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# Short-term wind power prediction based on IBOA-AdaBoost-RVM

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ABSTRACT

This study introduces an innovative model, namely IBOA-AdaBoost-RVM, which leverages the Improved Butterfly Optimization Algorithm (IBOA), Adaptive Boosting (AdaBoost), and Relevance Vector Machine (RVM). This model is used to solve the problem of low precision of wind power prediction. Initially, normalization is applied to reduce the influence of varying data dimensions. Subsequently, input variables are determined through the Pearson correlation method. Lastly, the efficacy of the introduced model is assessed across four distinct seasonal monthly data sets. The observed outcomes indicate that the proposed model outperforms other models in terms of evaluation metrics, with the average $R^2$, *RMSE*, *MAE*, and *MAPE* values across the four datasets being 0.954, 10.403, 7.032, and 0.645, respectively, show that the proposed method has potential in the field of wind power prediction.

## 1. Introduction

The surge in worldwide economic growth coupled with a steady increase in population figures has led to a growing need for energy, historically satisfied by the consumption of fossil fuels (He et al., 2024a). However, the widespread utilization of conventional energy sources in recent years has engendered increasingly severe issues such as environmental degradation and climate change (Abou et al., 2023). Consequently, promoting the development of clean energy has become a global consensus. Clean energy refers to forms of energy production and utilization that generate minimal to no pollutants, with wind energy being a notable example. Owing to its renewable nature, environmental friendliness, and abundant availability, the advancement of wind power has garnered significant attention worldwide (Tan et al., 2024).

Numerous researchers have explored various methodologies to strengthen the exactness of short-term wind power prediction, including physical, statistical, and artificial intelligence methods (Carpinone et al., 2015). While physical prediction methods necessitate solving complex partial differential equations, rendering them computationally intensive (Ye et al., 2017), statistical methods entail simpler modeling through statistical regression fitting of historical data but exhibit significant prediction errors when confronted with nonlinear and non-stationary wind power series (Sopeña et al., 2023). Artificial intelligence, particularly deep learning methods rooted in machine learning, has arisen as a promising avenue [Sait et al., 2024a]. Techniques like Convolutional Neural Networks (CNN) [Sait et al., 2024b; Ma et al., 2024] and Recurrent Neural Networks (RNN) [Mehta et al., 2024; Yuan et al., 2024a] within deep learning have gained extensive usage in the field of short-term wind energy forecasting.

In the field of machine learning, bias-variance tradeoff is a significant concept to explain the generalization effectiveness of an algorithm (Doroudi and Rastegar, 2023). The emergence of ensemble learning makes it possible to guarantee good generalization performance on complex monitoring data of wind power. As one of the popular ensemble learning algorithms, the AdaBoost algorithm stands out for its capacity to mitigate bias and variance by combining multiple weak learners, thereby improving the model's capacity for generalization. The adaBoost method has been commonly applied in various fields and has shown excellent capabilities in classification and regression problems (Zounemat-Kermani et al., 2021). An et al. (2021) introduced a wind

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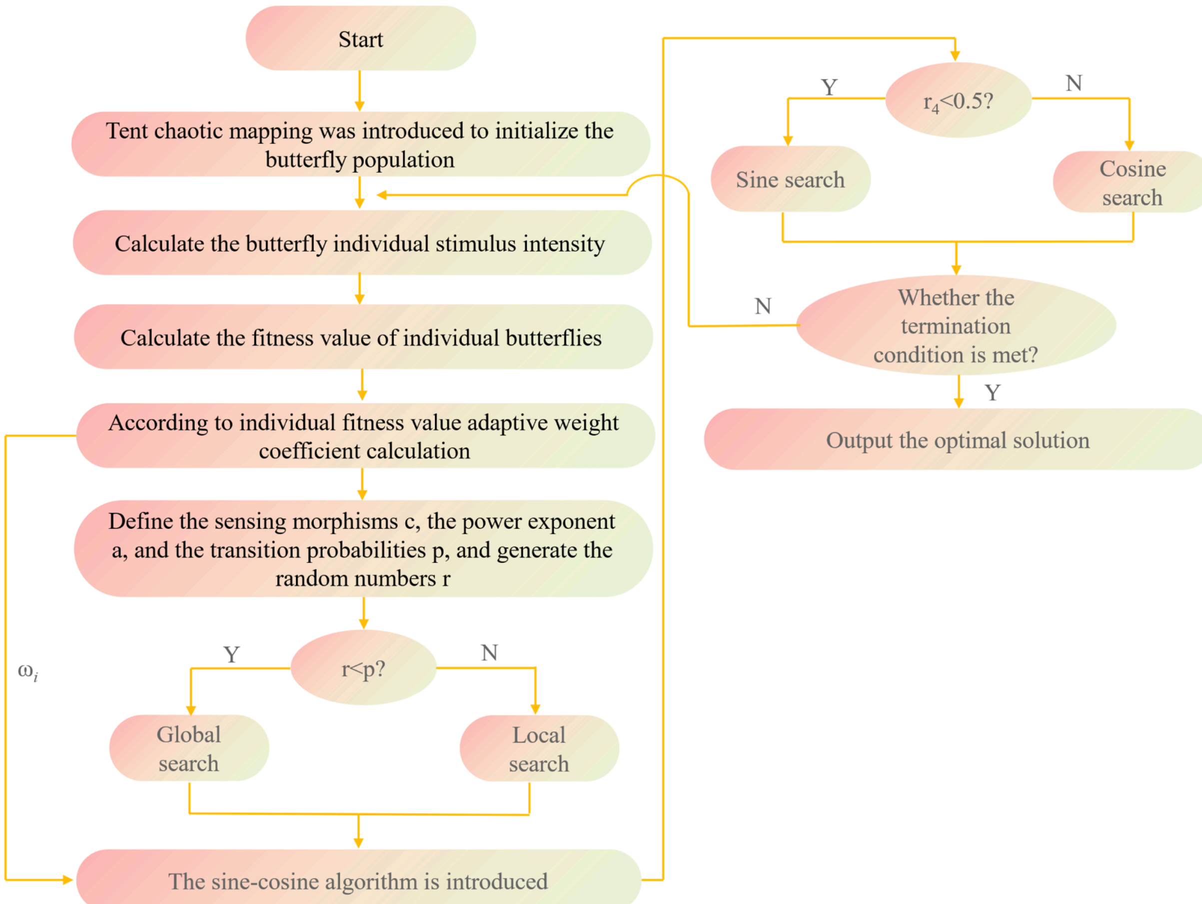


