A novel wind speed prediction method based on support vector machine optimized by genetic algorithm

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Abstract: - Wind energy is attracting more and more attention nowadays, because of the renewable, non-polluting characteristics. Accurate wind speed prediction can provide necessary technical support and guidance in the application of wind power in the electricity grid. In order to improve the accuracy of wind speed prediction, a combination genetic algorithm and support vector machine (SVM) model has been proposed to forecast wind speed. Firstly, grey model was adopted to accumulate the original wind speed data and weaken the randomness of data sequence, and then SVM model is used to predict the wind speed. Furthermore, using the regressive features of grey model to reduce the prediction results and obtain the final predicted value of wind speed. The comparison results with other popular predicting algorithms, BP and standard SVM, show that, the GA-SVM model can improve the forecasting accuracy of short term wind speed and is of a certain practical value.

Key-Words: - Wind energy, Wind speed prediction, Support vector machine (SVM), genetic algorithm (GA)

1 Introduction

With the deterioration of the energy and environmental problems, wind power generation is receiving growing attention due to its potential as the clean and renewable source of energy [1-3]. Wind speed prediction is essential for wind farm planning and power system operation [4-5]. Extremely complicated control over the generator is required to track the maximum wind energy utilization coefficient and the maximum power. By performing wind speed prediction and control, the control quantity of the generator can be acquired in advance, resulting in prompt adjustment and desired controlling results [6-9]. Long-term wind speed prediction can provide basic data for wind farm planning; short-term wind speed prediction is helpful for the electricity department in planning the supply schedule, reducing the operation cost of the electricity system and the backup, improving the cost-effectiveness of the system, reducing the impact of wind power fluctuation on the grid, and enhancing system security and reliability.

In recent years, researchers have distributed their important work in the wind speed predictions. The majority of previous approaches use modern regression techniques. In [10], Louka et al. studied the wind speed prediction in numerical method by Kalman filtering, which improved the required CPU time and showed remarkable forecasting accuracy. In 2005, Torres et al. used autoregressive moving average process and persistence models to predict the short-term wind speed, which could predict up to 10h in advance [11]. In [12], researchers proposed long-term wind speed forecasting method based on probabilistic Bayesian networks (BNs) in Spain. Besides that, most adopted methods are intelligent prediction method based on neural network due to the advantage of self-learning, self-organizing and highly adaptive properties. Such as multi-layer perceptrons [13], fuzzy-based neural approaches [14], two-hidden layer neural networks [15] and fast training neural approaches [16]. In spite of this huge work on modern methods for wind speed prediction from measuring towers, there are still some margin for improvement, coming from methodologies that have been under-explored in this problem.

As one of the machine learning research topics, support vector machine (SVM) is a novel general method for machine learning based on the statistical theory, which was proposed in the 1990s. It is designed to target learning of small samples. It is so theoretically robust that it avoids such problems as overlearning, insufficient learning, high dimensionality, non-linearity and local minuteness, which exist in other methods. Moreover, it has great learning and generalization abilities and has been successfully applied to many domains. In order to improve the prediction accuracy of wind speed prediction, a model genetic algorithm optimized support vector machine model is proposed to predict the wind speed.

2 Support vector machine

Support vector machine is a major breakthrough in machine learning in recent years based on the structural risk minimization criterion. Consider the data set of n samples $\{X_i, y_i,\ \ i=1,2,\cdots,n\}$, where $X_i \in R^m$ is an m-dimension vector, $y_i \in R$ is a real number, X_i is the input data, y_i is the output data. In SVM, the sample space is mapped from the original space R^m to the high-dimensional feature space R^h using the non-linear mapping $\varphi(x)$, constructing the optimization decision function in the high-dimension feature space:

$$y = \omega\varphi(X) + b \tag{1}$$

Where ω is the weight vector, $\omega \in R^h$ and b is the offset quantity.

