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A Prediction Method of Rail Corrugation Evolution Trend for Heavy Haul Railway Based on IPCA and ELWOA-LSSVM

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Abstract

Rail corrugation, as a prevalent type of rail damage in heavy railways, induces diseases in the track structure. In order to ensure the safe operation of trains, an improved whale optimization algorithm is proposed to optimize the rail corrugation evolution trend prediction model of the least squares support vector machine (IPCA-ELWOA-LSSVM). The elite reverse learning combined with the Lévy flight strategy is introduced to improve the whale optimization algorithm. The improved WOA (ELWOA) algorithm is used to continuously optimize the kernel parameter σ and the normalization parameter γ in the LSSVM model. Finally, the improved prediction model is validated using data from a domestic heavy-duty railway experimental line database and compared with the prediction model before optimization and the other commonly used models. The experimental results show that the ELWOA-LSSVM prediction model has the highest accuracy, which proves that the proposed method has high accuracy in predicting the rail corrugation evolution trend.

Keywords

Rail Corrugation, PCA, Evolution Trend Prediction, WOA, LSSVM

1. Introduction

With the continuous development of heavy-haul railways in our country, the axle weight of trains has continued to increase in recent years, resulting in an increase in the dynamic interface load [1]. Heavy-haul railways have often suffered rail surface plastic deformation and rail corrugation. The rail corrugation is a wave-like, periodic component of the rail top longitudinal defect on the rail direction. When the train runs through the track corrugation road, it will cause a serious wheel-rail impact, which can also lead to further damage [2] [3]. The service life of vehicle and track structure components has been sharply reduced, and the operation of the line has been seriously affected by the rapid deterioration of defects and untimely maintenance. Thus, the technology of predicting the evolution trend of corrugation of heavy-haul railway rail has been of high significance.

Currently, there are many studies combining the finite element method and dynamic simulation to study the generation mechanism and evolution of rail corrugation [4] [5]. Liu Xueyi [6] *et al.* developed a wheel-rail spatial coupling vibration model for analyzing the mechanism of corrugation and verified that theal self-excited vibration between the rail and the track is the main cause of corrugation in both straight and curved sections of the rail. Alfréd Pavlík [7] *et al.* carried out simulation analysis and prediction on the wear of wheel-rail contact during operation on tracks in SIMPACK software. Igeland A [8] *et al.* used the adaptive time step method to calculate the vertical force between the wheel and the rail and establish an initial track model with random irregularities. The evolution of the corrugation on the top of the rail was studied, and it was found that the bogie wheelbase is an important parameter. Its change will cause the resonance frequency of the bogie-rail coupling system to change, thus causing the wavelength of the corrugation to change.

The existing neural network models are not practical in solving the problems of small sample size and nonlinear rail corrugation data, while LSSVM [9] [10], with excellent generalization ability, has obvious advantages. One of the challenges is that the prediction accuracy of LSSVM model varies with different values of regularization parameters and kernel parameters. Thus, many researchers have studied the two-parameter optimization for LSSVM. Zuo Xueqian [11] *et al.* proposed a centrifugal pump condition predicting model that optimized the parameters of LVM Model by making full use of the particle swarm optimization (PSO) algorithm. Qu [12] *et al.* proposed integrating the fruit fly algorithm (FOA) with the least squares support vector machine model to enhance the accuracy of traffic flow forecasting. Wang Yunlong [13] *et al.* applied the GWO to optimize the parameters of the LSSVM model, which improved the algorithm's calculation and prediction speed, and the prediction of operating life of railway freight car wheels was carried out. Also, when predicting the evolution law of rail damage, the immune algorithm [14] and quantum adaptive particle swarm algorithm [15] can be integrated with LSSVM for application.

The research mentioned above utilized various population-based algorithms to optimize the hyper-parameters of LSSVM. However, it does not take into account the decrease of mutation diversity during the iteration process, which can lead to slow convergence in the initial stages, while others fail to converge in the later stages, making the final result trapped in the local optimum. Addressing the issues present in existing methods, this paper uses the improved whale optimization algorithm [16] for parameter optimization of LSSVM and innovatively employs elite opposition-based learning [17] and Lévy [18] flights, which can reduce the possibility of the algorithm getting trapped in local optima.Improve the convergence and search efficiency of the algorithm. Based on this, feature selection and dimensionality reduction are carried out using IPCA and constructing CCT fusion indicators. Then, the proposed prediction method combined with IPCA-ELWOA-LSSVM is used to cooperate with the rail corrugation evolution to obtain the trend prediction.

