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Liu Yongqian
North China Electric Power University

Jie Yan
North China Electric Power University

David Infield
University of Strathclyde

Linyue Gao
Iowa State University

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An optimized short-term wind power interval prediction method considering NWP accuracy

Yongqian Liu · Jie Yan · Shuang Han · Infield David · De Tian · Linyue Gao

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Abstract In recent years, the accuracy of the wind power prediction has been urgently studied and improved to satisfy the requirements of power system operation. In this paper, the relevance vector machine (RVM)-based models are established to predict the wind power and its interval for a given confidence level. An NWP improvement module is presented considering the characteristic of NWP error. Moreover, two parameter optimization algorithms are applied to further improve the prediction model and to compare each performance. To take three wind farms in China as examples, the performance of two RVM-based models optimized, respectively, by genetic algorithm (GA) and particle swarm optimization (PSO) are compared with predictions based on a genetic algorithm–artificial neural network (GA–ANN) and support vector machine. Results show that the proposed models have better prediction accuracy with GA–RVM model and more efficient calculation with PSO–RVM.

Keywords Wind power interval prediction · NWP accuracy · Relevance vector machine · Particle swarm optimization · Genetic algorithm

Y. Liu · J. Yan (✉) · S. Han · D. Tian · L. Gao
State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University (NCEPU), Beijing 102206, China
e-mail: jiejie3000@sina.com

I. David
Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow G11XW, UK

1 Introduction

With the rapid development of wind energy, the large-scale integration of wind power brought about apparent negative impact on the electric power system [1, 2]. Wind power prediction is one of the most important technologies to tackle the challenges that large scale wind power integration brings about to power system. However, it still needs to be further improved not only in terms of the accuracy but also the risk assessment.

Statistical wind power forecasting methods have been widely studied and gained lots of achievement, such as artificial neural network (ANN) [3–6] and support vector machine (SVM) [7–9]. ANN could theoretically approximate any nonlinear function but suffers over-fitting problem [10]. SVM avoids this problem and improves the generalization ability with small training samples. However, there are still some disadvantages of SVM [11]: the kernel function must satisfy Mercer's condition; cannot obtain uncertainty or probabilistic information; support vectors number increases linearly with the increase of training sample size.

To overcome above drawbacks, a probabilistic learning machine is introduced based on Bayesian theory and marginal likelihood functions that is relevance vector machine (RVM) [11]. RVM has excellent prediction performance and could offset main inadequacy of SVM [12–14]. The approach has been successfully applied in many fields such as load forecasting and fault classification [15–18].

It is significant to select the model parameters. Currently, there are many optimization techniques for example genetic algorithm (GA), particle swarm optimization (PSO), fuzzy inference system (FIS), fuzzy neural network (FNN), and wavelet theory. Among the above techniques, PSO and GA are the most widely used ones in the academic community. Ioannis et al. [19] presented an optimized wind speed forecasting and wind power forecasting model based on GA theory. The model improves the forecasts performance and brings forward the forecasts time steps from 30 min to 2 h. Change combined ordinary least square (OLS) and GA to optimize RBF neural network model to predict wind farm output [20]. Pratheepraj et al. [21] accurately and reliably predicted wind speed and the power generation of a small-scale wind farm using a PSO-neural hybrid system. This paper presents the application and performance comparison of PSO and GA optimization techniques for RVM-based wind power forecasting model.

In this paper, the RVM-based forecasting model is integrated with an numerical weather prediction (NWP) improvement module and a parameter searching module considering the forecasting influential factors like NWP errors and model parameters. PSO and GA are employed to search the optimal model parameters.

2 Wind farm descriptions

The analysis has been based on the data from three wind farms in China including mean wind farm output, mean wind speed collected from the SCADA, and mean wind speed from a wind measurement system and NWP system. The installed capacities of these three wind farms are 183 MW (quoted as wind farm 1#), 150 MW (quoted as wind farm 2#), and 100.5 MW (quoted as wind farm 3#). All the data were collected at 15 min intervals. The operational period covers 2010 except for October in wind farm 1#; 2011 year in wind farm 2# and wind farm 3#. Among the available data, 80 % are considered as candidate training samples and remaining 20 % are used as test samples. In this paper, NWP data are taken as the prediction model inputs involving wind speed, wind direction, atmospheric pressure, temperature, and relative humidity. Therefore, the error of NWP has significant impacts on the power prediction accuracy, especially for NWP wind speed.

Figure 1 presents the root mean square error (RMSE) of the NWP wind speed forecasts, and it shows similar changing trend along with different seasons. In Fig. 2, the standard deviation of meteorological parameters was presented for somewhat quantitative analysis of weather pattern stability. In summer, most of parameters (like wind speed, pressure, and temperature) are in low variation which suggests a stable weather pattern except for humidity showing relatively higher fluctuations because of frequent rainfall or storm. It is easier to simulate and learn these stable weather patterns and to make good prediction. Of course, the accuracy of three groups of NWP data appears to have slight differences. It is because three wind farms are located in different parts of China which undoubtedly have different seasonal characteristics. In addition, NWP system or model parameters would also contribute to this performance difference.