While solving the regression problem, the high-dimension space linear function fitting problem based on the above equation can be formulated as the following optimization problem:

$$\begin{cases} \min \varphi(\omega,b,e) = \frac{1}{2}\omega^T\omega + \frac{1}{2}C\sum_{i=1}^{n} e_k^2 \\ s.t. \\ y_k = \omega^T\varphi(X_k) + e_k \\ k = 1,2,\cdots,n \end{cases} \tag{2}$$

Where e_k is the error, C is the punitive parameter. By using the Lagrange's method of multipliers, the above constrained problem can be regarded as the following unrestricted optimization problem.

$$\begin{aligned} L(\omega,b,e,\alpha) &= \frac{1}{2}\omega^T\omega \\ &+ \frac{1}{2}C\sum_{i=1}^{n} e_k^2 - \sum_{i=1}^{n}\alpha_i\left\{\omega^T\varphi(X_i) + e_i + b - y_i\right\} \end{aligned} \tag{3}$$

Where α_i is the Lagrange multiplier. To solve for the saddle point of the above equation, let the partial derivative of its sum be zero, then we have:

$$\begin{pmatrix} 0 & l_v^T \\ l_v & \Omega + \frac{1}{\gamma}I \end{pmatrix}\begin{pmatrix} b \\ \alpha \end{pmatrix} = \begin{pmatrix} 0 \\ y \end{pmatrix} \tag{4}$$

Where $y = y_1, y_2, \cdots, y_n$, $l_v = 1,2,\cdots,n$, $\alpha = \alpha_1, \alpha_2, \cdots, \alpha_n$, $\Omega = \varphi(X_k)^T\varphi(X_k)$, $k = 1,2,\cdots,n$. Considering Mercer conditions, there exist the mapping function φ and the kernel function $k(.,.)$ which satisfy:

$$K(X_k, X_l) = \varphi(X_k)^T\varphi(X_l) \tag{5}$$

Where $K(X_k, X_l) = \exp\left(-\frac{(X_k - X_l)^2}{2\sigma^2}\right)$, and $\sigma > 0$ is the parameter of the kernel function. If the regression parameter and the offset b are computed, then the non-linear regression model of SVM is:

$$f(X) = \sum_{l=1}^{n} x_l K(X, X_l) + b \tag{6}$$

From the principles of SVM, it can be known that the optimal values of parameters C and σ must be determined to construct a model for accurately predicting wind speed. Hence, the genetic algorithm capable of effectively finding the optimum is chosen in this paper to optimize SVM parameters.

3 GA-based SVM

The genetic algorithm (GA) has four important stages: population initialization, selection, crossover and mutation, where the crossover and mutation process is essential to GA behaviors. Due to its proneness to premature convergence, Srinivas et al. introduced the self-adaptive control function with the crossover probability and the mutation probability into the crossover and mutation stages [17]. The crossover probability and the mutation probability are adjusted constantly to ensure gene diversity of the population and to prevent GA from premature convergence.

The experimental results are highly dependent on the punitive parameter C, insensitive loss parameter ε and the kernel function parameter σ in SVM. These parameters will be optimized via GA. This optimization problem is a range constrained search problem. Based on characteristics of the flow, these three parameters are limited to some ranges. Several important aspects of the GA-based SVM will be discussed thoroughly as below.

3.1 Chromosome coding

Chromosome coding is done to facilitate computation, converting the form of the problem's solution to the form of string recognizable for GA. Binary coding is chosen in this paper. The coding range of C, ε and σ for flow prediction is [0.1, 150], [0.01, 0.5] and [0.01, 10], respectively. Because 150 is in the range 2^7~2^8, the 8-digit binary is needed for parameter coding, and the coding length is dependent on the time interval. Decoding is done via the following equation.

$$X_j = \sum_{j=4k-3}^{4k} \left(x_j 2^{4k-j} \right) \tag{7}$$

Where X_j is the parameter, x_j is the j^{th} digit of the parameter' binary code, and x_j=0 or x_j=1.

3.2 Fitness function

The fitness function is designed to guide the selective evolution of the next generation. An accurate fitness function can improve the algorithm's speed and the optimal solution's quality. The objective of the SVM parameter optimization problem is to find the optimal parameters. Hence, the mean relative error is chosen for fitness evaluation.

(1) Selection of individuals: The objective of selecting individuals is to pass the properties of high-fitness excellent individuals to the next generation via duplication, so that the excellent individuals evolve constantly. The roulette strategy is chosen for individual selection in this paper. So the probability that the individual with a fitness of $G(i)$ is chosen and computed as:

$$P_n(i) = \frac{G(i)}{\sum_{i=1}^{N} G(i)} \tag{8}$$

(2) Crossover and mutation: the crossover operation is done to form an utterly new individual while retaining as many good genes of the parent as possible. The objective of mutation is to prevent the algorithm from being stuck in local optimum and to maintain the diversity of the population. Mutation happens in nature to adapt to the environment. The crossover probability and the mutation probability of the adaptive genetic algorithm can be self-adapted to avoid premature convergence of GA. The probability function is:

$$P_c(i) = \begin{cases} \dfrac{K_1 N\left(g_{\max} - g^{'}\right)}{\left(g_{\max} - g_{avg}\right)}, & g^{'} \geq g_{avg} \\ K_2, & g^{'} < g_{avg} \end{cases} \tag{9}$$

$$P_m(i) = \begin{cases} \dfrac{K_1 N\left(g_{\max} - g_i\right)}{\left(g_{\max} - g_{avg}\right)}, & g \geq g_{avg} \\ K_2, & g < g_{avg} \end{cases} \tag{10}$$

