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Distribution Characteristics of Ice Thickness on Transmission Lines Based on BWO-SVR

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Abstract. Regarding the distribution characteristics of ice thickness on transmission lines (TLs), the traditional method has poor prediction effect in multi-dimensional and high-noise data, low computational efficiency, and is prone to local optimal solution problems. This paper proposes an enhanced and more accurate analysis method of ice thickness distribution characteristics of transmission lines combined with the BWO-SVR (Beluga Optimization-Support Vector Regression) model. The collected TLs ice thickness data were processed to remove noise data and extract features related to ice thickness. The BWO algorithm was used to optimize the hyperparameters of the SVR model, simulate the beluga whale's predation behavior, achieve global optimal search, and avoid the local optimal problem that may occur in traditional optimization methods. The optimized SVR model was used for multi-level regression analysis to integrate data from different regions and periods to improve the reliability of the prediction. The cross-validation method was used to train the model, and the SVR was adjusted based on the ice thickness distribution characteristics in different areas, so that it can maintain good adaptability in various scenarios. The experimental results show that BWO-SVR has an average MSE (Mean Square Error) of 0.13 mm in the 12-month forecast, with better prediction accuracy. The average inference time under 10 different folds is 14.97 seconds, and the computational efficiency is superior.

Key words. Beluga Whale Optimization, Line Ice Thickness, Support Vector Regression, Thickness Distribution Characteristics, Transmission Lines

1. Introduction

Transmission line icing poses a major threat to the safety of power systems. In cold climates, ice accumulation can greatly increase the load on conductors, leading to line breakage, equipment damage and other accidents [1,2]. Accurately predicting the distribution of TLs icing thickness can help to take preventive measures promptly and reduce power outages and equipment failures caused by icing [3,4]. Machine learning technology has been developing rapidly in recent years, and the use of data-driven prediction methods has become an effective way to solve this problem.

Traditional TLs ice thickness prediction methods are mainly some physical models, empirical formulas or traditional machine learning methods. These methods have many limitations when processing high-dimensional and complex data. The prediction method of physical models uses historical data to determine extreme failure scenarios. The establishment of the model requires a lot of calculations, which is inefficient and lacks detailed descriptions [5,6]. Existing empirical formulas are only applicable to specific regions and specific conditions, lack strong generalization capabilities [7,8], and ignore the impact of regional differences and environmental changes on ice thickness, resulting in low prediction accuracy [9,10]. Among machine learning methods, algorithms such as support vector machines and decision trees have certain regression capabilities, but they perform poorly under high-noise data and multi-dimensional features [11,12]. When faced with complex meteorological data, the model is easily affected by data noise, and the volatility of the prediction results is large [13,14]. Traditional machine learning algorithms require manual feature selection, feature extraction is not comprehensive, and it is easy to miss key feature information, which limits the prediction effect [15,16]. Traditional optimization algorithms such as genetic algorithms and particle swarm optimization can optimize the parameters of the model to a certain extent, but it is not easy to jump out of the local optimal solution and cannot achieve global optimization [17,18]. These existing optimization methods have low computational efficiency when processing larger data sets and are unable to cope with complex ice prediction challenges. Faced with the changing and complex ice prediction requirements, existing methods are difficult to find a balance between accuracy and efficiency, which affects the credibility of the analysis of TLs ice thickness distribution characteristics [19,20]. Given these problems, improving the accuracy of current prediction technology, speeding up calculations and enhancing its adaptability have become key problems that need to be overcome.

This study combines the BWO algorithm with SVR and proposes a new TLs ice thickness distribution prediction method to solve the accuracy and efficiency problems of traditional methods in complex data processing. BWO is used to optimize the hyperparameters of SVR, simulate the predation behavior of beluga whales, enhance the global search ability of the model in high-dimensional and complex data space, and avoid the traditional optimization method from falling into the local optimal solution. The core of the method is to use the optimization process to improve the reliability of prediction, and can effectively predict the ice thickness distribution of TLs in different regions and under different meteorological conditions. The study also focused on data preprocessing and feature extraction. By removing noise data and extracting key features related to ice thickness, more accurate input information was provided to the models. By integrating data from different time periods and regions, the optimized SVR model can better obtain the changing patterns of ice thickness and has stronger adaptability. The model is trained and verified using the cross-validation method, which allows the model to have a certain degree of adaptability in different scenarios, providing an efficient and accurate solution for the prediction of ice thickness in the power system, so as to better cope with the challenges brought by climate change and extreme weather and ensure the safe operation of TLs.

2. Related Work

Research on the distribution characteristics of TLs ice thickness has made some progress, and many scholars are committed to exploring different methods to improve the accuracy of ice prediction. Some studies have proposed ice thickness prediction methods based on support vector machines [21,22], optimized kernel function selection and parameter adjustment, and improved the adaptability of the model to complex data [23,24]. Huang L proposed a transmission line icing prediction model based on the improved Harris Hawks optimization algorithm and the hybrid kernel extreme learning machine. The model has lower error, better prediction effect than other models, and good practicality [25]. Some studies have used multi-layer perceptron neural networks for nonlinear prediction of ice thickness and achieved good results, but due to the large amount of data, they still face the problem of low computational efficiency [26,27]. Some studies have combined meteorological data with machine learning methods to try to improve the accuracy of predictions by fusing multi-source data [28,29]. These methods have achieved certain results, but they rely on a large amount of artificial feature engineering and fail to effectively deal with data noise and local optimal solutions. At present, there is a certain amount of technical accumulation in the prediction of TLs ice thickness, but there is still a lack of an efficient and accurate solution. Further optimization is needed in the processing of high-noise and multi-dimensional data.