3 Principle of relevance vector machine

Given a set of input-target pairs $\{x_n, t_n\}_{n=1}^{N}$, assume that $t_i = y(x_i;\ w) + \varepsilon_i$, where ε_i is assumed to be mean-zero Gaussian with variance σ^2, and the Kernel function $K(x, x_i)$ has been considered which makes prediction by the function:

$$y(x;w) = w^{\mathrm{T}}\phi(x) = \sum_{i=1}^{M} w_i K(x, x_i) + w_0, \tag{1}$$

where $\phi(x)$ is the vector of basis function; $w = (w_1, w_2, \ldots, w_M)$ is the weights vector.

Therefore, the probabilistic formulation of RVM Model is defined as

$$p(t_n|x) = N\big(t_n|y(x_n), \sigma^2\big), \tag{2}$$

where N represents a Gaussian distribution over t_n with mean of $y(x_n)$ and variance σ^2.

The likelihood function of whole samples is defined as follows:

$$p\big(t|w,\sigma^2\big) = \big(2\pi\sigma^2\big)^{-\frac{N}{2}} \mathrm{e}^{\left\{-\frac{1}{2\sigma^2}\|t-\varphi w\|^2\right\}}. \tag{3}$$

To overcome over-fitting in the implementation of maximum-likelihood estimation for w and σ^2, constraint on weights w_i was imposed, that is ''prior'' probability distribution as follow:

$$p(w|\alpha) = \prod_{i=0}^{N} N\big(w_i|0, \alpha_i^{-1}\big), \tag{4}$$

where α is the $N + 1$ vector termed ''hyperparameters''.

The posterior probabilities over unknown samples could be obtained from Bayesian inference.

$$p\big(w,\alpha,\sigma^2|t\big) = \frac{p\big(t|w,\alpha,\sigma^2\big) \times p\big(w,\alpha,\sigma^2\big)}{p(t)}. \tag{5}$$

Assuming that new test target is t_*, new test input x_* is used to make prediction. Then, the distribution of prediction can be written as

$$p(t_*|t) = \int p\big(t_*|w,\alpha,\sigma^2\big) p\big(w,\alpha,\sigma^2|t\big)\mathrm{d}w\mathrm{d}\alpha\mathrm{d}\sigma^2. \tag{6}$$

The posterior distribution can consequently be rewritten as

$$p\big(w|t,\alpha,\sigma^2\big) = \frac{p\big(t|w,\sigma^2\big) \times p(w|\alpha)}{p\big(t|\alpha,\sigma^2\big)} = (2\pi)^{-\frac{N+1}{2}} \Big|\sum\Big|^{-\frac{1}{2}} \mathrm{e}^{\left\{-\frac{1}{2}(w-\mu)^{\mathrm{T}}\sum^{-1}(w-\mu)\right\}}. \tag{7}$$

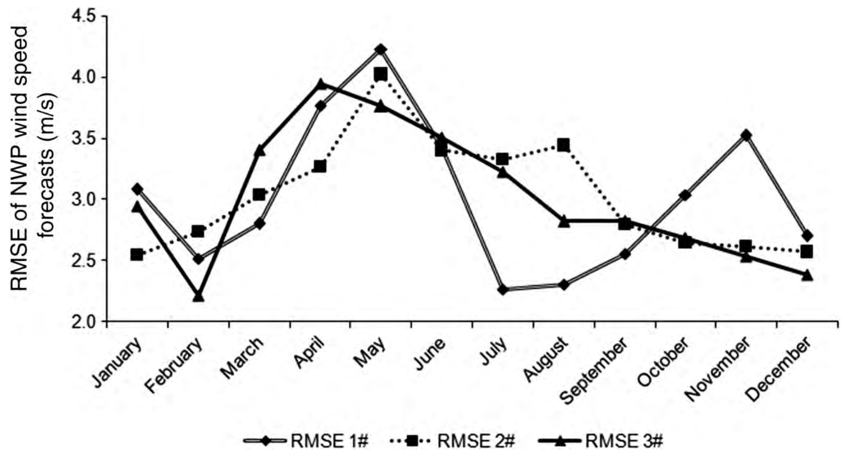

Fig. 1 Accuracy of wind speed from NWP for each month in 3 wind farms

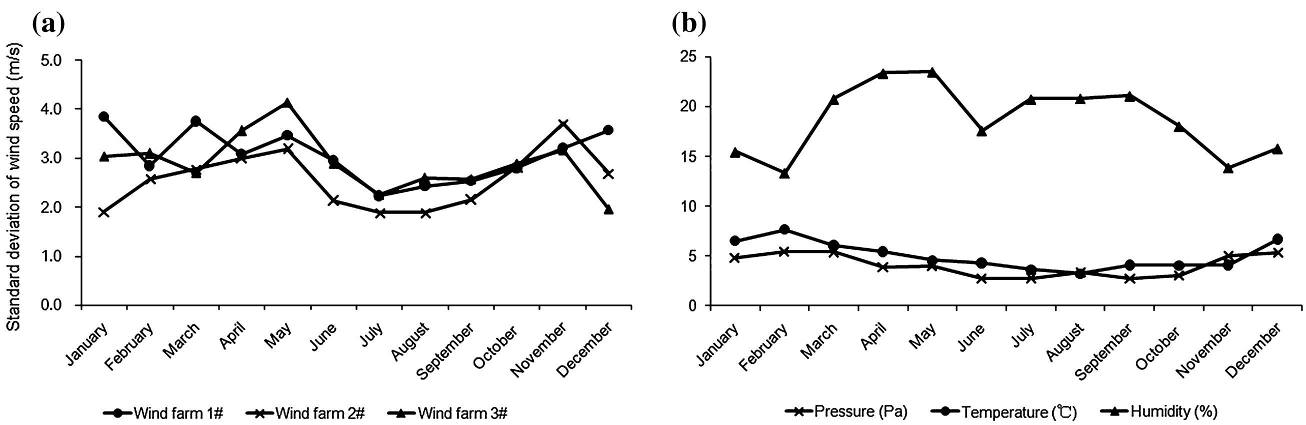

Fig. 2 Standard deviation of monthly weather parameters in 3 wind farms. **a** Standard deviation of wind speed in 3 wind farms. **b** Standard deviation of other weather factors in wind farm 1#