2. The Proposed Method

To accurately predict the evolution trend of rail corrugation, the flow chart of the rail corrugation evolution trend prediction process proposed in this paper is shown in Figure 1. Specifically, the first step is data collection pre-processing and heuristic feature extraction, whereby we remove features that do not give us good accuracy. Secondly, the multi-dimensional feature vectors are fused by improved principal components analysis (IPCA) to establish the comprehensive evaluation index CCT of wear, and the evolution process of CCT is inferred. Finally, the LSSVM network is trained using an enhanced whale optimization algorithm based on hybrid strategies (ELWOA). Obtain the optimal network weights, improve the accuracy of the network solution, and ultimately complete the prediction of the evolution trend of rail corrugation.

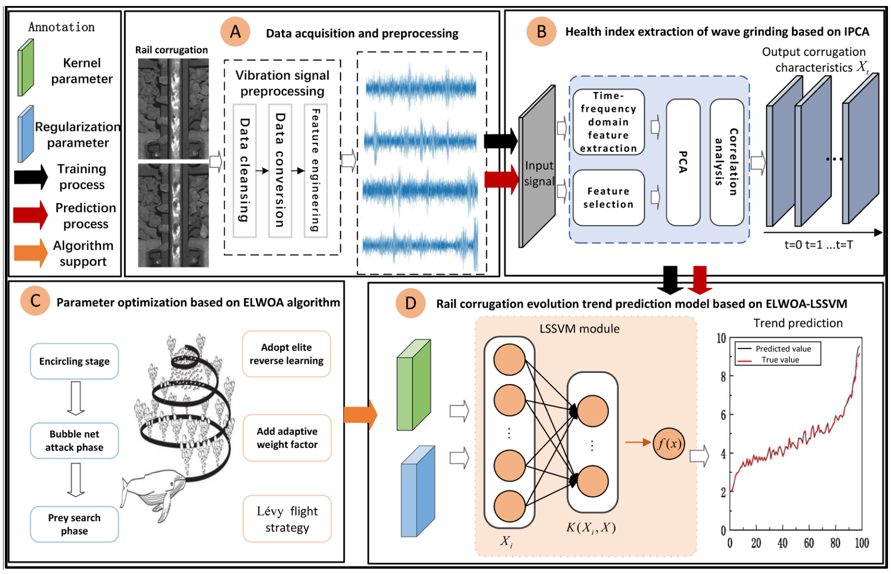

Figure 1. Flow chart for predicting the evolution trend of rail corrugation.

2.1. Extraction of Health Indicators

Even though traditional PCA [19] has been extensively applied in various fields owing to its simplicity and efficiency, it also suffers from various drawbacks. As an example, in the process of dimensionality reduction, the weights of each feature in the matrix after data standardization are numerically identical, while different feature vectors will definitely have different impacts on the final results in practice. To address this issue, we propose Pearson correlation analysis in this paper. The correlation coefficient r is an important concept in Pearson correlation analysis. It is commonly used to measure the strength of the relationship between two variables, and its calculation formula is shown below:

$$r = Corr(x,y) = \frac{\operatorname{cov}(x,y)}{\sqrt{Var(x)\cdot Var(y)}} \tag{1}$$

The Pearson method is used to calculate the correlation between each feature dimension and the evolution degree of corrugation damage, which can also be considered as the contribution of each feature to the final prediction result. Each dimension is reweighted according to the correlation coefficient, thereby increasing the impact of that feature on the final result. The vibration data of corrugation collected on a domestic railway is used as an example to observe the actual effect of IPCA. This database consists of 96 samples, each of which includes multi-dimensional time-frequency domain artificial features that affect the evolution of rail corrugation. Subsequently, the traditional PCA and the improved IPCA were employed to reduce the dimensionality of the sample based on the aforementioned algorithm, and the final intuition is shown in Figure 2.