To solve the problems of traditional methods, some researchers have tried to combine advanced optimization algorithms with traditional machine learning methods to improve the prediction ability of the model. As an emerging intelligent optimization algorithm, the BWO algorithm [30,31] has been applied to many fields and achieved good results. For example, in simulating the predation behavior of beluga whales, BWO can perform global search in complex optimization space, avoiding the dilemma of traditional optimization methods falling into the local optimal solution, In simulating the predation behavior of beluga whales, BWO can perform global search in complex optimization space, avoiding the dilemma of traditional optimization methods falling into the local optimal solution. Wang Z proposed an improved BWO algorithm for multi-objective capacity optimization of the system, which can reduce the overall cost of the system [32]; however, there are few studies that apply BWO to machine learning of ice thickness characteristics, which provides a new idea for this paper. As a powerful regression analysis tool, SVR [33] has shown excellent performance in many prediction problems. Some studies have combined BWO with SVR to successfully improve the accuracy and stability of system predictions and solve the shortcomings of traditional methods in high-dimensional data [34]. Chen Y proposed an online prediction model for TLs icing load driven by field data, which optimized the kernel function and model parameters of the SVR algorithm and improved the prediction accuracy and generalization. The model performed better than the traditional prediction model in the simulation analysis of actual icing events and can effectively support the deicing and maintenance decision-making of the transmission and transformation system. BWO simulates the predation behavior of beluga whales, optimizes the hyperparameters of the SVR model, and fully considers the high dimensionality and complexity of ice thickness data. Ice thickness data is affected by many factors, and traditional methods are prone to fall into local optimal solutions. BWO effectively avoids this problem through global search, improving the accuracy and generalization ability of the model in complex data. This optimization process improves the accuracy of ice thickness prediction, allowing the BWO-SVR model to better capture the nonlinear relationship between ice thickness and meteorological and line parameters, thereby enhancing the reliability of the prediction. Existing studies lack timeliness and cross-regional adaptability when dealing with TLs ice cover data with time series characteristics. This paper adopts a TLs ice cover thickness distribution analysis method based on the BWO-SVR model to improve the prediction accuracy and computational efficiency of the model.

3. Methods

A. Data Processing and Feature Extraction

Before model training, the collected TLs ice thickness data is processed to remove noise data and extract features related to ice thickness.

1) Data Denoising

The transmission line ice thickness data used in the study comes from the actual transmission line monitoring system. The data is collected from a high-voltage transmission line located in the Siberia region of Russia. The different areas covered by this line experience ice coverage throughout the year, so it was selected as the research object. The ice thickness data is measured by high-precision meteorological monitoring equipment and lidar systems, and the monitoring range covers multiple tower bases and key locations along the transmission line. The lidar system can accurately measure the ice thickness on the surface of the transmission line, and further correct the accuracy of the data by combining meteorological parameters such as temperature and humidity; the ice type is mainly rime ice, which is common in high humidity and low temperature environments and has strong condensation and adhesion. The measurement data is collected regularly on a monthly basis, covering the years 2022-2024, to ensure the comprehensiveness and representativeness of the data. The high precision and timeliness of these data provide a reliable basis for this study and ensure the effectiveness and scientificity of the analysis results.

In the processing of TLs ice thickness data, removing the noise data is a necessary step to improve the accuracy. Noise data mainly comes from sensor errors, external environmental interference, etc. If not processed, it may lead to inaccurate predictions during model training. Here, a noise detection and removal method based on statistical analysis is used.

The mean, variance and distribution characteristics of the data can be analyzed, and the Z-Score method can be used to identify and remove outliers. For each data point, the Z value is calculated:

$$Z_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

x_i is the i th data point, μ is the mean of the data, and σ is the standard deviation; The Z-value threshold is set to 3. When the absolute value of the Z-value of a data point is greater than 3, it is considered an outlier and removed. The selection of this threshold is based on the characteristics of normal distribution, that is, about 99.7% of the data points are within the range of plus or minus 3 standard deviations of the mean, so the data points with an absolute value of Z-value greater than 3 are considered extreme outliers; this method can effectively remove abnormal noise that deviates from most data points and improve the quality of the data.

Wavelet transform is used to filter the noise, wavelet decomposition is performed on the original data, signal components of different frequencies are obtained, a suitable threshold is selected, the high-frequency part is soft-thresholded, the effective signal of the low-frequency part is retained, and the data is reconstructed. The formula is:

$$\hat{f}(t) = \sum_{j=1}^{N} \alpha_j \cdot \psi_j(t) \quad (2)$$

$\hat{f}(t)$ is the denoised signal, α_j is the coefficient of wavelet transform, and $\psi_j(t)$ is the wavelet basis function; this step can significantly reduce the impact of noise and improve the stability and signal-to-noise ratio of the data.

