparing its results with the results obtained from other methods based different kernel function. RBF function is used in SVM. In experiments, this function is compared with the wavelet function. Regression diagram for this scenario is shown in Fig. 12. This figure illustrates that performance wavelet function better than RBF. This result is also clear from the Table 5 based on nMAE and nRMSE. Fig. 13 depicts the predicted value of the power for the next 50-houres with 1-hour time interval. It is clear that predict values of power based on PSO-LS-WSVM very close to real value. Fig. 14 is prediction error of PSO-LS-WSVM and PSO-LS-RBF-SVM.

5 Discussion

The predicting wind power is very important. PSO-LS-WSVM was evaluated based on three types of scenarios. In type 1, the goal is the algorithm determining the core parameters of the kernel and SVM. The performance of the SVM algorithm depends on optimization determination its parameters. In this paper, two methods are compared with each other. In this case, PSO was superior to GA. Compared to PSO; GA needs more operators for adjusting. The population size of PSO is nearly half of the population size of GA. The CPU time required for the PSO–SVM is less than that of GA–SVM. The numerical results in Figs. 6-8 and Table 3 illustrate this fact. In type 2, the goal is the solution of SVM equation; LS or QP. Solving the algorithm optimization equation has several solutions. In this paper, two methods are selected for this target. Based on the numerical results and through analysis, the linear method was better. The complexity of LS is less and the speed of response is much better. Results of Figs. 9-11 and Table 4 showed that LS-SVM better than QP-SVM. In type 3, PSO-LS-WSVM compared to PSO-LS-RBF-SVM, the goal is kernel function. Wavelet performance is better than RBF. The power of the wavelet function is much better, and the results of Figs. 12-14 and Table 5 illustrate this point.

The method presented in this paper was compared with other methods. The results of this comparison are shown in Table 6. This comparison is based on the nMAE (%) criteria. The error of proposed method in

Table 6 Comparison of MAPE results for wind power predicting for one lead hour.

Method	Ref	MAE (%)	Method	Ref	MAE (%)
Real valued neural network	[33]	22.53	BP Neural Network	[34]	17.16
complex-valued recurrent neural network	[33]	14.86	PSO-BNN	[1]	4.12
RBF Neural Network	[6]	12.96	LSSVM-GSA	[36]	3.47
Persistence Method	[34]	21.56	EI-PSO	[37]	3.36
WRNN	[35]	3.83	ELM	[38]	3.73
PSR-AAN	[5]	3.63	PDSTA-BNN	[1]	3.22

this article is less.

6 Conclusions

As wind integration grows dramatically, the requirements for solving various problems, which include competitive power quality, power system stability and reliability, transmission capacity upgrades and standards of interconnection, become more challenging. However, improved wind power predicting can be considered as one of the most efficient ways to overcome many of these problems. Hence, the improvement of the performance of WPP tool has significant economic and technical impact. In this paper, a new predicting method based on SVM is proposed. There are three differences between the proposed method and the conventional SVM approach: 1) LS SVM was used instead of QP-SVM, 2) In order to improve the performance of this algorithm, a wavelet kernel is used instead of conventional kernel function as RBF. 3) The main parameter of this function is determined by PSO. History wind power data translate into time series predicting. WPP–PSO-LS-WSVM is effective tools to maximize the power captured thus increasing the reliability of wind power for wind farms. The prediction method for wind power based on PSO-LS-WSVM is a valid method to predict wind power. The PSO-LS-WSVM model accurate predict of wind power with a look-ahead time of up to 24 h. The final results of the test systems based on 2.5 MW wind turbine verified the feasibility and effectiveness of the proposed method to predict wind power series. Comparison with other methods proved that the proposed method is competitive in terms of dealing with wind power predicting.

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