Therefore, the RVM learning process is a search for α, σ^2 which achieves by using maximum marginal likelihood estimation methods as follows:

$$p\left(t|\alpha,\sigma^2\right)=(2\pi)^{-\frac{N}{2}}|\sigma^2 I+\varphi A^{-1}\varphi^{\mathrm{T}}|^{-\frac{1}{2}}\exp\left\{-\frac{1}{2}t^{\mathrm{T}}(\sigma^2 I+\varphi A^{-1}\varphi^{\mathrm{T}})^{-1}t\right\}. \tag{8}$$

α, σ^2 can be calculated by setting the relevant derivative of function (7) to zero. It could be obtained by

$$\alpha_i^{\mathrm{new}}=\frac{1-\alpha_i\sum ii}{\mu_i^2}, \tag{9}$$

$$\left(\sigma^2\right)^{\mathrm{new}}=\frac{\|t-\phi\mu\|^2}{N-\sum_i(1-\alpha_i\sum ii)}, \tag{10}$$

$$\mu=\sigma^{-2}\sum\varphi^{\mathrm{T}}t, \tag{11}$$

$$\sum=\left(\sigma^{-2}\sum\phi^{\mathrm{T}}t+A\right)^{-1}, \tag{12}$$

where μ_i is the ith mean of posterior from Eq. (11); $\sum_{ii}$ is the ith diagonal element of posterior covariance from Eq. (12), and computed by α, σ^2 from current iteration results; and N indicates the number of sample data points.

When α_i becomes extremely large, w_i goes to zero because of constraint by the prior. For w_i with small α_i, RVM fits the sample data better. Iteration should continue until a suitably chosen convergence condition is fulfilled. During the process of parameter estimation, most of $\alpha_i\to\infty$ and the corresponding $w_i=0$. This leads to nonparticipation in the prediction calculation for many terms of the kernel matrix. In this way the RVM can achieve the desired sparsity that reduces computational effort.

Iteration proceeds by making predictions based on the given weight of the posterior distribution which is adjusted to maximize the values of α_{MP}, σ^2_{MP}. With new inputs x_*, predictions can be calculated by the following equations:

$$p\left(t_*|t,\alpha_{\mathrm{MP}},\sigma_{\mathrm{MP}}^2\right)=\int p\left(t_*|w,\sigma_{\mathrm{MP}}^2\right)p\left(w|t,\alpha_{\mathrm{MP}},\sigma_{\mathrm{MP}}^2\right)\mathrm{d}w = N\left(t_*|y_*,\sigma_*^2\right), \tag{13}$$

$$y_*=\mu^{\mathrm{T}}\varphi(x_*), \tag{14}$$

$$\sigma_*^2=\sigma_{\mathrm{MP}}^2+\phi(x_*)^{\mathrm{T}}\sum\varphi(x_*). \tag{15}$$

4 Wind power interval prediction model

4.1 Model structure

The structure of the RVM-based wind power prediction model comprises NWP improving, parameters optimizing, and RVM forecasting.

In NWP improving phase, the measured met mast wind speed and the raw NWP wind speed are transferred to LS-based NWP improving module. The revised NWP wind speed would have higher accuracy than that of the raw NWP data. Then the improving NWP wind speed and other weather prediction data (if any) are prepared to go into the next phase. And then, in parameters optimization phase, two optimization techniques—PSO and GA—are, respectively, applied to determine the most suitable kernel width and initial value of the RVM. The performance of these two techniques would be discussed in the case study. Finally, the training samples and optimized parameters are transferred to RVM model in the training and forecasting phase.

4.2 Improvement of NWP accuracy

The weather prediction, especially wind speed forecasts, is the key factors to wind power prediction accuracy. Cubic relationship between wind speed and power output means that even tiny wind speed forecasting error would trigger very large wind power forecasting error, and there is inevitable deviation between NWP wind speed and the actual wind speed. Thus, it is possible to improve the wind power prediction performance by using improved NWP data. In this paper, least square method is utilized to improve raw NWP wind speed aiming at reducing the systematic errors and errors caused by model defects.

Assume that $\{x_i\}$ is the time series of the raw NWP wind speed, while $\{y_i\}$ is the measured wind speed in a same period. The n orders polynomial is used to approximately mapping the relationship between x_i and y_i.

$$y_i\approx f(x)=a_0+a_1x+a_2x^2+\cdots+a_nx^n=\sum_{j=0}^{n}a_jx_i^j, \tag{16}$$

where $S(\alpha_0, \alpha_1, \ldots, \alpha_n)$ denotes the coefficients of polynomial.