The sliding window method is used to smooth the data, and the sliding window method performs local averaging on the data to remove small fluctuations and reduce the interference of high-frequency noise. The number of windows represents the window size used in the moving average method, that is, the number of data points considered each time the average is calculated. The choice of window size depends on the actual situation of the data. Selecting an appropriate window length allows the smoothed data to maintain the original trend while removing noise.

2) Feature Extraction

Feature extraction is the core step in analyzing the distribution characteristics of TLs ice thickness. Extracting features related to ice thickness can effectively help the model capture the potential laws in the data. This process mainly includes the extraction and fusion of meteorological data and line parameters.

Extract key features such as temperature, humidity, and wind speed from meteorological data. These meteorological factors have an important impact on the formation and development of ice cover. Temperature is an important factor affecting ice cover. Its fluctuation directly determines the thickness of ice cover. The trend of temperature change can be extracted through differential calculation:

$$\Delta T = T_t - T_{t-1} \quad (3)$$

ΔT is the temperature difference, T_t and T_{t-1} are the temperatures at time t and $t-1$ respectively. This feature helps to obtain the impact of temperature fluctuations on ice thickness changes. The combined use of wind speed and humidity can reflect the effect of external climate conditions on ice thickness; the study also introduced the sliding mean and standard deviation of meteorological data to improve the model's expressiveness as a dynamic feature input model.

The extraction of line parameters involves the geometric characteristics and electrical parameters of the line. The height, span, conductor material information and ice accumulation of the line depend on the distribution density. The thermal conductivity of the conductor material affects the heat exchange rate and indirectly affects the thickness of the ice. Reasonable modeling of these physical parameters can provide more accurate feature input for the model.

For the numerical processing of line parameters, the standardization method is used to normalize parameters of different scales to avoid the influence of features of different dimensions on the weight distribution during model training. This processing method ensures the weight balance of different features.

The extraction and fusion of meteorological data and line parameters generated a feature set containing information of multiple dimensions. These features provide reliable input for the subsequent SVR model, helping the model to obtain the nonlinear relationship between different variables, and adopt appropriate feature selection and fusion in multidimensional data to avoid the problem of feature redundancy.

The combined method of data denoising and feature extraction effectively improves data quality and provides a solid foundation for the optimization and prediction of the BWO-SVR model.

B. BWO Algorithm Optimizes SVR Model

1) Simulation of Beluga Whale Predation Behavior and Global Optimal Search

The hyperparameters of the SVR model are optimized and the beluga whale predation behavior is simulated to achieve global optimal search. The beluga whale predation strategies include hunting, chasing and blocking. The behavior simulates the search for the optimal solution in the search space. The BWO algorithm uses the interaction between individuals and groups to guide the search process based on these natural behaviors.

Individuals adjust their position using a series of update formulas as follows:

$$X_i^{t+1} = X_i^t + A \cdot \left| C \cdot X^* - X_i^t \right| \quad (4)$$

X_i^{t+1} represents the updated position of the i th candidate solution in the $t+1$ generation, X_i^t is its position information in the current generation, A is the step factor, C is a constant, and X^* is the position of the current global optimal solution. By controlling the changes in the step factor and the constant, the algorithm can perform local refinement and global exploration in the search space, avoiding the local optimal problem that may occur in traditional optimization algorithms. This method allows the BWO algorithm to effectively guide the search process on a global scale and use the containment strategy to ensure the efficiency of the search.

The algorithm adopts the "cooperative work" mechanism in the beluga whale hunting process, and the accelerated search of multiple candidate solutions can cooperate with each other when close to the optimal solution, which can accelerate the convergence of the optimal solution; the mechanism of the algorithm is realized through the individual distance adjustment and collaborative update formula:

$$\mathrm{W}_i^{t+1} = X_i^t + \beta \cdot \left(X_j^t - X_i^t \right) \quad (5)$$

β is the adjustment factor, and X_j^t is the solution adjacent to the individual i position. This collaborative adjustment mechanism allows multiple solutions to converge to the global optimal solution together, improving search efficiency.

2) SVR Hyperparameter Optimization and Prediction Performance Improvement

In the stage of the BWO algorithm optimizing the SVR model, the optimization of hyperparameters plays a key role; using the BWO algorithm can effectively improve the prediction accuracy. The algorithm initializes each hyperparameter and updates according to the search mechanism of the algorithm in each iteration period. The hyperparameters in SVR use the following objective function to measure the model performance:

$$f(X) = \frac{1}{N} \sum_{i=1}^{N} \left| y_i - \hat{y}_i \right| + \lambda \cdot \sum_{k=1}^{M} \left| w_k \right| \quad (6)$$

y_i is the actual value, $\hat{y}_i$ is the predicted value, λ is the regularization factor. The objective function comprehensively considers the prediction error and complexity, adjusts C and gamma, and the algorithm seeks the optimal solution that can minimize the objective function in each iteration. In SVR, C controls the error tolerance, and gamma affects the complexity of nonlinear mapping. Correctly optimizing these hyperparameters plays a significant role in improving prediction accuracy.