**Fig. 1.** IBOA frame diagram.

power forecasting model (AdaBoost-PSO-ELM), and verified it through the data of wind turbines in Turkey. The findings from the experiment indicate that AdaBoost-PSO-ELM achieves a superior accuracy rate. Ren et al. (2022) introduced an improved genetic algorithm-assisted AdaBoost double-layer learner (GA-ADA-RF) for predicting the oil temperature of tunnel boring machines, and the experiment revealed that the GA-ADA-RF has better predictive capability.

While the aforementioned evidence highlights the efficacy of the AdaBoost algorithm, it also underscores its inherent limitations, notably susceptibility to overfitting and its constrained capability to address nonlinear challenges (Vincent and Duraipandian, 2024). Hence, this study introduces the Relevance Vector Machine (RVM) as a solution to mitigate these drawbacks. RVM, a variant of SVM, exhibits inherent sparsity, thereby mitigating overfitting during training (Qiu et al., 2024). Furthermore, RVM's utilization of kernel functions enables effective handling of nonlinear problems, thereby compensating for AdaBoost's deficiencies.

Given the AdaBoost algorithm's capacity to diminish both variance and bias while enhancing model generalization, coupled with the intrinsic strengths of RVM that can compensate for AdaBoost's limitations, this research integrates RVM as a weak learner within the AdaBoost framework to advance model efficacy. Moreover, the selection of hyperparameters holds paramount importance in influencing the performance of machine learning algorithms, with an optimal combination significantly enhancing model performance. Swarm intelligence optimization algorithms, simulating population hunting behaviors in nature, demonstrate remarkable prowess in optimizing hyperparameters and are frequently employed for this purpose (El-Kenawy et al., 2024a; Yuan et al., 2023a; Abdollahzadeh et al., 2024; Yuan et al., 2024b). However, swarm intelligence algorithms frequently suffer from the drawbacks of a skewed distribution in the initial population and a tendency to converge to local optima rather than global solutions (El-Kenawy et al., 2024b; Duzgun et al., 2024; Chu et al., 2024). Therefore, this study proposes an improved butterfly optimization algorithm to determine the best combination of hyperparameters for the prediction model.

## 2. Related algorithms

### 2.1. Adaptive boosting (AdaBoost)

AdaBoost is a renowned ensemble algorithm (Freund and Schapire, 1997). During each iteration, AdaBoost adjusts the weight of individual samples, assigning higher weights to previously misclassified samples to emphasize their importance in subsequent iterations. Consequently, the new learner focuses more on these challenging instances. Ultimately, AdaBoost combines these learners through weighted voting to yield predicted sample values, thereby enhancing the overall learner's performance.

### 2.2. Relevance vector machine (RVM)

RVM, a machine learning algorithm rooted in Bayesian theory (Tipping, 2001), serves as a sparse probability model utilized for both classification and regression analyses. Notably, the sparsity of the RVM algorithm is a key characteristic: during training, most weights tend towards infinity, effectively nullifying the contribution of corresponding features to the model. Consequently, RVM automatically identifies and emphasizes the most crucial features for the prediction task while disregarding irrelevant ones.