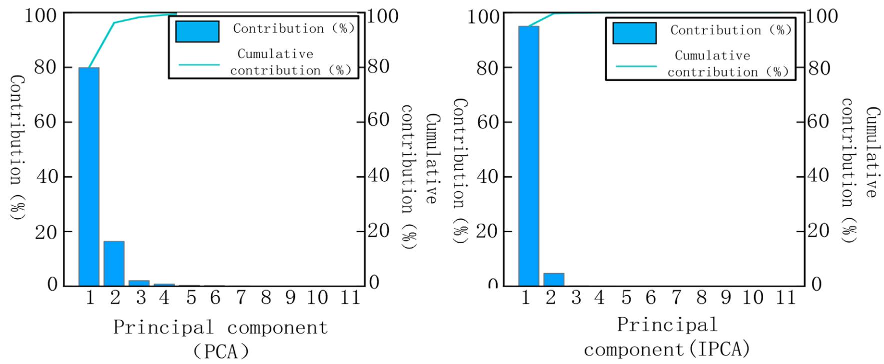

Figure 2. Data processing comparison.

Figure 2 shows the dimensionality reduction result of the same data. By comparing PCA and IPCA, we find that the IPCA method retained 95% of the variance in the data. This indicates that compared to PCA, IPCA has reduced the impact of correlations between features on the prediction results, significantly improving its dimensionality reduction capabilities, and making the health indicators more consistent with the evolution trend of rail corrugation.

2.2. Construction of the Forecasting Model

2.2.1. LSSVM Model

As a complete theoretical system of advanced statistical theory, LSSVM is a prominent improvement of SVM. So, the quadratic optimization problem can be converted to solving a system of linear equations, which greatly simplifies the problem. It has been prolifically found successful in the areas of data regression, pattern recognition, time series prediction, etc. The steps to use LSSVM are:

1) For a given training set $T=\{(x_1, y_1),(x_2, y_2),\cdots,(x_l, y_l)\}\in(\chi\times\gamma)^l$ (where: $x_i\in\chi=R^k$; $y_i\in\gamma=R$; x_i are the sample inputs of the model, and y_i are the sample outputs of the model), LSSVM can obtain a function (*f*) through sample training, which can convert inputs into outputs to classify or regress data. First, the inputs are transformed into high-dimensional (*H*) feature through nonlinear mapping ($x\to\varphi$), then classification is realized in the feature space, and thus the optimal decision function for training data set can be established:

$$f(x)=\omega^T\varphi(x)+b \tag{2}$$

where: ω are the coefficients the hyperplane; b is the bias; φ is the nonlinear mapping function.

2) The objective problem is to calculate ω and b in the optimal decision function based on the principle of structural risk minimization:

$$\left\{\begin{array}{l}\min\limits_{\omega,b,e} J(\omega,b,e)=\frac{1}{2}\|\omega\|^2+\frac{\gamma}{2}\sum\limits_{i=1}^{l}e_i^2\\ s.t. y_i\left[\omega_i\varphi_i(x_i)+b_i\right]=1-e_i\end{array}\right\} \tag{3}$$

where: γ is the parameter; $i=1,2,\cdots,l$; e_i is the allowed classification error.

3) When calculating ω and b in the optimal decision function, the Lagrange equation needs to be introduced for solution, and according to the operator the Lagrange equation, it can be calculated that:

$$\begin{aligned}&L(\omega,b,e,\alpha)=J(\omega,b,e)\\&-\sum_{i}^{l}\alpha_i\left\{y_i\left[\omega_i\varphi(x_i)+b_i\right]-1+e_i\right\}\end{aligned} \tag{4}$$

4) By further derivation based on the Karush-Kuhn-Tucker (KKT) conditions, the formula (4) can be obtained:

$$\begin{cases}\dfrac{\partial L}{\partial\omega}=0\Rightarrow\omega_i=\sum\limits_{i=1}^{l}\alpha_i y_i\varphi(x_i)\\ \dfrac{\partial L}{\partial b}=0\Rightarrow\sum\limits_{i=1}^{l}\alpha_i y_i=0\\ \dfrac{\partial L}{\partial e_i}=0\Rightarrow\alpha_i=\gamma e_i\\ \dfrac{\partial L}{\partial\alpha_i}=0\Rightarrow\left\{y_i\left[\omega_i\varphi(x_i)+b_i\right]-1+e_i\right\}=0\end{cases} \tag{5}$$

5) Eliminating ω and e_i in Equation (5) will transform Equation (5) into:

$$f(x)=\sum_{i=1}^{l}\alpha_i K(x,x_i)+b_i \tag{6}$$

In the formula, $K(x,x_i)$ is the kernel function used to transform data from low-dimensional space to high-dimensional space. The radial kernel function used in this is:

$$K(x_i)=\exp\left(\frac{-\|x_i\|^2}{2\sigma^2}\right) \tag{7}$$

In the formula, σ is the kernel function width, and after solving the unknown data in formula (7), the data prediction effect can be achieved.