Where $g_{\max}$ is the highest fitness of the current generation, g_{avg} is the average fitness of the current generation, g_i is the fitness of the i^{th} individual in the current generation, g` is the individual with higher fitness in the two crossover individuals of the current generation, N is the chromosome length, $\frac{\left(g_{\max} - g^{'}\right)}{\left(g_{\max} - g_{avg}\right)}$ represents how good the individual with higher fitness in the two crossover individuals is among the current generation, $\frac{\left(g_{\max} - g_i\right)}{\left(g_{\max} - g_{avg}\right)}$ represents how good the i^{th} individual is among the current generation, K_1 and K_2 are the adjustment coefficients.

3.3 Training of SVM

In the above Section, important steps of GA-based SVM is introduced. Next, we will give the details of the proposed process for optimizing SVM parameters via GA. Specific steps are as follows:

(1) Initialize by performing binary coding on the three parameters of SVM and the coding ranges are specified in Section 3.1;

(2) Initialize the population, and determine the size of the population for GA and the maximum number of iterations;

(3) Perform fitness evaluation;

(4) Assess the performance of the population based on the optimization criterion (the maximum number of iterations). If the conditions are satisfied, then output the parameters as the optimum of SVM, and then output the well-trained SVM model; otherwise, jump to (5);

(5) Carry out the selection, crossover and mutation operations of GA to generate the next generation and perform the genetic operations on the next generation.

The process for predicting the short-term wind speed via the grey GA-based SVM is given in Fig.1.

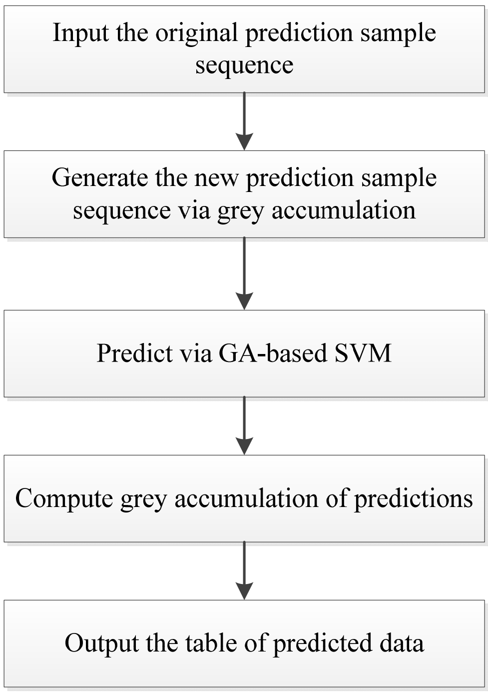

Fig.1 Process for predicting the wind speed via the GA-based SVM

4 Experimental demonstration and precision analysis

4.1 Preprocessing of historical data

The original wind speed dataset is a set of time-varying data. Due to the large number of factors that may influence the wind speed, the wind speed sequence is a non-stationary time sequence. If the prediction model is constructed directly using the original wind speed data, then the model's accuracy and the algorithm's learning and training speed will be severely affected. Therefore, the original data can be preprocessed before the construction of the prediction model, so that the effect from the non-stationary data can be reduced substantially. So the data sequence needs to be processed for the phase space construction by generating a proper input/output vector (X_t, Y_t), where $X_t = \{x_{t-m}, x_{t-m+1}, \ldots, x_{t-1}\}$, $Y_t = x_t$, m is the dimensionality of the input vector, and x^i_is the i^{th} wind speed.

The non-stationary of the original data samples can be effectively alleviated via difference processing. The data that has been processed for stationary needs to be normalized and there are many methods for normalization. In this paper, the input/output vector (X, Y) is normalized using Eq.(11).

$$\begin{cases} X(n,i) = \left(X(n,i) - M - X(n)\right) \big/ D - X(n) \\ Y(n) = \left(Y(k) - M - Y\right) \big/ D - Y \\ n = 1, 2, \cdots, U \\ i = 1, 2, \cdots, V \end{cases} \tag{11}$$

Where M-X(n) and D-X(n) denote the mean and variance of the n^{th} column of the input vector X; M-X *and* D-Y denote the mean and variance of the output vector; U is the dimensionality of the vector, and V is the number of gliding.