In order to search the optimum coefficients for fitting the given pairs of data, the quadratic sum of the residual error δ would be adjusted to be the minimum. m is the sample size and $1 < i < m$.

$$\min\sum_{i=1}^{m}(\delta_i)^2=\min\sum_{i=1}^{m}[f(x_i)-y_i]^2 = \min\sum_{i=0}^{m}\left[\sum_{j=0}^{n}\alpha_jx_i^j-y_i\right]^2. \tag{17}$$

It is thus clear that the quadratic sum of the residual error is the function of polynomial coefficients α_i.

$$S(\alpha_0,\alpha_1,\ldots,\alpha_n)=h\left(\sum_{i=1}^{N}(\delta_i)^2\right). \tag{18}$$

To obtain the $S(\alpha_0, \alpha_1, \ldots, \alpha_n)$ when the function of $(\delta)^2$ is at its minimal value. The polynomial matrix of α_j is as follows:

$$\frac{\partial S}{\partial\alpha_j}=2\sum_{i=0}^{n}\left(\sum_{i=0}^{n}\alpha_jx_i^j-y_i\right)\times x_i^j=0, \quad (i=0,1,\ldots,n;\ j=0,1,\ldots,m), \tag{19}$$

$$\begin{bmatrix} m+1 & \sum_{i=0}^m x_i & \cdots & \sum_{i=0}^m x_i^n \\ \sum_{i=0}^m x_i & \sum_{i=0}^m x_i^2 & \cdots & \sum_{i=0}^m x_i^{n+1} \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{i=0}^m x_i^n & \sum_{i=0}^m x_i^{n+1} & \cdots & \sum_{i=0}^m x_i^{2n} \end{bmatrix}\begin{bmatrix} a_0 \\ a_1 \\ \cdots \\ \cdots \\ a_n \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^m y_i \\ \sum_{i=0}^m x_jy_i \\ \cdots \\ \sum_{i=0}^m x_i^ny_i \end{bmatrix}. \tag{20}$$

4.3 Optimization of model parameters

Due to the significant impact of model parameters on forecasting accuracy, PSO and GA have been adopted to search for the optimal kernel width and initial value of RVM model.

In RVM model, the Gaussian kernel function is adopted as

$$K(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right), \tag{21}$$

where σ is the width of kernel function.

4.3.1 PSO

The applied adaptive function is RMSE. Their speed and location are updated using following functions:

$$v_{i,d}^{k+1} = \omega v_{i,d}^{k} + c_1 \mathrm{rand}()\left(pb_{i,d}^{k} - x_{i,d}^{k}\right) + c_2 \mathrm{rand}()\left(gb_{i,d}^{k} - x_{i,d}^{k}\right), \tag{22}$$

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1}, \tag{23}$$

where c_1 and c_2 are learning factors; rand() is the uniform random number [0,1]; $v_{i,d}^{k}$ and $x_{i,d}^{k}$ are the speed and location of the ith particles in the kth iteration in d-dimension; $pb_{i,d}^{k}$ and $gb_{i,d}^{k}$ are, respectively, the individual best location and group best location of the ith particle in d-dimension; ω is the inertial weight factor [22].

In this case, the scale of particle swarm is 30; iteration number is 200; the learning factors are both 2.05; the inertial weight factor is within the scope of (0.4, 0.9).

4.3.2 GA

The steps of a GA process contain initialization, fitness function calculation, selection, crossover, and mutation.

Initialization: GA randomly generates initial model parameters. The population scale N is generally between 20 and 100.

Fitness function calculation: Fitness function is to evaluate the individual fitness.

Selection: GA operates roulette algorithm to select the chromosome of population according to individual fitness. The winning individuals survive and pass their reproductive information down to a new population.

Crossover: the chromosomes in every two individuals are randomly exchanged at crossover probability P_c. Normally, the scope of crossover probability is (0.6, 1.0).

Mutation: each individual chromosome changes one or several genes at probability of P_m to keep population diversity and to improve the searching ability. The scope is usually (0.005, 0.01).

GA seeks to maximize the fitness of the population by selecting the fittest individuals. The iteration would not terminate until the individuals reach their own maximum fitness. Otherwise GA process would circulate from ''Selection'' step [23, 24].

In this case, the initial population scale *sizepop* is 100; the genetic generation number Ngen is 300; the probabilities of crossover and mutation are $P_c = 0.7$ and $P_m = 0.005$, respectively.

4.4 An intuitive explanation

The training samples' accuracy has a clear relationship with the accuracy of the wind power deterministic forecasting. This motivates us to use the most ''relevant'' NWPs to predict using a very limited size of training samples. Moreover, it is possible to obtain the potential wind power fluctuation interval under a certain confidential level or nominal coverage rates according to RVM theory. Or, it is also possible to "dress" every deterministic forecasting power with its corresponding forecasting intervals under different confidential level which is referred as predictive density, only if various confidential levels are set.

5 Case study

5.1 Evaluation

To evaluate the performance of proposed models, two RVM-based models optimized by GA and PSO (GA–RVM and PSO–RVM) are compared with forecasts based on SVM and an ANN optimized by GA (GA–ANN) in terms of forecast accuracy, model complexity, and running time. For comparability, all methods use the same input variables, training samples, and test samples. Note that SVM and RVM-based model utilizes monthly samples, while the GA–ANN trains the models with yearly samples due to its demand for much larger training data sets.

A frequently used error criterion is adopted for the comparisons: RMSE as shown in equation in [10]. It can give a more representative evaluation of the prediction error over an extended time period.

5.2 Analysis and discussion

A least squares method with three orders polynomial is applied to correct raw NWP data in order to reduce systematic error. Mean wind speed is the assessment item of the proposed module. Data from 1 to 15 in each month are used as training samples, while 16 to the end of each month as the test samples. The results show in Fig. 3 that in most months, the statistic characteristic of NWP data would be more close to the actual situation.