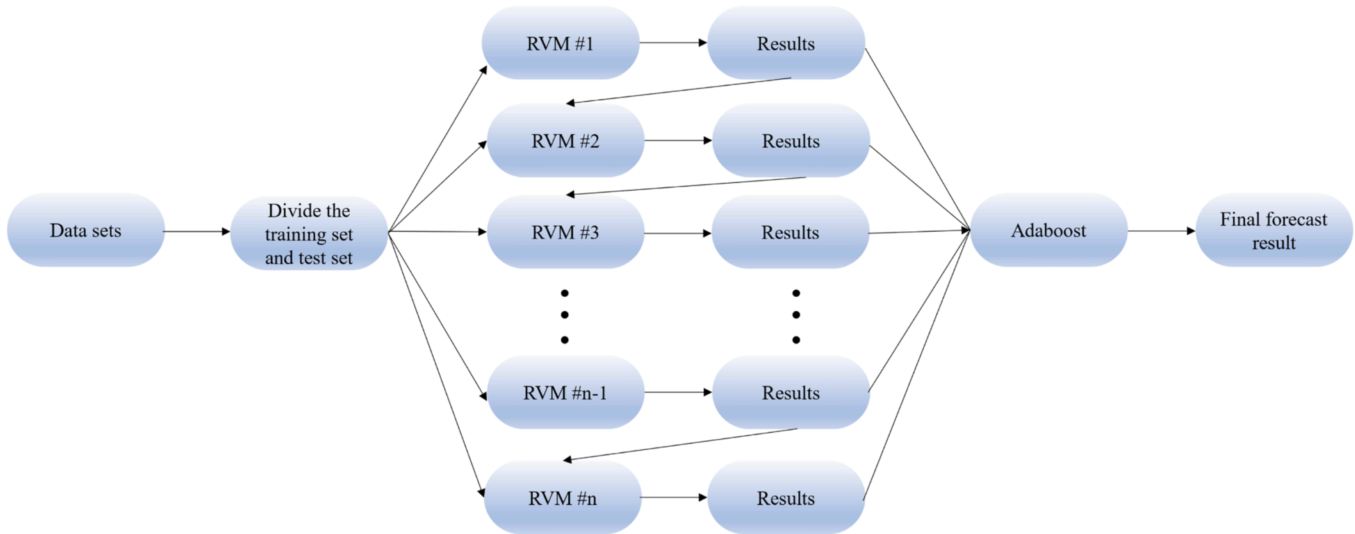


**Fig. 2.** AdaBoost-RVM frame diagram.

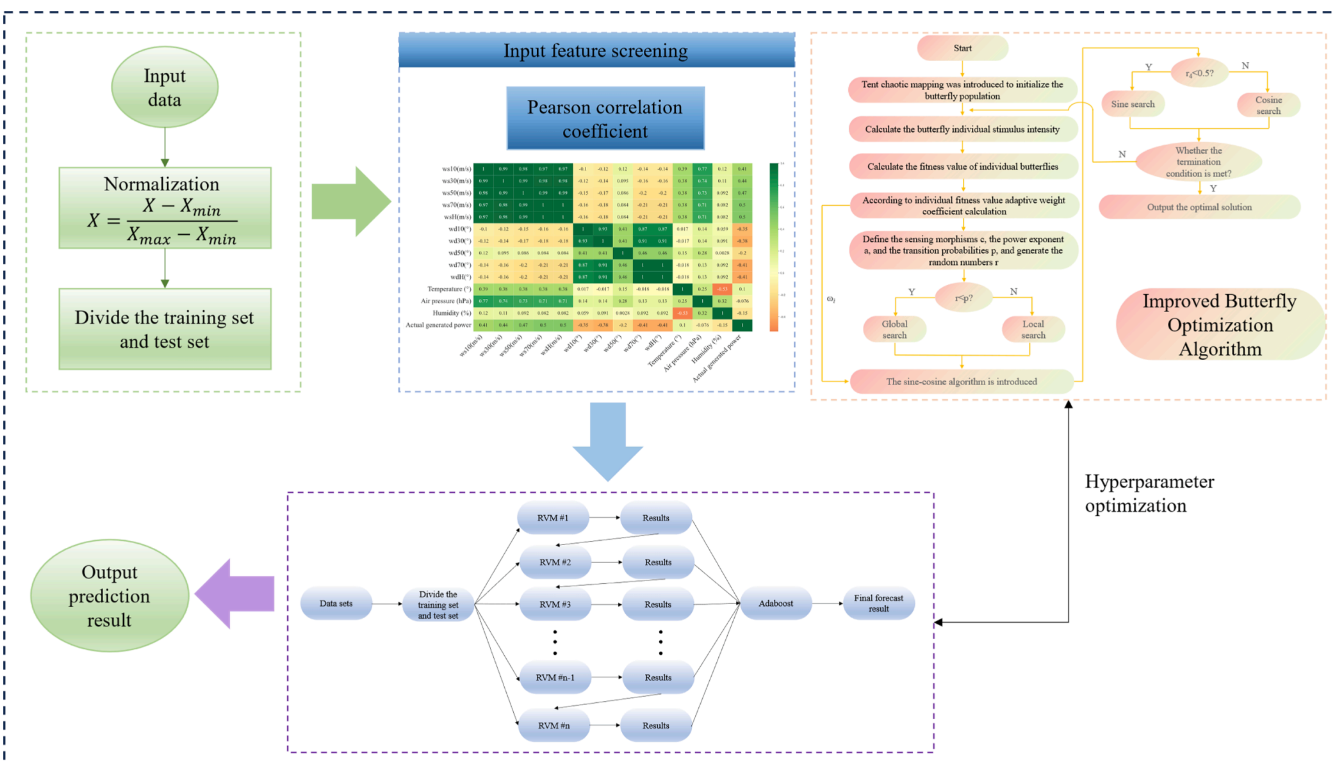


**Fig. 3.** IBOA-AdaBoost-RVM prediction flow chart.

### 2.3. *Butterfly optimization algorithm (BOA)*

Butterfly optimization algorithm (BOA) (Arora and Singh, 2019) is a *meta*-heuristic algorithm for global optimization inspired by natural heuristics, initially introduced by Arora and Singh in 2019. It emulates the cooperative movement of butterflies towards a food source, a behavior observed in nature. Butterflies navigate by receiving, sensing, and analyzing odors in the air to locate potential food sources or mates.

## 3. The proposed algorithm (IBOA-AdaBoost-RVM)

### 3.1. *Improved butterfly optimization algorithm (IBOA)*

Chaotic mapping, characterized by attributes such as good ergodicity, non-repeatability, unpredictability, and non-periodicity, is leveraged to enrich population diversity and enhance algorithm performance (Peng et al., 2023; Xing et al., 2024). In the original butterfly optimization algorithm, butterfly diversity suffers due to random initialization of the population. Therefore, this study introduces Tent chaotic mapping to uniformly distribute the butterfly population and broaden its search range. It is defined as:

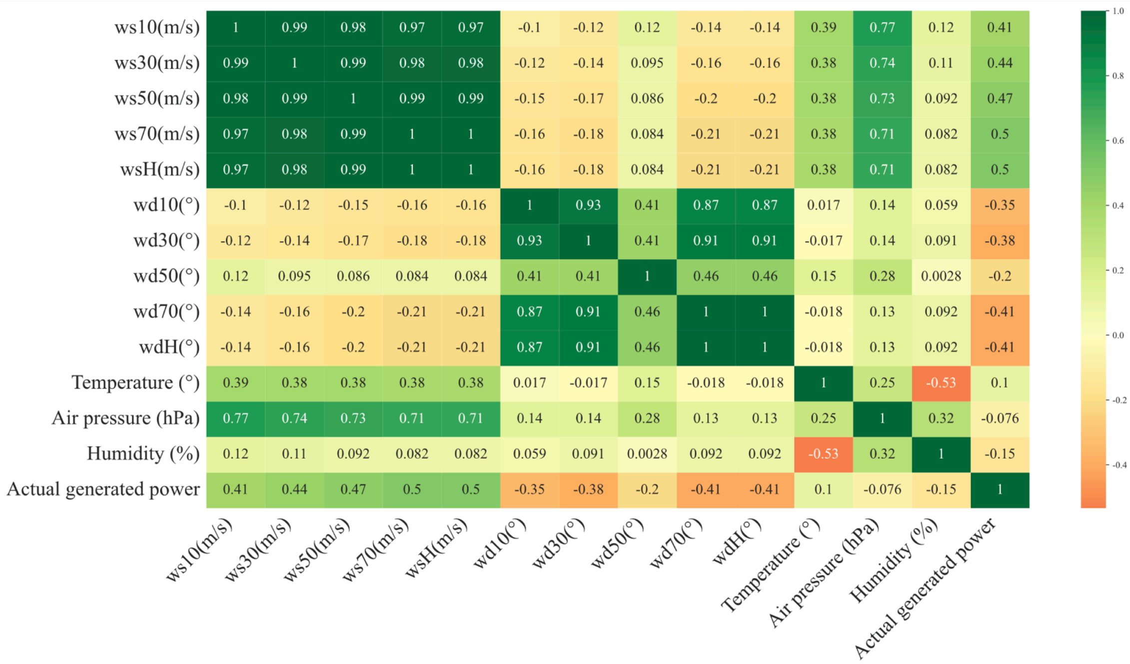


**Fig. 4.** The correlation between various characteristics and actual power generation.

**Table 1**
Partial parameters and abbreviations in the heat map.

| Abbreviations | Parameters |
|---|---|
| ws10 (m/s) | Wind tower 10 m wind speed (m/s) |
| ws30 (m/s) | Wind tower 30 m wind speed (m/s) |
| ws50 (m/s) | Wind tower 50 m wind speed (m/s) |
| ws70 (m/s) | Wind tower 70 m wind speed (m/s) |
| wsH (m/s) | Hub height Wind speed (m/s) |
| wd10 (°) | Wind tower 10 m Wind direction (°) |
| wd30 (°) | Wind tower 30 m Wind direction (°) |
| wd50 (°) | Wind tower 50 m Wind direction (°) |
| wd70 (°) | Wind tower 70 m Wind direction (°) |
| wdH (°) | Hub height Wind direction (°) |

**Table 2**
Evaluation indicators of the forecast results of different models in March.

| | Mdoel1 | Model2 | Model3 | Model4 | Model5 | Model6 |
|---|---|---|---|---|---|---|
| $R^2$ | **0.971** | 0.953 | 0.944 | 0.918 | 0.950 | 0.960 |
| RMSE | **11.060** | 14.167 | 15.366 | 18.604 | 14.437 | 13.076 |
| MAE | **7.047** | 9.300 | 10.197 | 13.479 | 10.341 | 8.821 |
| MAPE | **0.418** | 0.505 | 0.426 | 0.897 | 0.920 | 0.525 |

$$x_{n+1} = f(x_n) = \begin{cases} x_n/a, x_n \in [0,a) \\ (1-x_n)/(1-a), x_n \in [a,1) \end{cases} \tag{1}$$

Where $a \in (0,1)$.

The search step length of a single butterfly is not set in the original BOA algorithm. During the operation of the algorithm, due to the high degree of freedom of individuals, the search step length is not limited, resulting in fast search speed in the early stage of the search, low search accuracy in the late stage, and easy-to-fall into the local optimum or far from the global optimum. To avoid the restriction of butterfly individual search step size due to this situation, this study proposes a weight coefficient that adaptively adjusts according to individual fitness value, and the formula is as follows:

$$\omega_i = \frac{F_b - F_w}{F_i - F_w} \tag{2}$$

where, $F_i$ is the current individual fitness value, $F_b$ and $F_w$ are the current global optimal and worst fitness values, respectively.

If the fitness value of the current individual is nearly equivalent to the worst global fitness, the higher the weight coefficient assigned to that individual, the greater the step size they will take in their movement, aimed at avoiding entrapment in a local optimum. If the current individual fitness value is much different from the global worst value, that is, it is nearer to the global optimal value, then the weight coefficient of the individual is smaller, and the smaller moving step size ensures the high-precision search of the population in the later stage of the algorithm, and avoids the individual skipping the global optimal value, which reduces the performance of the algorithm.

Furthermore, following the "No free lunch" theorem (Rashki and Faes, 2023; Yuan et al., 2023b), a single algorithm cannot be fully applicable to all problems, so this work introduces a sine–cosine algorithm to improve the search phase of butterfly optimization algorithm. Combined with the adaptive weight coefficient, the formula of the global search stage and the local search stage of butterfly optimization algorithm can be updated as:

$$x_i^{t+1} = \begin{cases} \omega_i \times [x_i^t + r_1 \times \sin(r_2) \times |r_3 \times g^* - x_i^t|], r_4 < 0.5 \\ \omega_i \times [x_i^t + r_1 \times \cos(r_2) \times |r_3 \times g^* - x_i^t|], r_4 > 0.5 \end{cases} \tag{3}$$

$$x_i^{t+1} = \begin{cases} \omega_i \times [x_i^t + r_1 \times \sin(r_2) \times |r_3 \times x_j^t - x_k^t|], r_4 < 0.5 \\ \omega_i \times [x_i^t + r_1 \times \cos(r_2) \times |r_3 \times x_j^t - x_k^t|], r_4 > 0.5 \end{cases} \tag{4}$$

where $r_1 = a \times (1 - t/t_{max})$, $a$ is a constant and the value is 2, $t$ is the current number of iterations, $t_{max}$ is the maximum number of iterations, $r_2$ is the random number between 0 and 2 $\pi$, $r_3$ is the random number between 0 and 2, and $r_4$ is the random number between 0 and 1. The flow chart of IBOA is shown in Fig. 1.