4.2 Performance metrics of the prediction model

There are many methods for evaluating the performance of the prediction model. The mean absolute error (MAE) and mean standard error (MSE) are chosen as the metrics in this paper. And they can be expressed as:

$$MAE = \frac{1}{k}\sum_{i=n+1}^{n+k} \frac{\left|s_i - \hat{s}_i\right|}{s_i} \times 100\% \tag{12}$$

$$MSE = \sqrt{\frac{1}{k}\sum_{i=n+1}^{n+k} \left(\frac{\left|s_i - \hat{s}_i\right|}{s_i}\right)^2} \tag{13}$$

The experiment adopted multiple sets of measured wind speed data from different sampling scales. The first dataset is sampling by 15 minutes for 12 hours to test the short-term forecasting capability, and obtain 48 wind speed points. The second dataset is sampling by 1 hour for a day, and get 24 wind speed points. Finally, the third data set is sampling by one day for a week to observe the long-term scale prediction capability.

Figure 2 shows the prediction result by the proposed GA-SVM method, it can be seen that, the prediction result can reflect the change of wind speed and have high forecasting precision. In addition, Figure 3 presents the prediction error, with the maximum error value, minimum error value and average error value are 27.87%, 0.37% and 5.7%, respectively.

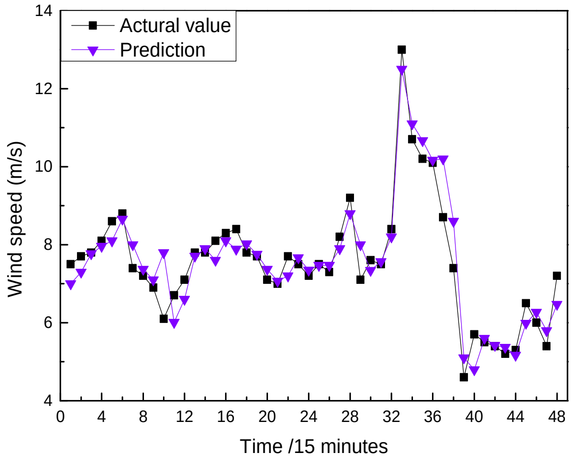

Fig.2 Forecasting result of wind speed for 12 hours

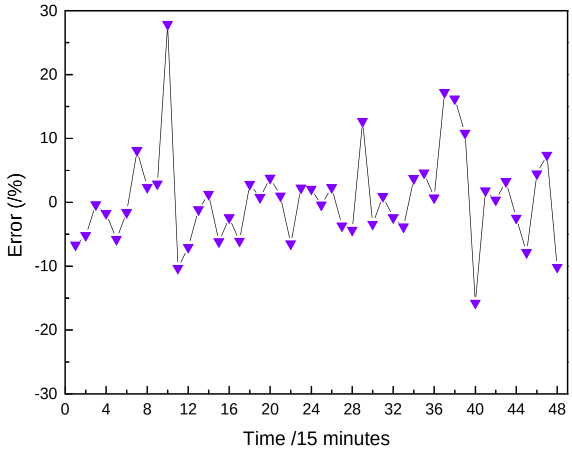

Fig.3 Error of forecasting result for 12 hours

In order to evaluate the applicability and superiority of the wind speed prediction model proposed in this paper with other prediction algorithms, a comparison analysis is given as shown Figure 4. It can be seen that for most prediction instances, the absolute error of GA-SVM is smaller than that of other methods, the prediction value close to the true value of wind speed. Figure 5 demonstrations the corresponding forecasting error of different prediction algorithms, in which, the error distribution range of GA-SVM is from 0.41% to 20%, for BP-ANN method is 1.97% to 27.5%, and 3.45% to 35% for standard SVM method. On the other hand, the average error for these three methods are 7.31%, 9.65% and 10.11%, respectively. It can be clearly seen that the GA-SVM has much higher precision of prediction.