Figure 4 shows the full-year forecasting accuracy of SVM, GA–ANN, and RVM-based model. In general, RMSE of the predictions provided by two RVM-based models is considerably lower than that of SVM and GA–ANN. Moreover, the yearly average RMSE of GA–RVM in three wind farms is less than that of PSO–RVM by about 3.5 %, 6.7 %, and 3.3 %. Meanwhile, the RMSE of GA–RVM is less than that of SVM by about 24.2 %, 24.2 %, and 20.1 %. It reveals impressive performance for the RVM-based models in wind power prediction, especially the forecasting ability of RVM with GA optimization technique.

Figures 5, 6, and 7 show the interval forecasting results at 90 % confidence level on 4 days from different seasons. The interval forecasting calculates the possible power

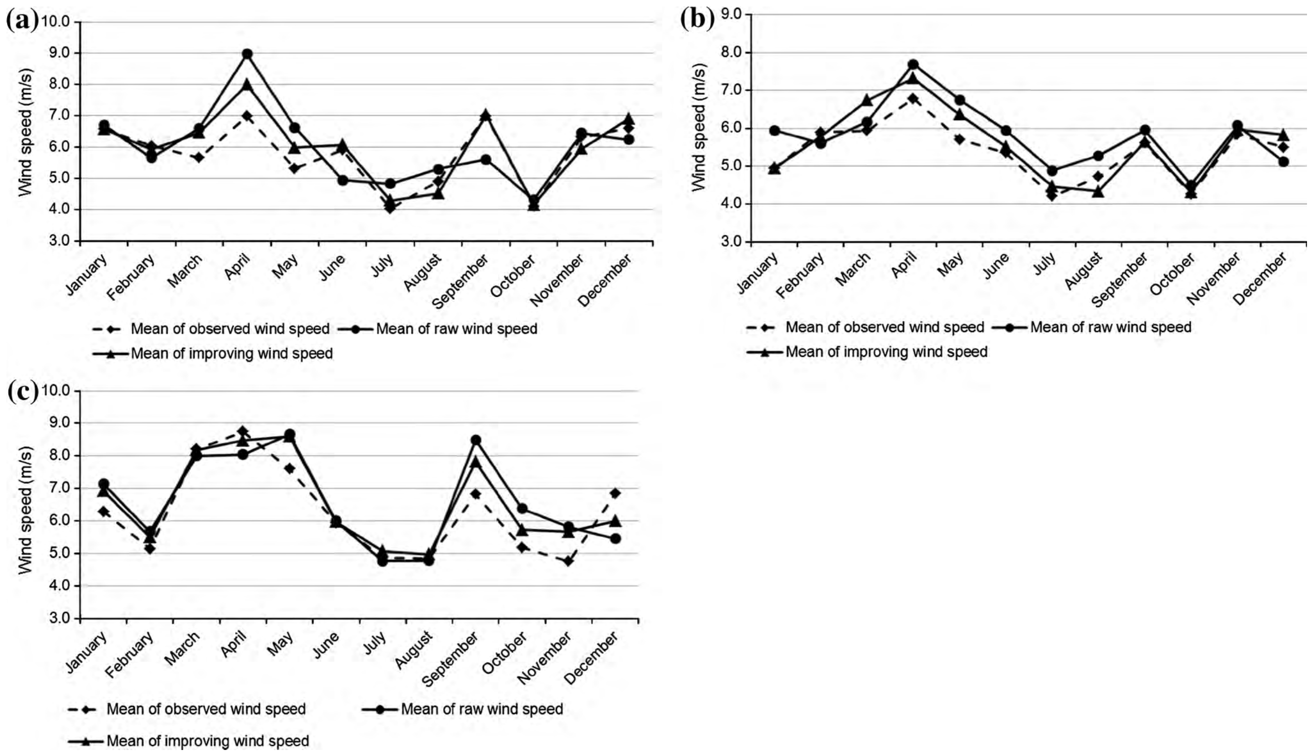

Fig. 3 Correction of NWP wind speed in 3 wind farms. **a** Results in wind farm 1#. **b** Results in wind farm 2#. **c** Results in wind farm 3#