### 3.2. *Adaptive boosting based on relevance vector machine (AdaBoost-RVM)*

Traditional AdaBoost uses decision trees as weak learners (Zhan et al., 2024). However, decision tree models are susceptible to overfitting, diminishing the model's generalization capacity, and they have

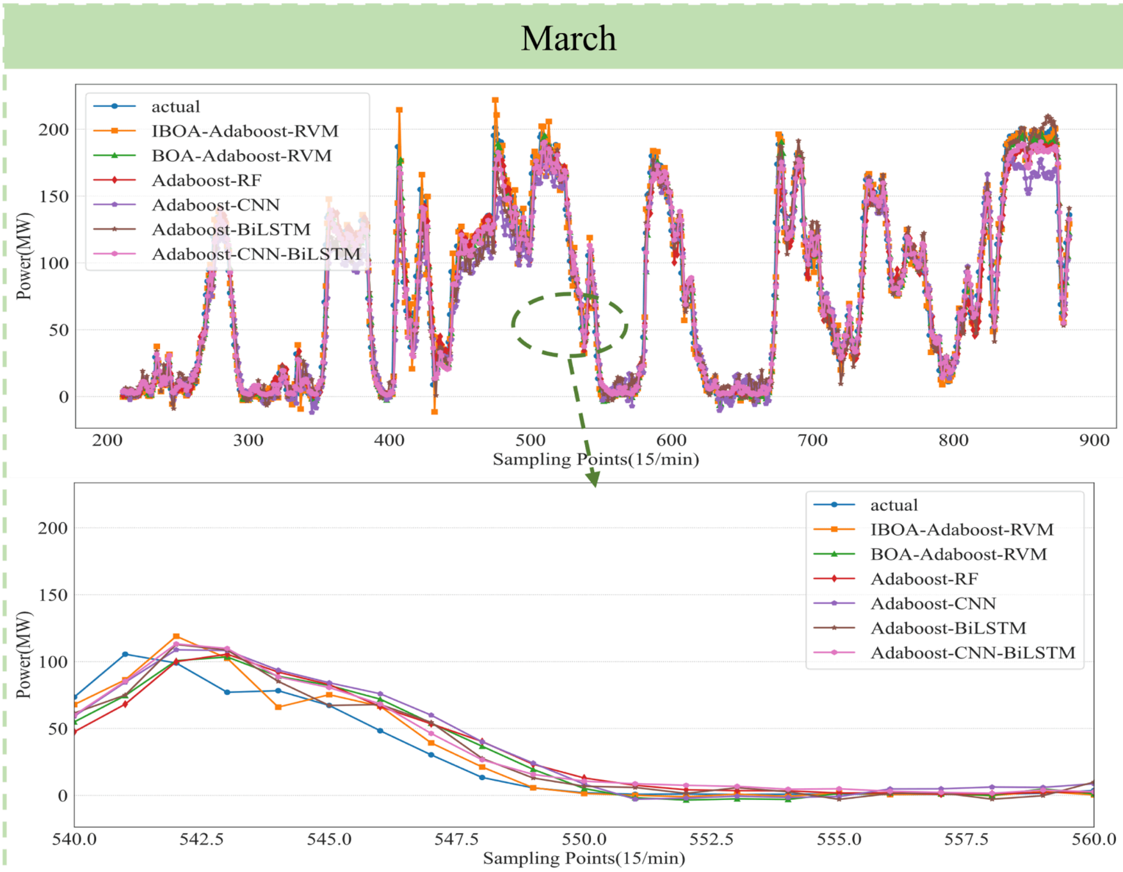


**Fig. 5.** Prediction curves of different models in March.

**Table 3**
Evaluation indicators of the forecast results of different models in June.

| | Mdoel1 | Model2 | Model3 | Model4 | Model5 | Model6 |
|---|---|---|---|---|---|---|
| $R^2$ | **0.962** | 0.943 | 0.902 | 0.900 | 0.940 | 0.948 |
| RMSE | **7.905** | 9.625 | 12.612 | 12.771 | 9.878 | 9.254 |
| MAE | **5.503** | 6.543 | 8.178 | 9.515 | 7.160 | 6.354 |
| MAPE | **0.776** | 0.884 | 1.768 | 1.668 | 1.006 | 0.906 |

limited efficacy in addressing nonlinear problems (He et al., 2024b). The inherent sparsity of the RVM model aids in enhancing the model's generalization ability and mitigating the risk of overfitting. Additionally, RVM can be extended to handle nonlinear problems through kernel techniques, enabling it to tackle more intricate datasets (Zhang et al., 2023). Hence, this study capitalizes on the strengths of both RVM and AdaBoost by utilizing RVM as a weak learner within the AdaBoost framework. The model structure is shown in Fig. 2.

### 3.3. The IBOA-AdaBoost-RVM prediction model

To sum up, the flow of the IBOA-AdaBoost-RVM model introduced in this work is shown in Fig. 3.

Step 1: Acquire the power production data of the wind farm, and normalize the data to prepare for the subsequent research.

Step 2: Calculate the Pearson correlation coefficient of each input and output variable, and select the appropriate input variable.

Step 3: Weather and power data are used for short-term wind power prediction, and the improved butterfly optimization algorithm optimizes the model's hyperparameters.