The BWO algorithm allows the model to globally search for appropriate hyperparameter values, avoiding the local optimality problem that may be encountered in traditional grid search and random search methods. The BWO algorithm continuously optimizes parameters through multiple iterations and collaborative mechanisms, gradually approaching the optimal solution.

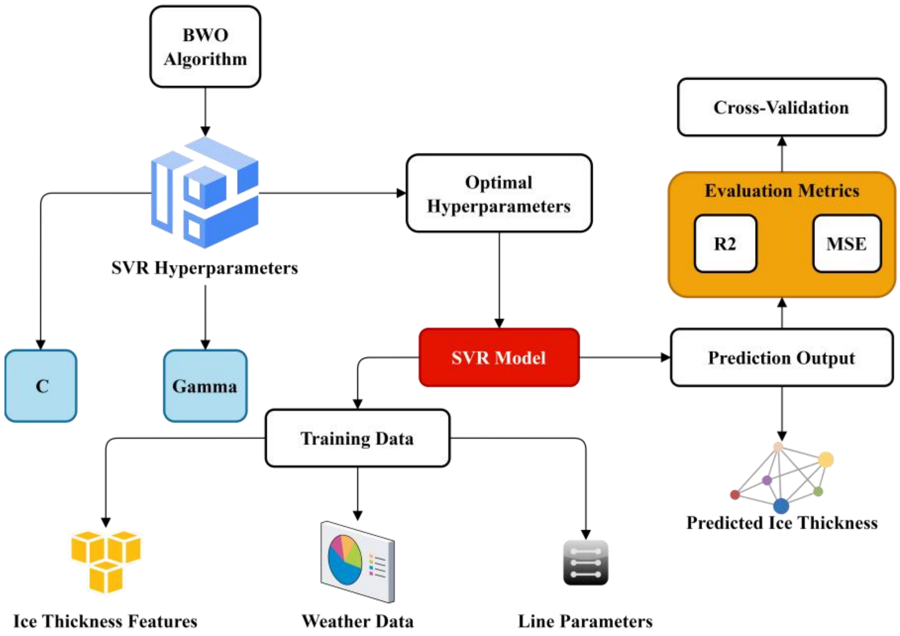

Figure 1. The model structure using the BWO.

Figure 1 illustrates the optimization of the model structure using the BWO. The BWO algorithm is responsible for optimizing the hyperparameters of the SVR model, including penalty factors and kernel function parameters. It can stimulate beluga predation behavior for global search to avoid the local problems of traditional optimization methods. The training data is input into the SVR model, including features related to ice thickness, meteorological data and line parameters; these data are subjected to regression analysis by SVR to ultimately generate predicted ice thickness; the optimized SVR model outputs the prediction results after optimizing hyperparameters to improve accuracy and reliability. MSE and R^2 can quantitatively evaluate the performance of the model, and it can show high generalization ability in different regions and time periods. This process reflects the close integration of data processing, feature extraction and optimization process, making the model have efficient prediction and accuracy.

C. Multi-level Regression Analysis and Fusion

The optimized SVR model is used for multi-level regression analysis to integrate data from different regions and different time periods to improve the accuracy and reliability of predictions.

1) Multi-Level Regression Analysis of Data From Different Regions

Data from different regions are processed to make accurate predictions in different prediction scenarios. The data from each region were analyzed to extract potential feature differences between regions. Using the optimized SVR, the ice thickness data in each region is modeled independently, and the model in each region is trained and optimized on the local dataset, in a way that can adapt to the specific data distribution within the region.

The regression results of different regions are combined, and the prediction results of each region model are combined by using the weighted average method. The prediction value after the fusion can be expressed as follows:

$$\hat{y}_{fused} = \sum_{i=1}^{S} w_i \cdot \hat{q}_i \quad (7)$$

S is the number of regions, w_i is the weighting coefficient of the i region, and $\hat{q}_i$ is the predicted value of the i region. The weighting coefficient is dynamically adjusted according to the prediction accuracy of each region, using the verified error as the basis for the weight. Regions with smaller errors have larger weights.

The data heterogeneity between regions also needs to be considered during fusion. The climate conditions, geographical environment and other factors in different regions may lead to significant differences in the distribution of ice thickness. The regression models for different regional characteristics need to be optimized through SVR. The impact of regional differences on the final prediction results should also be considered in the fusion stage. By adjusting the weighting coefficients, the algorithm can reduce the prediction bias caused by regional differences to a certain extent and improve the accuracy and reliability of the final prediction.

2) Multi-Level Regression Analysis of Data From Different Time Periods

In addition to regional differences, time is also an important factor affecting the thickness of TLs ice cover. In addition to multi-level regression analysis of data from different regions, it is also necessary to consider the fusion of data from different time periods, model the TLs ice cover thickness data in different time periods, obtain the change rules in the time dimension.