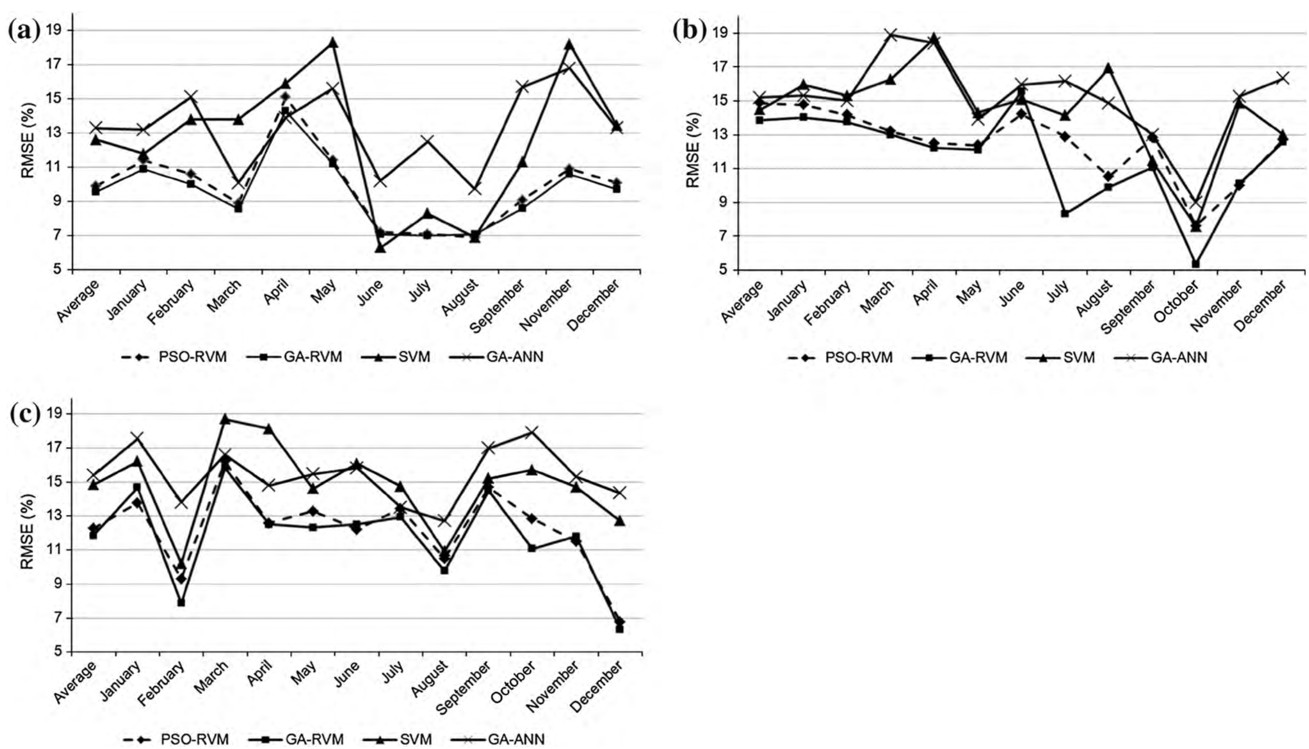

Fig. 4 Comparisons of forecasts accuracy for each month. **a** Forecasting results in wind farm 1#. **b** Forecasting results in wind farm 2#. **c** Forecasting results in wind farm 3#

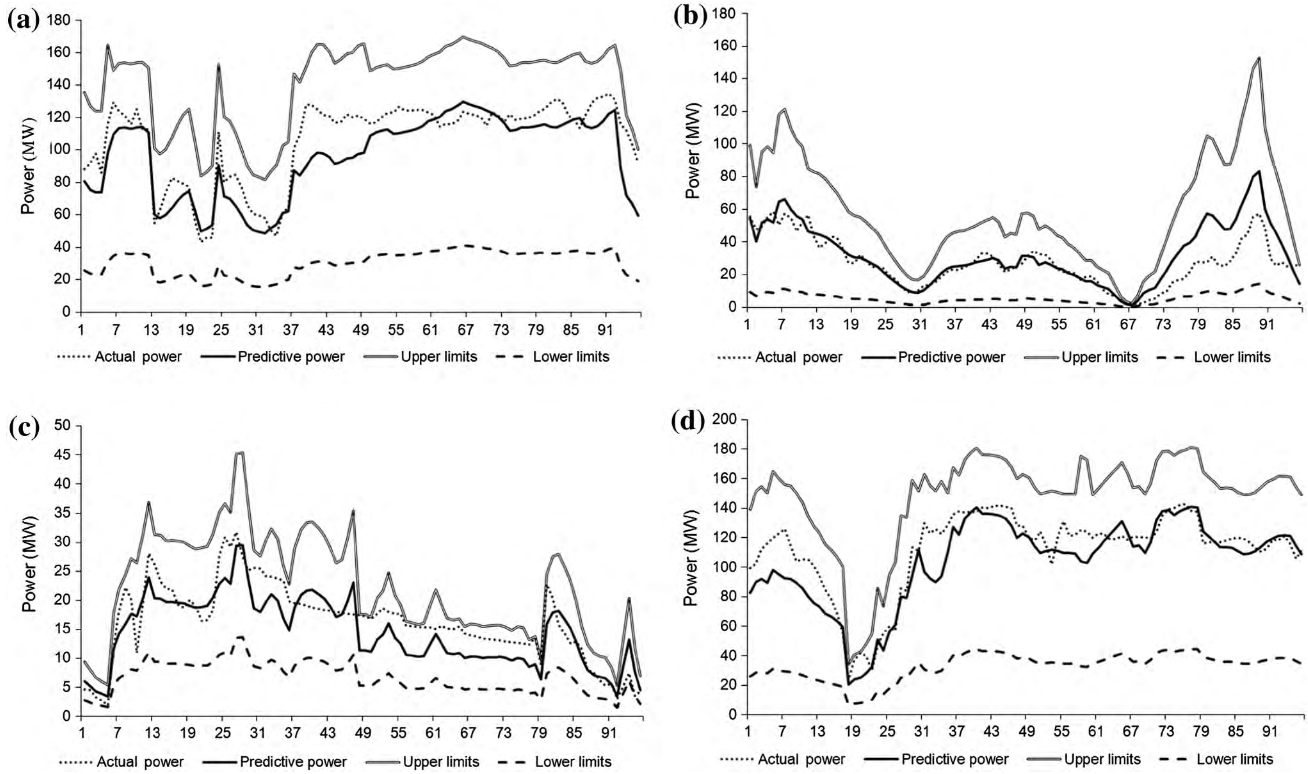

Fig. 5 Interval forecast results in wind farm 1#. **a** Results on March 25. **b** Results on September 26. **c** Results on August 25. **d** Results on December 24