Step 4: Output final model prediction results.

## 4. Experimental simulation and result discussion

### 4.1. Data description

The dataset comprises measurements taken at a frequency of 15 min. The division between the training and test sets adheres to a ratio of 7:3. The input variables encompass measurements of wind speed, wind direction, temperature, air pressure, and humidity. The validity and reliability of the model are verified by real wind power data. Moreover, to alleviate the impact stemming from the differing scales of the data and augment the precision of the prediction outcomes, this study implements normalization (Hu et al., 2018) as part of the data preprocessing stage.

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

where, $x_i'$ represents the normalized data, $x_i$ represents the original data, $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the original data, respectively.

### 4.2. Input feature selection

The Pearson method is a common way to measure the degree of correlation between two variables (Zhao et al., 2024). From Fig. 4 (refer to Table 1 for details), it is evident that characteristics highly correlated with actual power generation primarily include wind speed and wind direction attributes. Consequently, wind speed and direction characteristics (excluding the 50-meter wind direction of the wind tower) are chosen as input features for the model in this study.

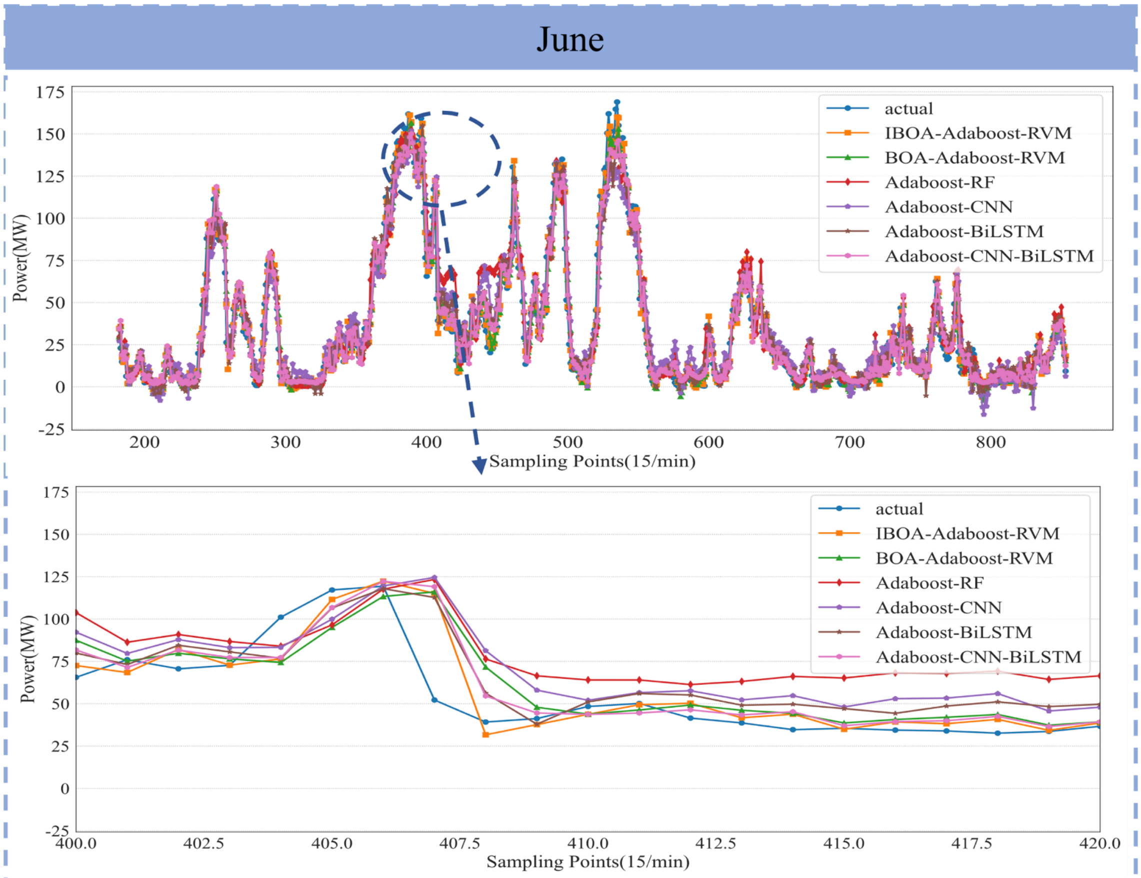


**Fig. 6.** Prediction curves of different models in June.

**Table 4**
Evaluation indicators of the forecast results of different models in September.

| | Mdoel1 | Model2 | Model3 | Model4 | Model5 | Model6 |
|---|---|---|---|---|---|---|
| $R^2$ | **0.961** | 0.926 | 0.915 | 0.909 | 0.932 | 0.931 |
| RMSE | **8.069** | 11.141 | 11.972 | 12.370 | 10.680 | 10.749 |
| MAE | **4.722** | 5.974 | 6.616 | 7.452 | 6.413 | 6.877 |
| MAPE | 0.948 | **0.726** | 0.827 | 1.735 | 1.420 | 1.512 |

### *4.3. Evaluation indicators*

This article selects the coefficient of determination ($R^2$), root mean square error (*RMSE*), mean absolute percentage error (*MAPE*), and mean absolute percentage error (*MAE*) to evaluate the accuracy of the model's prediction results.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i' - y_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i' - y_i}{y_i}\right| \times 100\% \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i' - y_i| \tag{9}$$

where, $n$ is the total number of samples, $y_i'$ is the predicted wind power value, $y_i$ is the actual wind power value, $\overline{y}$ is the average of the actual wind power values.