In actual operation, the data in the time period needs to be divided according to the time series so that the data in each time period has similar time characteristics. When performing regression analysis, the time factor can be used as an important feature in the model and introduced into the optimized SVR model for training. Let the data set be $D=\{(x_1,y_1),(x_2,y_2),\cdots,(x_n,y_n)\}$, x_n represents the input feature. The data is grouped according to different time periods. Assume that the data of the kth time period is independently input into the SVR model for modeling during the training process. The objective function of each model is as follows:

$$f_k(x)=\sum_{i=1}^{n_k}\left(\left|y_i^k-\hat{y}_i^k\right|+\lambda\cdot\sum_{j=1}^{m_k}\left|w_j^k\right|\right) \quad (8)$$

n_k is the amount of data in the k th time period, and m_k is the feature dimension of the k th time period.

When fusing data from multiple time periods, a strategy similar to regional data fusion is adopted, and the prediction results of the models in each time period are combined using the weighted average method. The determination of the weight coefficient is also based on the error value in the verification. Smaller errors correspond to larger weights, giving these time periods higher trust in the prediction. The final prediction result after fusion is:

$$\hat{y}_{\text{fused}}=\sum_{k=1}^{M}w_k\cdot\hat{y}_k \quad (9)$$

M is the number of time periods, w_k is the weighting coefficient of the k time period, and $\hat{y}_k$ is the predicted value of the k time period. After the fusion of time period data, the ice thickness can be accurately predicted at different time scales.

In addition to the weighted average method, principal component analysis can also be used to reduce the dimension of time period data in data fusion, reduce the computational complexity, and improve the prediction speed. In the feature extraction of time period data, different feature combinations are required for the different characteristics of the data in each time period. Introducing these feature combinations in the SVR model can better reflect the impact of time factors on ice thickness and improve the fitting ability of the model. Table 1 shows the ice thickness data of TLs in different regions.

Table 1. Transmission lines ice thickness data of different regions.

Region ID	Number of samples (items)	Mean Ice Thickness (mm)	Temperature Range (°C)	Wind Speed Range (m/s)	Regional Description
1	150	50.2	-20 to -10	2.5 to 5.2	High-latitude mountainous area, cold climate, strong winds.
2	200	38.7	-12 to -8	1.8 to 3.0	Low mountainous area, lower temperatures, moderate winds.
3	180	29.4	-5 to -2	1.0 to 2.8	Mountain edge, mild climate, lower wind speed.
4	220	41.6	-8 to -4	2.0 to 3.8	Lowland area, higher wind speed, colder temperatures.

D. Model Training and Optimization Adjustment

This paper uses the cross-validation method for training and adjusts the SVR based on the ice thickness distribution characteristics in different regions. In model training and optimization, this paper uses the cross-validation method. This method can maximize the use of the data set in each round of training, evaluate the performance on unseen data, and reduce the accidental impact of data division. MSE was used as the evaluation index for each round of validation, with the formula:

$$MSE=\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2 \quad (10)$$

Calculate the error of each round, evaluate the performance of the model on different training sets and validation sets, and determine the optimal hyperparameter combination; cross-validation allows each part of the data in the training process to have the opportunity to be used as a validation set.

The ice thickness data characteristics of different regions can be personalized and optimized. Geographical and climatic conditions in different regions may cause differences in the distribution of ice thickness, which directly affects the prediction effect. A single global model may not be able to adapt to the specific needs of all regions, and the model must be adjusted independently according to the characteristics of each region. The weight of the features can be adjusted according to factors such as meteorological data and geographical parameters in the region; the temperature in cold regions has a greater impact on the ice thickness, and warm regions need to consider the impact of temperature fluctuations and humidity changes more.

$$MSE_r = \frac{1}{N_r}\sum_{i=1}^{N_r} w_r \left(y_i^r - \hat{y}_i^r\right)^2 \quad (11)$$

This regional adjustment enhances the model's adaptability to regional data distribution and improves its predictive ability in practical applications. Each region can be trained and optimized independently, combined with the cross-validation method to ensure the generalization ability of the model in different regions. The optimization adjustment of regional differences also helps to avoid overfitting problems caused by overfitting of data in a certain region.

4. Method Effect Evaluation

A. Impact of Different Window Sizes on Data Smoothing and Sensitivity Analysis of Hyperparameters

Figure 2 shows the effect of using the sliding average method to smooth time series data with high-intensity noise under different window sizes. The black curve represents the original noise data, and the smoothing effect under different window sizes is compared. Window 3 shows strong fluctuations, fails to effectively remove noise, and has the worst smoothing effect. Window 5 is improved compared to Window 3, but the noise is still not completely removed, and the data fluctuation is still large. Window 7 shows the best smoothing effect. The noise is effectively removed, and the data shows a relatively stable trend, which can better reflect the changes in ice thickness. Window 10 removes the noise, but because the window is too large, over-smoothing causes unnatural data fluctuations, which weakens the trend changes and shows a large difference. Window 7 is the best choice, which can effectively remove noise and maintain the stability of data changes.

Figure 3 shows the sensitivity analysis of hyperparameters C and Gamma. Different combinations of C and Gamma show obvious changes in the model error. The error is the smallest in a smaller range of C and Gamma values. This shows that the hyperparameter combination corresponding to this area can significantly improve the predictive performance of the model. When the hyperparameter value is too high, the error increases and the model performance is not ideal. The data intuitively reflects the sensitivity of the model to the C and Gamma hyperparameters, providing a clear direction for subsequent optimization. This analysis can identify the hyperparameter combinations that have a greater impact on model performance and optimize the model's prediction capabilities.