During the learning and forecasting of data applying the LSSVM algorithm, the normalization parameter γ and the kernel function parameter σ would exert an influence on the algorithm's applied results since the error of this algorithm decreases as we increment the parameter. But what will happen if the value of the γ parameters is too high, then the complexity of the algorithm also increases. The time to conduct model training and prediction work will be longer, and this algorithm is also very easy to overfit. This means that some other parameters σ can affect the generalization ability of the algorithm. So, we currently have no codes that are high-end worth finding out the values in general, so the algorithm LSSVM application is difficult to achieve the optimal. To overcome this, optimal values of these two parameters will be found based on iterative updates using the WOA algorithm in this study. The process of using this model is shown in Figure 3.

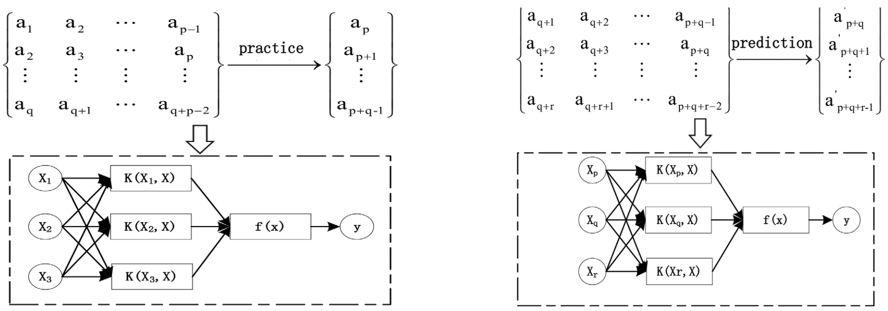

Figure 3. LSSVM model.

2.2.2. Optimization of the WOA Algorithm

Whale optimization algorithm is a meta heuristic optimization algorithm based on whale group behavior. WOA mainly simulates the foraging behavior of humpback whales in bubble nets. Compared with heuristic algorithms, such as particle swarm optimization PSO algorithm with single population updating mechanism, genetic algorithm GA and ant colony optimization ACO algorithm, WOA has three independently solved population renewal mechanisms: encirclement contraction, bubble net attack and wandering foraging. In order to achieve better algorithm performance, it can realize the separate operation, control and balance of global exploration and local development.

In addition, WOA also has the advantages of simple algorithm principle, easy programming and simple parameter setting, which has attracted the attention of many scholars and related researchers emerged endlessly. And it is widely used in support vector machines, artificial neural networks, discrete combinatorial optimization, complex function optimization, feature selection and other fields.

As the number of iterations increases, the population diversity of the traditional WOA algorithm decreases in the later stages of iteration and it is easy to get trapped in local optimum. So, a hybrid strategy to improve the ELWOA algorithm is proposed for this purpose. The specific improvements are as follows.

1) Population initialization based on elite opposition-based learning

Opposition-based Learning (OBL) is a new algorithm proposed in 2005. The basic idea is to solve the inverse solution of the feasible solution of the problem and evaluate the reverse solution and feasible solution. Selecting a better solution for the next generation of individuals and improving the optimization efficiency of the algorithm.

However, reverse learning has some blindness, and the search space of the reverse solution may not be more conducive to the search space of the current solution. In view of this situation, join the elite strategy and introduce elite individuals. Reverse learning through elite individuals, making full use of the effective information of elite individuals and generating elite inverse solutions. Selecting excellent individuals from the current solution and elite reverse solution as the elite reverse learning of the next generation population.

Based on elite opposition-based learning, the initialized population is optimized to produce elite opposition-based learning population individuals $\overline{X_i}$.

$$\overline{X_i} = k\left(L+U\right)-\overline{X_i} \tag{8}$$

where $\overline{X_i}$ represents position information of the current individual, L represents the minimum value of the feasible solution, U represents the maximum value of the feasible solution, and k is a random between (0, 1).