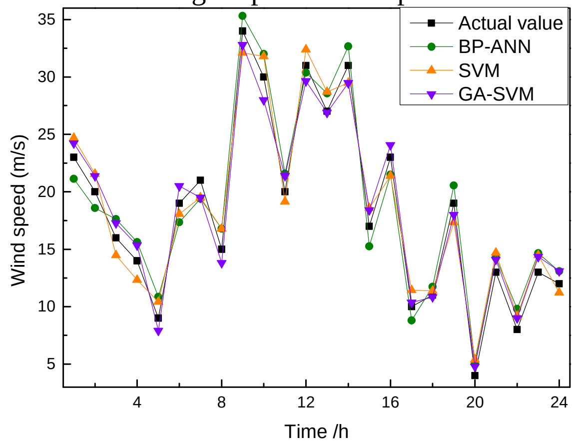

Fig.4 Measured wind speeds and prediction by different models

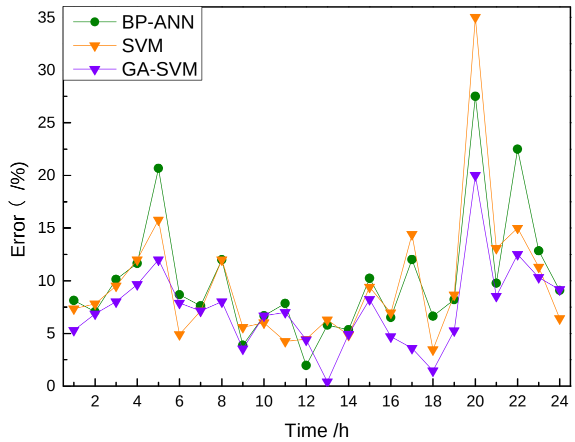

Fig.5 Prediction error of different forecasting methods

Furthermore, Figure 6 and Figure 7 show the MAE and MSE of different models for a week. It can be obviously observed that the proposed GA-SVM method has lowest MAE and MSE value than that of other models.

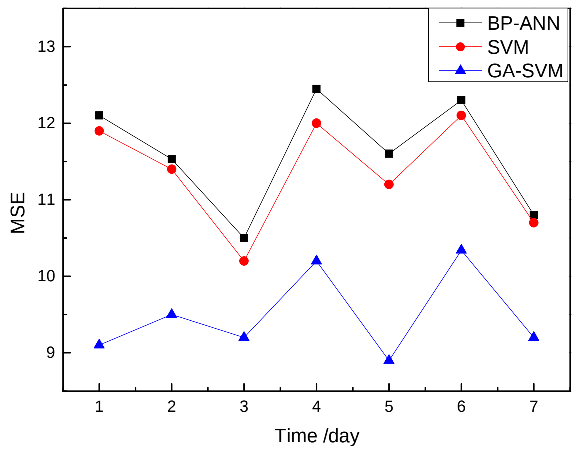

Fig.6 MSE value of different prediction methods for a week

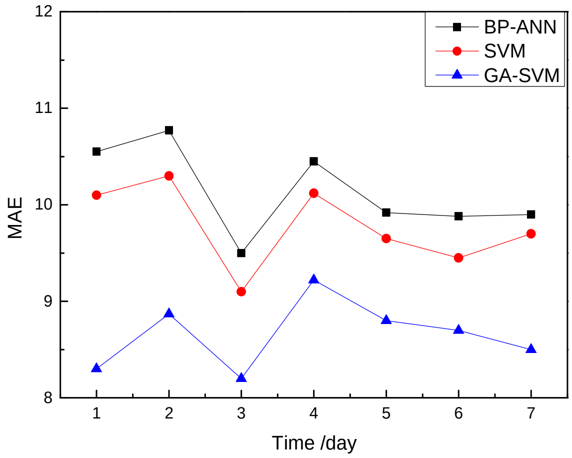

Fig.7 MAE value of different prediction methods for a week

5 Conclusion

The wind speed prediction is important for power system operation research, which can provide important reference for the power load forecasting. This paper proposes a model for predicting the wind speed in different time scales by using the grey GA-based SVM. The SVM parameters are optimized through GA to solve the defects of SVM. The strengths of the grey model and SVM are combined to improve the accuracy of wind speed prediction. Experimental results show that the proposed model outperforms other prediction methods in terms of accuracy, demonstrating the effectiveness and feasibility of the proposed model. Our work is theoretically and practically helpful in predicting the power of the wind electricity.

From the prediction results, it can be seen that, the prediction effect of a certain lag according to the fluctuation of wind speed data. So, in the next phase work, we consider to establish more combination model and do a more in-depth research in order to achieve better prediction results. Furthermore, the change of wind speed is related to the terrain, seasonal climate and other natural factors, so an accurate prediction model should also contain these parameters in further research.

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