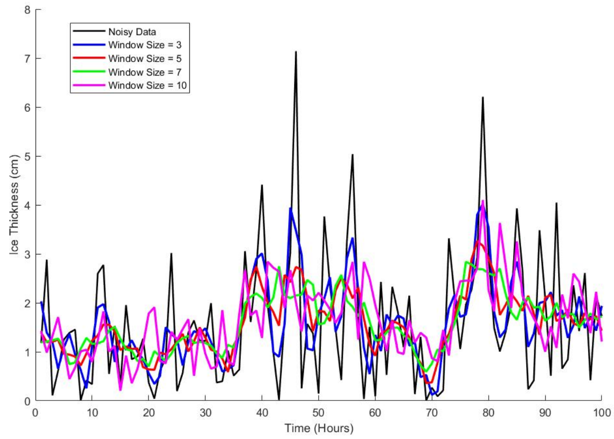

Figure 2. Effect of different window sizes on data smoothing.

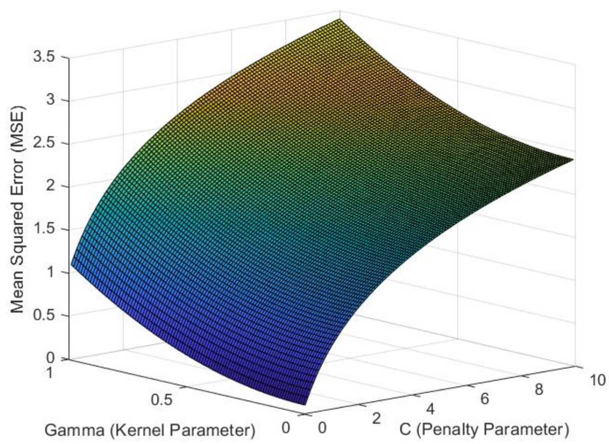

Figure 3. Hyperparameter sensitivity analysis.

B. Distribution Feature Analysis and Prediction Effect Evaluation

Table 2 is the setting table of the experimental parameters. Table 3 shows the distribution characteristics of TLs ice thickness in different regions, including maximum value, minimum value, standard deviation, kurtosis and skewness. The maximum ice thickness in region 3 is 76.4 mm, which is significantly higher than that in other regions. The ice in this region is more serious and the standard deviation is larger, indicating that the ice thickness fluctuates greatly. The minimum value in area 3 is 23.1 mm, and the standard deviation is low, indicating that the ice cover in this area is light and relatively stable; the skewness value reflects the distribution pattern of ice thickness in each area, and the ice thickness in each area is significantly different, providing key data support for subsequent modeling and analysis.

Table 2. Table of experimental parameters settings.

Parameter	Value	Description
Dataset Split	10-fold Cross Validation	The dataset is randomly divided into 10 subsets for 10 rounds of training and validation
SVR Kernel Function	RBF Kernel	The kernel function used to construct the SVR model, suitable for non-linear data fitting
epsilon (SVR)	0.1	The tolerance of the SVR model, setting the permissible error range for support vectors
BWO Population Size	50	The population size in the Beluga Whale Optimization algorithm, affecting the breadth of the search process
BWO Iterations	200	The maximum number of iterations in the BWO algorithm, controlling the search precision
XGBoost Max Depth	6	The maximum depth of trees in the XGBoost model, affecting the model's complexity
Learning Rate (XGBoost)	0.05	The learning rate in XGBoost, controlling the contribution size of each tree
SVR Penalty Parameter (C)	1	The penalty parameter in SVR, balancing model complexity and error tolerance
BWO Mutation Rate	0.4	The mutation rate in the BWO algorithm, determining the randomness of the search process
BWO Convergence Threshold	1.00E-06	The convergence threshold in the BWO algorithm, determining when to stop iterations
XGBoost Subsample Ratio	0.8	The subsample ratio in XGBoost, used to reduce overfitting
XGBoost Training Rounds	100	The maximum number of training rounds in XGBoost, controlling the number of iterations during training

Table 3. Results of ice thickness distribution feature analysis.

Region ID	Max Ice Thickness (mm)	Min Ice Thickness (mm)	Ice Thickness Std Dev (mm)	Kurtosis	Skewness
1	76.4	7.3	33.1	-0.45	0.15
2	55.6	4.4	29.5	-0.33	0.2
3	42.4	3.3	23.1	-0.1	0.3
4	68.8	6.0	32.9	-0.25	0.12

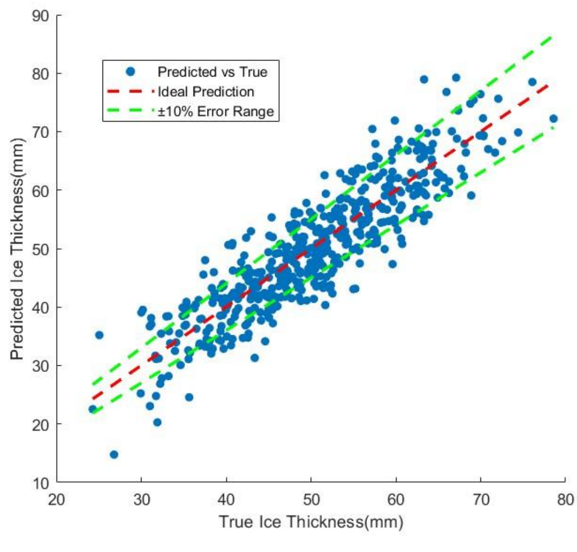

Figure 4. Model prediction and true value.