After being optimized by elite inverse learning, the fitness function values of the corresponding individuals are calculated. By comparing the fitness function values of the current individuals and the optimized individuals, select the individuals with better fitness values as the initial population individuals. Using the following elite inverse learning to optimize the randomly initialized population:

$$X_i = \begin{cases} \overline{X_i}, f\left(\overline{X_i}\right) < f\left(X_i\right) \\ X_i, else \end{cases} \tag{9}$$

2) Adaptive weights

An exponentially changing adaptive weight method is adopted. In the early stage of the algorithm, larger weights are used to achieve stronger global search performance, ensuring the search range. As the number of iterations increases, the weight values decrease exponentially when approaching the optimal solution, which greatly enhances the local optimization ability of the algorithm. The formula is as follows:

$$\omega = \sin\left(\frac{\pi \cdot t}{2 \cdot T_{\max}} + \pi\right) + 1 \tag{10}$$

where t is the current number of iterations and $T_{\max}$ is the maximum number of iterations.

After adding the adaptive weight factor, the optimization process of the optimization algorithm is expressed as:

$$X\left(t+1\right) = \omega \cdot X*\left(t\right) - A \cdot D \tag{11}$$

$$X(t+1) = \omega \cdot X*(t) + \mathrm{D}' \cdot e^{bl} \cos(2\pi l) \tag{12}$$

$$X(t+1) = \omega \cdot X_{rand}(t) - \mathrm{A} \cdot \mathrm{D} \tag{13}$$

where D is the distance between the whale and the prey; A is an adjusted coefficient; b is a constant representing the shape the spiral; and l is a random number between $[-1,1]$.

3) Lévy flight

Lévy flight is a stochastic search strategy that has been widely used in various intelligent optimization algorithms. The whale optimization algorithm uses the Lévy flight strategy to search in a small range near the optimal position, effectively expanding the search range and allowing the population to escape from local optima.

The position update formula using Lévy flights:

$$X(t+1) = X(t) + \alpha(t) L(\beta) X(t) \tag{14}$$

where: is the position information of the individual in the generation; is the step size scaling factor; is the optimization step size coefficient.

2.2.3. Prediction Model Based on ELWOA-LSSVM

In the process of predicting the evolution trend of rail corrugation, the WOA-LSSVM algorithm model established in this study essentially uses WOA algorithm to optimize the parameters in the LSSVM algorithm and then uses the optimized algorithm model to predict the evolution trend of corrugation damage points single line conditions.

1) Read the original vibration dataset and reduce the dimensionality of the dataset.

2) Set the algorithm parameters of ELWOA, such as the number of populations N, the maximum number of iterations T, and the spatial dimension dim. Generate the initial population individuals randomly within the feasible solution of the function and calculate the fitness values of the individuals.

3) Use the elite opposition-based learning to optimize the randomly initialized population individuals. By comparing the values before and after optimization, set the position of the individual with the better fitness value as the optimal position.

4) Update the individual positions according to the parameters at different stages. When $p < 0.5$, if $|A| < 1$, update the whale's position using Equation (11); if $|A| \geq 1$, update the whale's position using Equation (12); When $p \geq 0.5$, update the whale's position using Equation (13).

5) Use Equation (14) to perform Lévy flight strategy optimization update on the optimal. Compare the fitness values before and after optimization. If the fitness value of the optimized individual is less than the fitness value of the original individual, keep the position fitness value of the optimized individual, otherwise discard it.

6) If the number of iterations has reached the maximum number of iterations,

the algorithm iteration process ends, the optimal individual position and fitness function value at that time are output. Otherwise, return to step 2) to continue the optimization search.

7) After the ends, input the optimized parameters into the model. Specifically, the process of using this combined model is shown in Figure 4.