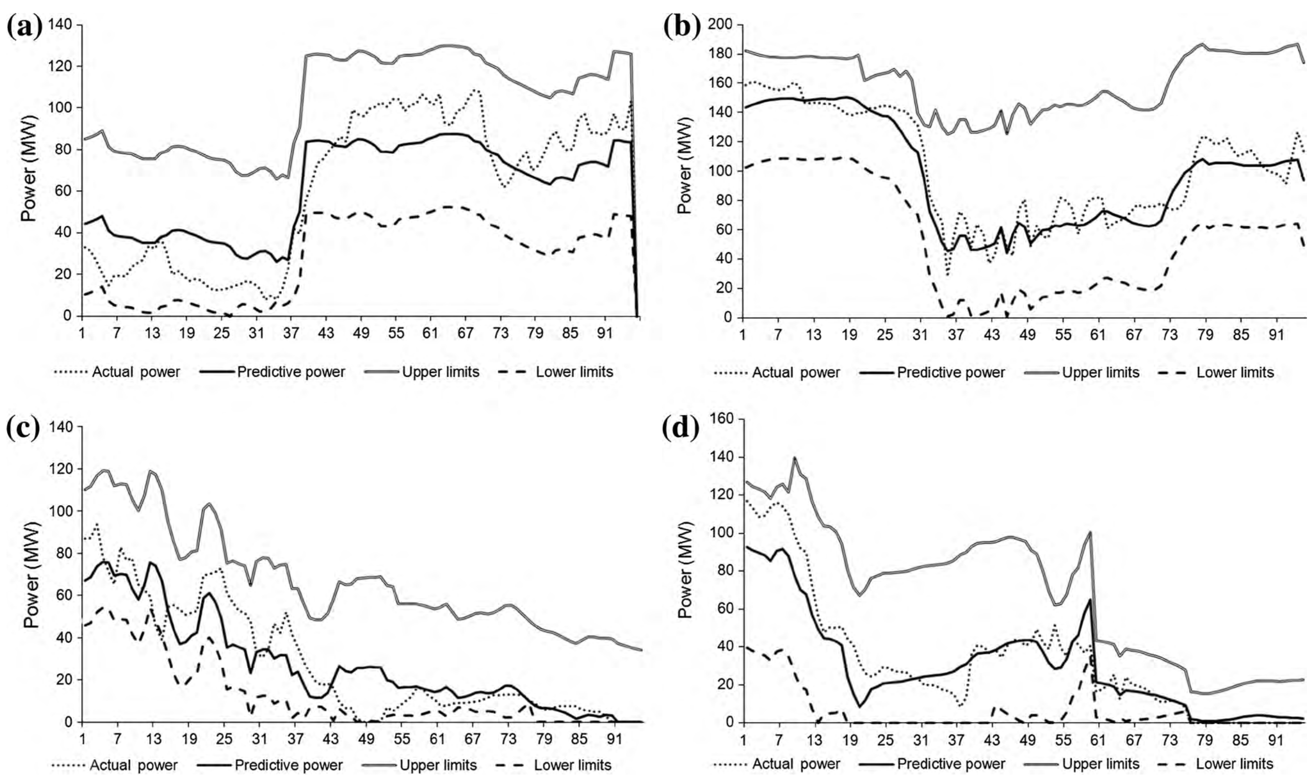

Fig. 6 Interval forecast results in wind farm 2#. **a** Results on January 22. **b** Results on April 30. **c** Results on July 27. **d** Results on November 24