Figure 4 shows the contrast between the predicted and true values of the SVR model. Each scattered point represents a data sample, and the red dotted line is the ideal prediction line, that is, the predicted value is completely equal to the true value; The green dotted line is the 10% error line. Most of the data points are within the 10% error line, which means that the model's prediction results are close to the true value and the overall prediction is accurate. However, there are still some points that deviate from the ideal line and show a certain error, indicating that the model's prediction accuracy is slightly reduced in some samples. These errors may be related to the noise in the data, the complexity of specific areas, or the hyperparameter selection of the model. The distribution trend of the points shows that the SVR model can better capture the changing pattern of ice thickness, but there is still room for improvement, especially when dealing with specific areas or extreme values. The model may need to be further optimized. Introducing more efficient hyperparameter optimization strategies such as genetic algorithms or particle swarm optimization, enhancing data preprocessing and outlier detection, and adopting multi-model fusion and regional adaptive adjustment can better improve local prediction accuracy and enhance overall robustness.

The prediction accuracy uses MSE as an evaluation indicator to quantify the difference between the prediction result and the actual value. MSE is a commonly used evaluation standard that can effectively reflect the error distribution. SVR can effectively handle complex nonlinear relationships through nonlinear mapping, and XGBoost uses ensemble learning and tree structure models to improve prediction accuracy through multiple iterations. These methods still have challenges in hyperparameter optimization and are easily affected by local optimality. In contrast, this paper combines the SVR optimized by the BWO algorithm to optimize hyperparameters by simulating the predation behavior of white whales in nature, avoiding the local optimality problem of traditional methods, and improving the prediction accuracy and computational efficiency of the model, showing a strong advantage. In the evaluation, BWO-SVR is compared with traditional SVR and XGBoost (Extreme Gradient Boosting) to ensure the reliability of the evaluation results. All data are divided by month to verify the adaptability in different time periods. For each month, three methods are used for training and prediction, and the MSE value of each month is calculated. These MSE values are compared to judge the prediction accuracy of BWO-SVR in each time period, and the performance is differentiated with other algorithms to verify its superiority in different environments.

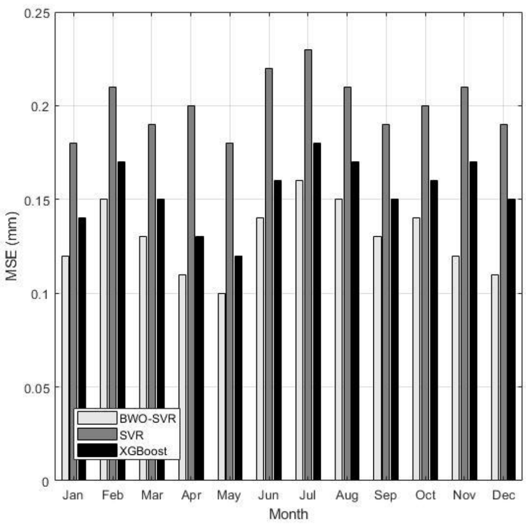

Figure 5. Comparison of MSE of different models.

Figure 5 compares the prediction accuracy of the three models of BWO-SVR, SVR and XGBoost in 12 months, using MSE as the evaluation indicator. The MSE value of BWO-SVR is low in most months, showing strong prediction ability, with an average MSE of 0.13 mm. The MSE of BWO-SVR is significantly lower than that of the other two models, indicating that it fits the data more accurately in these months and can effectively reduce errors. The MSE of the SVR model is generally high, especially in June and July, indicating that it has poor adaptability to the data in these months, which may be due to large noise interference and insufficient parameter optimization; the MSE value of the XGBoost model is at a medium level in most months and is relatively stable. Its performance is close to that of BWO-SVR, but slightly inferior overall. The data reflects the difference in prediction effects of different models in different months. BWO-SVR, with its lower error value, shows superiority and strong adaptability under multi-dimensional data.

C. Computational Efficiency Comparison

The computational efficiency comparison uses the ten-fold cross-validation method to evaluate the inference time of each model at different folds. The data set is randomly divided into ten subsets, one of which is selected as the validation set each time, and the rest are used as the training set. The training and validation are repeated ten times to ensure the extensiveness and reliability of the evaluation results.

In each fold validation, the inference time of the BWO-SVR model, the traditional SVR model, and the XGBoost algorithm are recorded respectively, focusing on the time consumption of each model in the data processing, feature selection, and prediction process. The inference time is calculated. The evaluation focuses on comparing the execution efficiency of different models under the same data set and analyzing the advantages of BWO-SVR when processing the data set. This comparison can comprehensively evaluate the improvement of BWO-SVR in computing efficiency and directly compare it with other algorithms to ensure its high efficiency in practical applications.