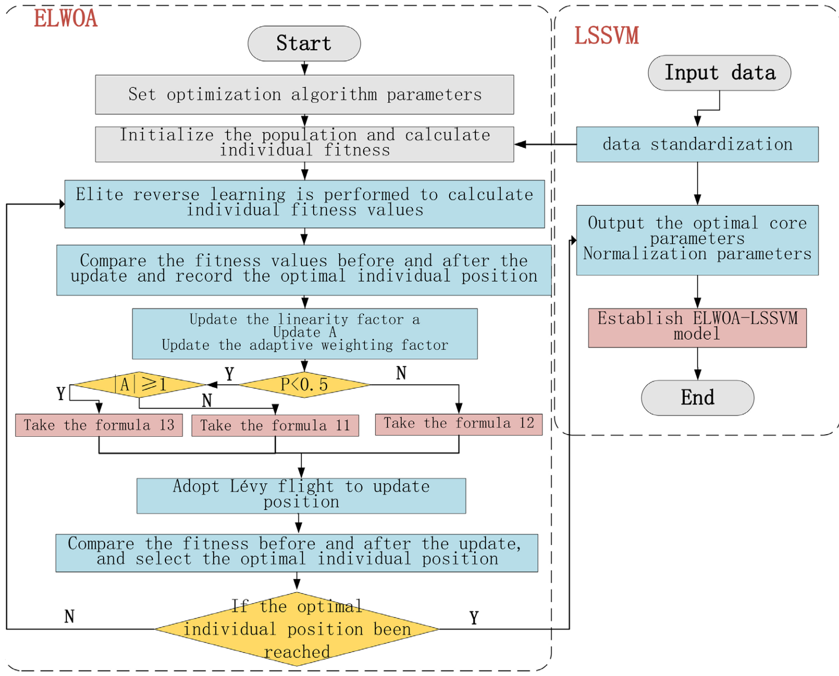

Figure 4. Flowchart of the ELWOA-LSSVM model.

3. Experimental Analysis

3.1. Feature Extraction Preprocessing

The data originates from a domestic railway experimental line section, where uninterrupted testing was conducted for several months. The original vibration data is collected using an acceleration vibration sensor. From the early stage of rail corrugation to development until rail replacement, the vibration data of the rail was collected at each identical sampling interval, a total of 98 times before and after. The sampling frequency is 4 kHz, and each time 2500 sample points are taken.

Each set of waves grinding data contains 98 × 2500 sample points. In order to avoid the drawback of evaluating the evolution degree of wave wear based on a single feature, which is too one-sided. This paper establishes a comprehensive CCT indicator by integrating high-dimensional feature data sets and compares them with the RMS indicator. First, the statistical features of each sample were extracted, such as: maximum value, kurtosis, peak factor… etc., totaling 2. The data dimensions become 98 × 26. And then, after eliminating the indicators with poor performance, 12 indicators were left, reducing the data dimension to 98 × 12. Finally, the 12-dimensional features are reduced in dimensionality using the IPCA method. The 98-dimensional feature vector is obtained as the CCT indicator to characterize the evolution trend of rail corrugation damage. Take group A as an example, the obtained CCT vector results are shown in Figure 5.

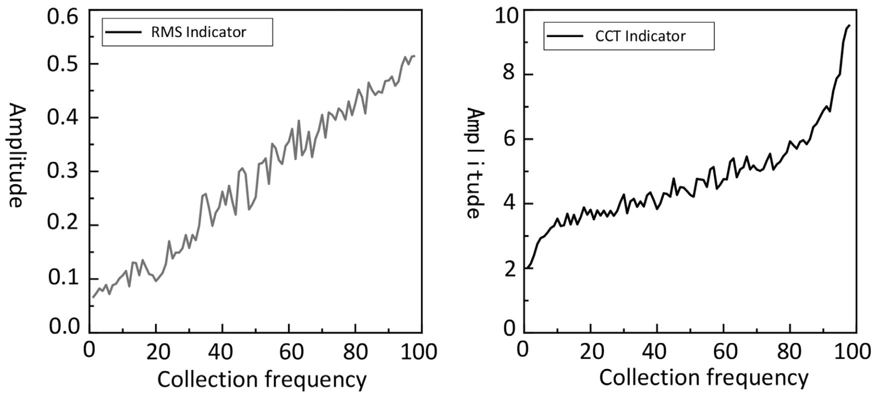

Figure 5. CCT Fusion Indicators.

As can be seen from Figure 5, the CCT indicator has a small fluctuation, indicating better overall performance. In order to further verify their validity, the CCT and RMS were used as indicators of wave wear evolution for trend prediction, and the results are shown in the following Figure 6.