### *4.4. Experimental comparison*

#### *4.4.1. Experimental comparison in March*

Table 2 displays the results of the four evaluation indicators for the introduced model and other comparative models using the spring March dataset. Furthermore, Model1 to Model6 represent the performance of the following models: IBOA-AdaBoost-RVM, BOA-AdaBoost-RVM, AdaBoost-RF, AdaBoost-CNN, AdaBoost-BiLSTM, and AdaBoost-CNN-BiLSTM, respectively.

Compared with BOA-AdaBoost-RVM, the IBOA-AdaBoost-RVM model exhibits a 1.8 % increase in the $R^2$ value, a 21.9 % decrease in *RMSE*, a 24.2 % decrease in *MAE*, and a 17.2 % decrease in *MAPE*. Furthermore, employing Random Forest (RF), Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory Neural Network (BiLSTM), etc., as weak learners for AdaBoost results in weaker performance across all four-evaluation metrics compared to AdaBoost-RVM. From Fig. 5, it is evident that all six models demonstrate satisfactory fitting results for wind power data in March of spring. Nevertheless, upon closer inspection of the locally enlarged graph, it becomes apparent that the IBOA-AdaBoost-RVM model exhibits the most favorable fitting effect, closely aligning with the actual wind power values.

#### *4.4.2. Experimental comparison in June*

Table 3 shows four evaluation indicators of different models on the summer June data set. The four evaluation indicators of the introduced method outperformed the comparative models, with the $R^2$ values increasing by 2.0 %, 6.7 %, 6.9 %, 2.3 %, and 1.5 %, respectively. Additionally, the *RMSE* values decreased by 17.9 %, 37.3 %, 38.1 %, 19.9 %, and 14.6 %, while the *MAE* values decreased by 15.9 %, 32.7 %,

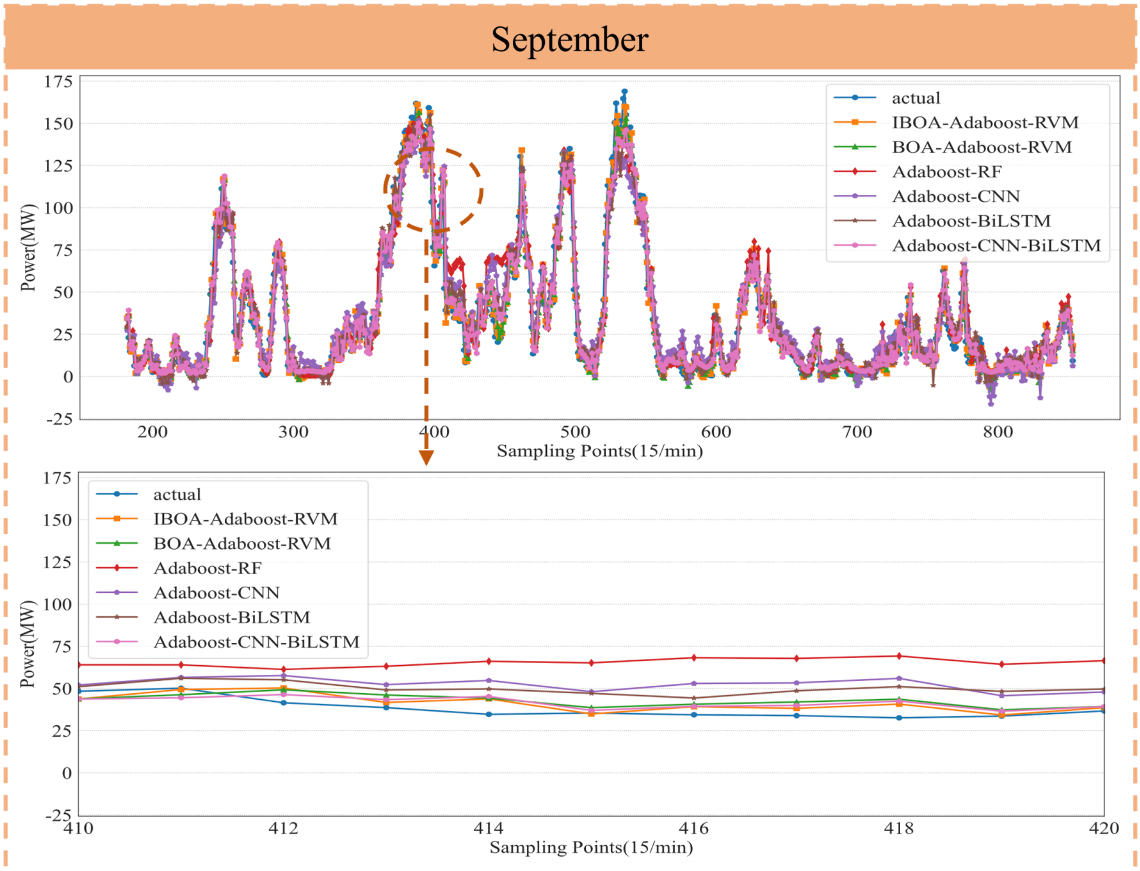


**Fig. 7.** Prediction curves of different models in September.

**Table 5**
Evaluation indicators of the forecast results of different models in December.

| | Mdoel1 | Model2 | Model3 | Model4 | Model5 | Model6 |
|---|---|---|---|---|---|---|
| $R^2$ | **0.920** | 0.910 | 0.757 | 0.853 | 0.891 | 0.819 |
| RMSE | **14.576** | 15.383 | 25.410 | 19.763 | 16.988 | 21.897 |
| MAE | **10.854** | 11.371 | 17.140 | 14.976 | 12.811 | 16.259 |
| MAPE | **0.438** | 0.499 | 0.811 | 0.585 | 0.521 | 0.619 |

42.2 %, 23.1 %, and 13.4 %, and the *MAPE* values decreased by 12.2 %, 56.1 %, 53.5 %, 22.9 %, and 14.3 %, respectively. Fig. 6 provides further support for the proposed improvement strategy and demonstrates the accuracy of the proposed model.