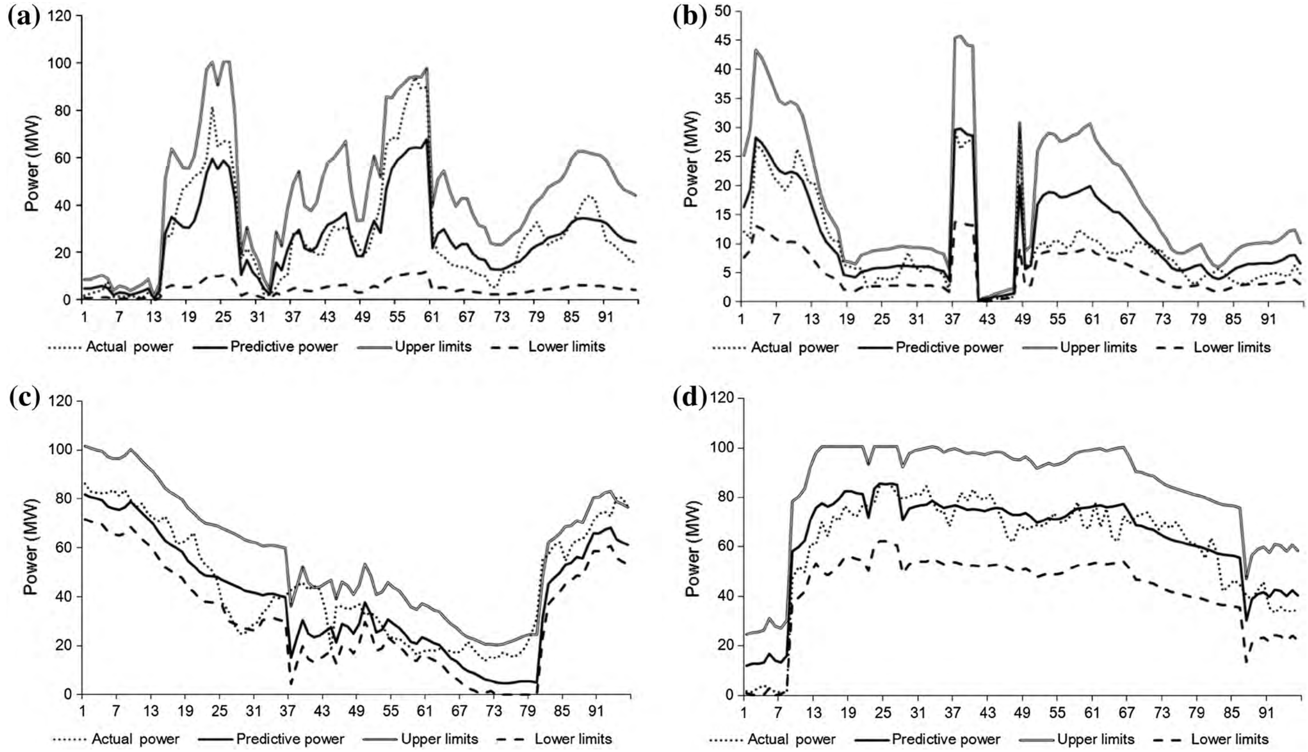

Fig. 7 Interval forecast results in wind farm 3#. **a** Results on May 25. **b** Results on August 23. **c** Results on October 24. **d** Results on December 18

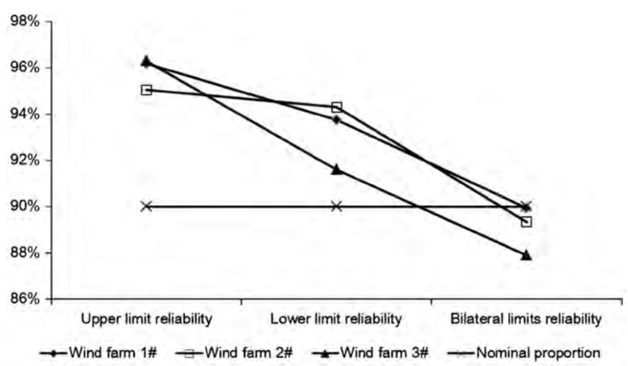

Fig. 8 Reliability of the uncertainty estimates

range at a given confidential level instead of one power value in deterministic forecasting. If the actual power is outside of this power range, then the uncertainty analysis is questionable. Figure 8 draws the proportions of unquestionable results in three wind farms. The upper (or lower) limit reliability means the percentage of the actual power below (or above) the upper (or lower) limits. The bilateral limits reliability demonstrates the overall reliability which shows the percentage of the actual power between the upper limits and the lower limits. It is clear to see from the figure that the upper reliability is higher than the lower reliability. It makes sense because it helps minimize the allocated reserves, and the overall reliability is around the nominal 90 % confidence level which validates the proposed model.

Table 1 Comparisons of computational efficiency and vector number for each model

	Training time (s)	Test time (s)	Number of vectors involved
PSO–RVM	15.33	0.66	86.44
GA–RVM	29.16	0.73	90.35
SVM	14.94	0.71	100.12
GA–ANN	384.17	4.18	–

Note: 2.79 GHz processor with 3.12 GB RAM

As for the intervals of the forecasts, it is reasonable if the interval is slightly larger than the prediction error, because it could reflect the prediction risk and help allocate enough reserves. In three wind farms, there is successively 52 %, 75 %, and 41 % of all forecast intervals in the range 0–20 MW. Only 3.2 %, 4.5 %, and 6.2 % of forecast intervals are over 60 MW which economically saves reserves even if the prediction errors are very large. The proposed model generally covers the prediction error and gives consideration to risk resistance and economical operation.

The computational efficiency is measured with three wind farms in question. The average results are presented in Table 1. Two RVM-based models cost less running time and have fewer vectors, especially for PSO–RVM model. It shows efficient preference of PSO for online or ultra-short-term operation. Besides, it seems that GA sacrifices some running time for higher accuracy which is advantageous for short-term forecasting.

6 Conclusions

In this paper, wind power interval prediction model is established based on RVM theory considering NWP accuracy. There are three wind farms in China used to validate the superiority of the proposed model and the parameter optimization techniques in terms of forecasts accuracy and the running efficiency. An LS-based model is first applied to improve the raw NWP wind speed data. The results show that the improving NWP data could reflect the actual wind speed statistical characteristics more accurately. Besides, GA and PSO algorisms are, respectively, employed to optimize the model parameters to further improve the accuracy of the power forecasts. The performance of GA–RVM and PSO–RVM are compared to that of GA–ANN and SVM. Both RVM-based models outperform SVM and GA–ANN in terms of prediction accuracy (by about 22 % to SVM). The full-year average RMSE of GA–RVM is less than that of PSO–RVM in these three cases revealing better forecasts ability of GA technique. Meanwhile, PSO–RVM is of preference as for running efficiency compared to that of GA–RVM which is advantageous to on-line or ultra-short term operation, while GA seems to more fit in short-term forecasting. In summary, the improvement of the raw NWP wind speed and two optimization techniques could enhance prediction accuracy and practicality.

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