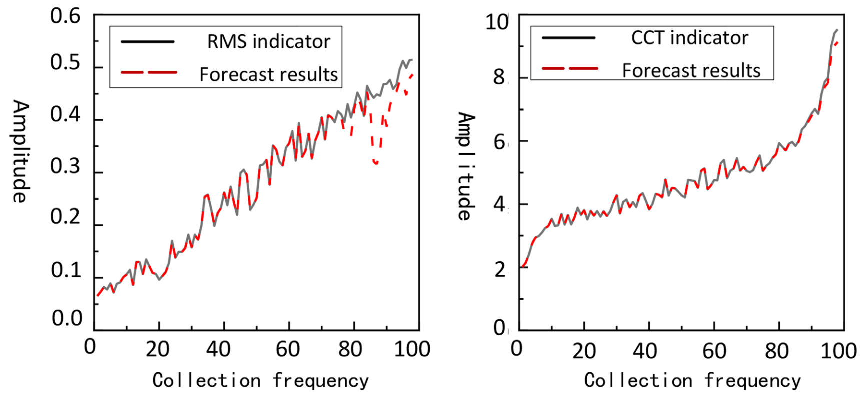

Figure 6. Trend prediction results of different degradation indicators.

According to Table 1, the RMS as a wave wear evaluation indicator has a large prediction error. This confirms the potential inadequacy of relying on a single indicator for evaluation. Compared with RMS features, the CCT features established in this paper have smaller relative prediction errors and higher prediction accuracy. So, it can better reflect the evolution trend of wave wear damage.

Table 1. Relative errors of predicted degradation indicators.

Feature indicators	Prediction model	Training set MAPE	Test set MAPE
RMS indicator	ELWOA-LSSVM	0.267%	10.567%
CCT fusion indicator	ELWOA-LSSVM	0.097%	1.018%

3.2. Result Analysis

After constructing the CCT performance degradation indicators for the four working conditions of rail corrugation using the aforementioned IPCA method, the kernel parameters and regularization parameters of the least squares support vector machine are optimized by an improved whale algorithm. Set the population size pop = 5, the maximum number of iterations max_iter = 50, the dimension of the population space dim = 2, upper bound of the variables ub is [10,000, 10,000], and the lower bound lb is [10, 10]. Divide the data into training sets and test sets at a ratio of 3:1 for prediction. Respectively utilizing: BPNN, POS-LSSVM, POA-LSSVM, ELWOA-LSSVM models for comparison. The results of all four methods are averaged over 10 runs, and the prediction results are shown in the figure.

As can be seen from Figure 7, when CCT is used as the indicator of corrugation evolution, the accuracy of model prediction from too low is ELWOA-LSSVM, POA-LSSVM, PSO-LSSVM, and BPNN.

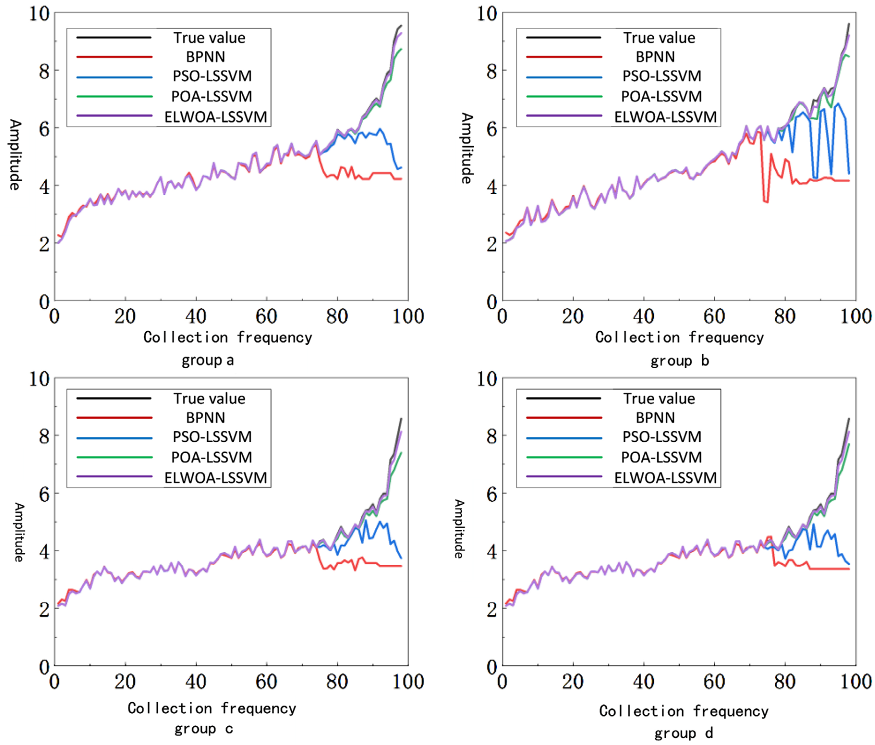

Figure 7. Predicted evolution trends of rail corrugation for each group.