#### 4.4.3. *Experimental comparison in September*

As depicted in Table 4, on the autumn September dataset, the $R^2$, *RMSE*, and *MAE* values of IBOA-AdaBoost-RVM outperform those of the comparison model. Although the proposed method did not achieve optimal results for all four-evaluation metrics, BOA-AdaBoost-RVM obtained the optimal *MAPE* value. This outcome further substantiates the feasibility of utilizing RVM as a weak learner for AdaBoost in this study. Moreover, upon examining the image in Fig. 7, it was observed that the introduced method can better capture the trend of changes in true values.

#### 4.4.4. *Experimental comparison in December*

As can be seen from Table5, among the six models, only the $R^2$ values of IBOA-AdaBoost-RVM and BOA-AdaBoost-RVM exceed 0.9, with BOA-AdaBoost-RVM reaching 0.92. When compared to AdaBoost-RF, the proposed method demonstrates a 21.5 % increase in $R^2$ value, a 42.6 % reduction in *RMSE*, a 36.7 % decrease in *MAE*, and a 45.9 % decrease in *MAPE*. This further underscore the advanced nature of the method proposed in this study. Fig. 8 provides additional evidence supporting this conclusion.

## 5. Conclusions

In this study, an innovative model, named IBOA-AdaBoost-RVM, is proposed. The performance of the IBOA-AdaBoost-RVM is verified by four distinct seasonal monthly data sets. Results demonstrate that IBOA-AdaBoost-RVM achieves high forecasting accuracy. The model's prediction results across four different seasons and months consistently yield optimal outcomes, indicative of its robust generalization ability and applicability.

In the future work, data from different geographic locations are considered and compared with more advanced algorithms to further validate the model's excellence. In addition, future studies need to consider applying the model to different forms of renewable energy, such as solar energy, hydrogen energy, and so on.

## CRediT authorship contribution statement

**Yongliang Yuan:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Funding acquisition. **Qingkang Yang:** Writing – original draft, Methodology, Investigation. **Jianji Ren:** Writing – review & editing, Supervision, Resources. **Kunpeng Li:** Writing – review & editing, Supervision, Methodology. **Zhenxi Wang:** Formal analysis, Conceptualization. **Yanan Li:** Supervision, Resources. **Wu Zhao:** Supervision, Formal analysis. **Haiqing Liu:** Resources.

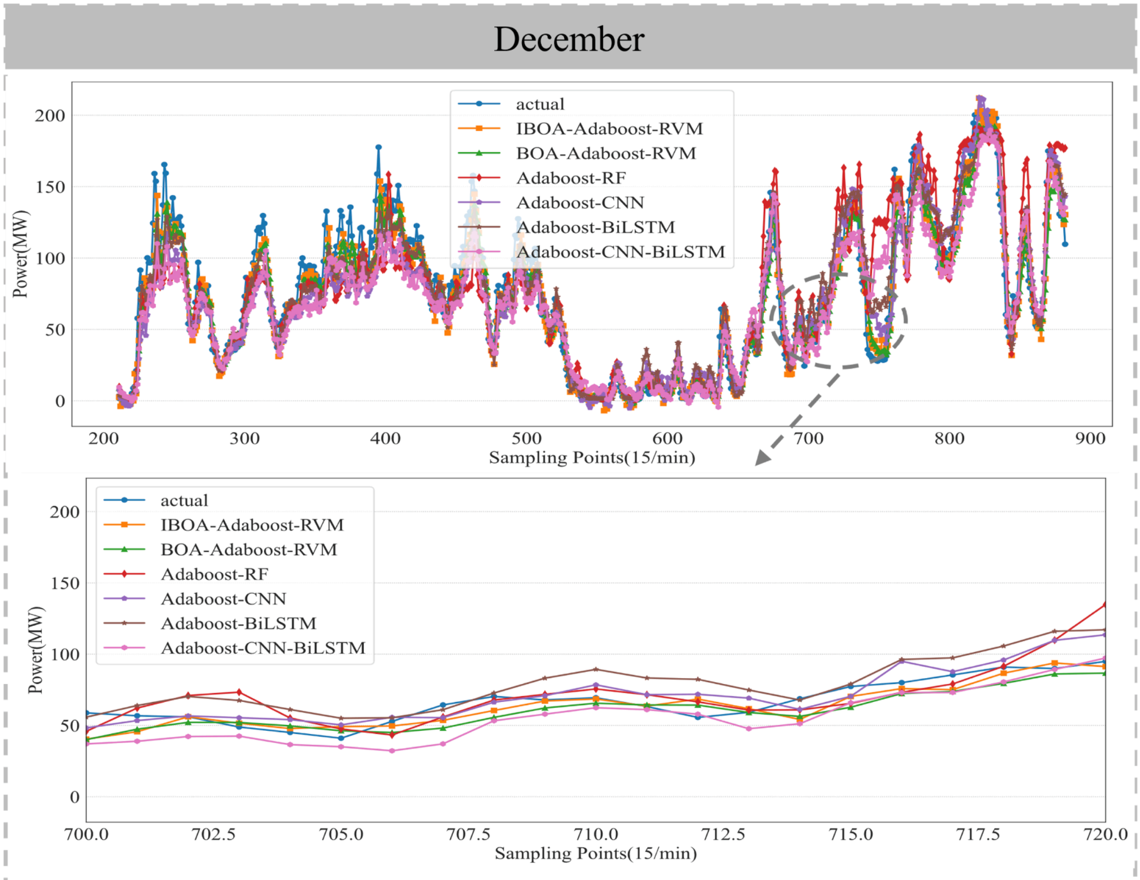


**Fig. 8.** Prediction curves of different models in December.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jksus.2024.103550.

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