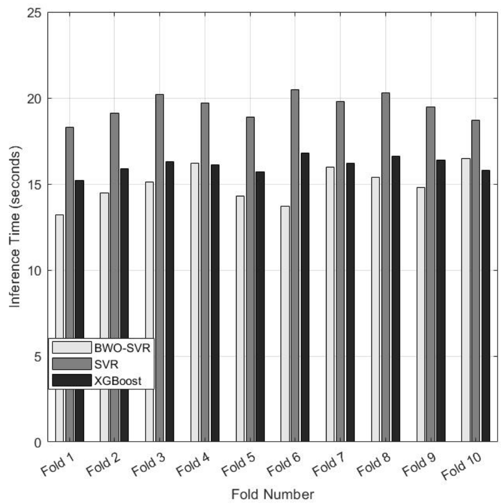

Figure 6. Comparison of inference time of different models.

Figure 6 shows the comparison of inference time of three models under 10 different folds. The inference time of BWO-SVR fluctuates between different folds, with the lowest being 13.2 seconds and the highest being 16.5 seconds. The average inference time is 14.97 seconds, which shows the adaptability of the model on different data subsets; The inference time of the SVR model is generally longer at fold 6, indicating that its computational overhead is large when processing complex data; the inference time of XGBoost is between BWO-SVR and SVR, showing a relatively balanced inference efficiency, and performs well at most folds, but does not surpass BWO-SVR. BWO-SVR has a shorter reasoning time in most cases, showing strong stability and efficiency. The data changes reveal the advantages and disadvantages of different models in reasoning speed, suggesting that the performance in different data scenarios should be considered when selecting a model.

D. 4Goodness of Fit Evaluation

The goodness of fit evaluation uses R^2 to measure the fitting effect of the BWO-SVR model algorithm on the training set and the validation set. R^2 is an important indicator for evaluating the predictive performance of the regression model, which can reflect the model's ability to explain data variation and its fitting accuracy.

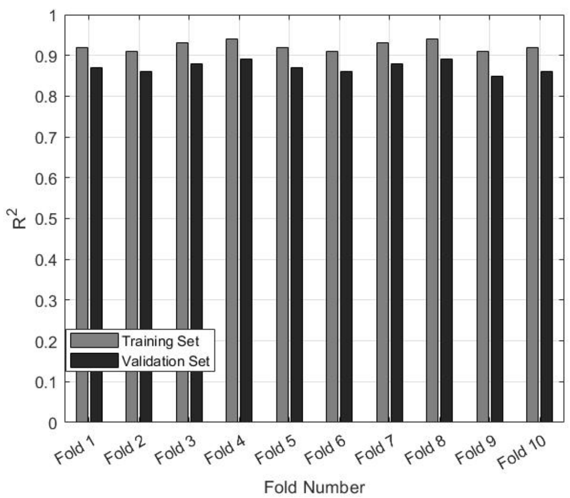

Figure 7. Determination coefficient of BWO-SVR in training and validation.

Figure 7 shows the R^2 comparison of the training set and validation set of the BWO-SVR model on 10 folds. The determination coefficient of the training set is generally high, ranging from 0.91 to 0.94, indicating that the model has a strong fitting ability on the training data. The coefficient of determination of the validation set is low, between 0.85 and 0.89, showing a certain degree of overfitting, but the fitting effect of the validation set is still good, indicating that the model has strong generalization ability and can adapt to different data sets well. In all folds, the fitting effect of the BWO-SVR model remains stable, verifying the robustness and accuracy of the model. The BWO-SVR model can provide relatively consistent prediction performance when processing data with different folds.

5. Conclusions

This paper proposes an enhanced and more accurate analysis method of ice thickness distribution characteristics of transmission lines combined with the BWO-SVR model. The BWO algorithm was used to optimize the hyperparameters of the support vector regression model, successfully avoiding the local optimal trap that traditional optimization methods are prone to fall into, and improving the prediction accuracy. Combined with multi-level regression analysis and data fusion technology, the reliability of the prediction results is enhanced. When processing comprehensive data from different regions and different time periods, the adaptability of the model is particularly prominent. After comparative evaluation with traditional models, the experiment found that the BWO-SVR model showed significant advantages in prediction accuracy, calculation speed and fitting degree. Using the ten-fold cross validation and R^2 evaluation methods, the experiment further ensured the efficient operation of the model in a complex data environment. Regarding predicting the distribution characteristics of TLs ice thickness, the model performed well, showing obvious advantages in calculation speed and model adaptability, providing strong technical support for TLs ice monitoring and disaster prevention and mitigation work. In the future, the paper can try to further expand the scope of application of this method and explore how to combine more diverse data sources to further optimize model performance.

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Author Contribution

[Yang Yang]: Developed and planned the study, performed experiments, and interpreted results. Edited and refined the manuscript with a focus on critical intellectual contributions.

[Hongxia Wang, Mingguan Zhao]: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

[Xinsheng Dong]: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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