The prediction performance of the BPNN model is the worst. This is because the model requires a large amount of training data, but the amount of data used in this paper is limited. Therefore, the prediction accuracy is reduced and cannot meet the expected effect; the PSO-LSSVM model has made certain improvements compared to the BPNN model. However, the deviation between the model and the measured values is still too large. The prediction performance of the POA-LSSVM model is significantly better than the previous three models, and the prediction accuracy is further improved. However, due to the inherent flaws of the algorithm itself, such as the tendency to get trapped in local optima, it still fails to make predictions in later stages. The performance of the ELWOA-LSSVM model is optimal among all models. It can predict the evolution trend of wave wear more accurately, with smaller error values.

In order to better evaluate the accuracy of the proposed model's predictions, the mean absolute error (*MAE*), root mean square error (*RMSE*), and coefficient of determination (R^2) are used as evaluation methods. The specific expressions are:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{15}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2} \tag{17}$$

It can be seen from Table 2 that the improved model, regardless of which evaluation criteria is used, has significantly improved performance compared to other comparison models: taking group a as an example, compared to POA-LSSVM, its mean absolute error is reduced by 0.095, while the root mean square error is reduced by 0.1553, and the correlation coefficient is increased by 0.0419. While other comparison models are less accurate than the model proposed in this article. This indicates that the ELWOA-LSSVM model is effective in predicting

Table 2. Performance comparison of the proposed method and other models.

Test group	Prediction model	MAE	RMSE	R^2
Group a	BPNN	2.3084	2.6884	−3.4377
	POS-LSSVM	1.1590	1.8885	−1.1898
	POA-LSSVM	0.1785	0.2971	0.9458
	ELWOA-LSSVM	0.0835	0.1418	0.9877
Group b	BPNN	1.9169	2.2748	−2.5578
	POS-LSSVM	1.0009	1.6249	−0.8152
	POA-LSSVM	0.2163	0.3583	0.9117
	ELWOA-LSSVM	0.0810	0.1350	0.9875
Group c	BPNN	2.6271	2.8797	−7.5437
	POS-LSSVM	1.1007	1.6835	−1.9200
	POA-LSSVM	0.2003	0.3426	0.8791
	ELWOA-LSSVM	0.0803	0.1436	0.9788
Group c	BPNN	1.9169	2.2748	−2.5578
	POS-LSSVM	1.0184	1.6438	−0.8576
	POA-LSSVM	0.2163	0.3583	0.9117
	ELWOA-LSSVM	0.0810	0.1350	0.9874

the evolution trend of rail corrugation, but it has not fully approached the real curve, especially since there are still some errors in the final stage of the prediction. The main reason for this is that in the prediction of grinding evolution trends, the predicted results will be used as the input for the next model, which will lead to further accumulation, thus greatly affecting the accuracy of later predictions.

4. Conclusions

This paper addresses the difficulties in determining the evolution indicators of rail corrugation damage and the fact that the predictive performance of traditional LSSVM models is heavily influenced by regularization and kernel parameters. It proposes a new IPCA-ELWOA-LSSVM prediction network for the evolution trend of corrugation damage, and uses the vibration data from a railway experimental line segment in China for analysis and verification, leading to the following conclusions.

1) Extracting multi-domain artificial features from the ground rail can more comprehensively reflect the degradation information of the rail vibration signal compared to single-domain features. Improving the PCA method by introducing Pearson correlation analysis, which reduces the impact of correlations among features on the evolution of wave wear damage. This makes the fusion index CCT more consistent with the evolution of wave grinding.

2) The improved ELWOA-LSSVM with mixed strategy is used for the trend prediction of rail corrugation evolution. By comparing multiple groups of experiments, it shows that this model has faster training speed and more accurate prediction results, the lower the probability of falling into local optimum and the better the algorithm stability. It has been verified that the method proposed in this paper is reasonable and effective.

3) However, this paper only predicts the evolution trend of wave wear damage points under single line conditions. In future work, we will further study the applicability and validity of the modeling method proposed in this paper for joint modeling analysis of multiple wave wear points under various line conditions and multiple working conditions.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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