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Transmission Line Galloping Prediction Based on GA-BP-SVM Combined Method

YING WEI AND XUELIAN GAO
School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China
Corresponding author: Xuelian Gao (xuelian_gao@ncepu.edu.cn)

ABSTRACT The paper proposes a method to construct a model for transmission line galloping prediction using machine learning algorithms to address the transmission line galloping problem, which can result in transmission line loss and pose a greater risk to the safety of electricity in society. First, to reduce sensor noise interference, a unilateral sliding time window is used for micro-meteorological data correction, and then gray correlation analysis method and the specific gravity method are used to obtain the influence weights of micro-meteorological elements. The galloping prediction models are constructed using six algorithms, with the GA-BP algorithm model and the SVM algorithm model having better prediction effects based on performance metrics. The GA-BP-SVM combined model is constructed on this basis, and all of its performance metrics are optimal. This model's prediction accuracy in both galloping and no galloping states reaches 95.5%; the probability of correct prediction when predicted as galloping reaches 95.1%; the probability that actual galloping can be predicted reaches 92.5%. The F1-score of the combined model reaches 0.938, which indicates that it has the best prediction effect. The prediction method described in the paper is accurate and practical, and operation and maintenance personnel can flexibly develop inspection strategies and anti-galloping measures based on the prediction results to ensure the safe and stable operation of transmission lines.

INDEX TERMS Transmission line galloping, combined prediction, sliding time window, SVM, GA-BP neural network.

I. INTRODUCTION

Transmission lines are built in the natural environment, and their structural safety and stability are at risk from the elements. Galloping is one of the most common types of transmission line faults, where the wire is subjected to a specific angle of attack and wind speed, causing a large-amplitude and low-frequency self-excited vibration, referred to as galloping. Galloping can result in a variety of hazards, including minor ones like flashovers and tripping accidents, as well as more serious ones like damage to fixtures and insulators, broken wires, and even downed towers [1]–[3]. Due to the high risk of galloping, a lot of research has been done on galloping prevention and control in various countries. The following are the three most important aspects: ① Installing anti-galloping devices on transmission lines, such as torsion dampers and inter-line spacers, to reduce the magnitude of galloping by altering the aerodynamic or structural characteristics of transmission lines. ② Galloping prediction is achieved by simulating the motion of transmission lines using galloping aerodynamic theory (e.g. Den Hartog vertical galloping theory, O Nigol torsion galloping theory). ③ Constructing a machine learning model to correlate galloping with the influencing factors to achieve galloping prediction.

Because galloping is influenced by topography and environmental factors, anti-galloping device selection and installation differ from region to region, making it difficult to conduct a comprehensive prevention and control study [4], [5]. Due to the flow-solid coupling between transmission lines and airflow, as well as the geometric nonlinear motion of transmission lines, it is also difficult to achieve galloping prediction by simulating conductor motion [6], [7]. As a result, although both methods have been studied for a long time, neither has made a breakthrough. However, with the continuous improvement of the performance of online galloping monitoring devices in recent years, the method of correlating galloping with influence factors now has a large amount of monitoring data as the foundation. Therefore, how to use existing data to build machine learning models for galloping prediction has piqued the interest of many researchers

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in the field of galloping prevention and control [8], [9]. Among machine learning algorithms, artificial neural networks and SVM are powerful and effective at solving complex nonlinear problems. They have been used in a variety of fields, such as predicting short-term electric loads and the dynamic mechanical response behaviors of alloys [10]–[13], and are now powerful methods for constructing galloping prediction models. In the literature [14], a back-propagation (BP) neural network model is proposed to predict the galloping features including the frequencies, vibration amplitudes, and the maximum conductor tension using span length, initial wind angle of attack, and wind speed as input variables. In the literature [15], the accident probability induced by galloping is analyzed using logistic regression analysis. The discriminant level of the computed model is evaluated using the AUC values of the ROC curves of the prediction model. The results demonstrated that the logistic regression analysis was effective in distinguishing between power lines with and without galloping. Literature [16] proposes a support vector machine (SVM) and AdaBoost bi-level classifier-based early warning method for transmission line galloping. Data mining of historical weather parameters is used to construct a prediction model based on SVM classifier, and AdaBoost classifier is used to realize the galloping warning. The effectiveness of the proposed method is tested using historical power grid galloping events. In the literature [17], the initial weights and threshold of the BP neural network are first optimized using genetic algorithm, and then a GA-BP neural network model is constructed for early warning of transmission line galloping. Literature [18] uses a weighted gray correlation projection method to select samples that have a high correlation with the samples to be predicted as the training sample, and then constructs a random forest model to determine whether to issue a galloping warning based on the voting results of all decision trees.

The papers mentioned above did a useful exploration of galloping prediction, but there was no data correction of the influencing factors, resulting in significant noise interference. And because they can only predict whether the galloping occurs but not the magnitude of the galloping, the prediction results are relatively broad. Furthermore, they only used one algorithm for prediction, and the model they constructed did not fit the galloping data well, the prediction performance still has a lot of room for improvement. Therefore, the goal of this paper is to improve the galloping prediction effect as much as possible. To begin, the influencing factors are corrected to reduce the noise interference generated by the sensors. The weights of the influencing factors are then calculated by the gray correlation analysis method and the specific gravity method. After weighting the influencing factors, we obtain weighted data that can more clearly characterize the galloping pattern. The weighted data is then used as input variables to construct the galloping prediction model using various machine learning algorithms, and the prediction results are evaluated using performance metrics. On this basis, the GA-BP-SVM combined prediction model is constructed, and it has been experimentally proven that the model has the most ideal prediction effect, can predict galloping amplitude in advance, and realizes the galloping early warning function with more accurate and practical results.

II. MICRO-METEOROLOGICAL DATA CORRECTION

Micro-meteorological sensors are installed on the towers of overhead transmission lines to monitor environmental information. In this paper, the influencing factors are the various micro-meteorological elements measured by the micro-meteorological sensors, such as temperature, humidity, air pressure, wind direction, wind speed, and so on. Noise interference is easily generated during sensor operation, and it can be broadly classified into two types: one caused by environmental factors or external interference during the measurement process, and the other generated by the sensor network during signal conditioning and analog-to-digital conversion [19]. To improve the effect of galloping prediction, the data from the micro-meteorological sensors should be corrected first to reduce noise interference.

A. DATA CORRECTION BY UNILATERAL SLIDING TIME WINDOW ALGORITHM

The ideal data correction method should ensure that the corrected micro-meteorological element curves are smooth and free of abrupt changes, and that the current value is related to the previous moment's state. The sliding time window algorithm can provide a good balance between these two requirements [20], [21]. Furthermore, the paper uses the unilateral sliding time window algorithm for data correction. There are two reasons for this: First, time moves in only one direction, so data values at a given point are only related to the previous state and not the subsequent state; second, because sliding time windows detect data sequentially from left to right, unilateral time windows only use data that have been corrected before a specific point. The bilateral time window, on the other hand, uses data before and after a specific point, making it impossible to determine if there are any anomalies in the data after this point.

The following are the steps to correcting the data:

1) Determine the predicted values of micro-meteorological elements at the moment t_i.

Given a temporal micro-meteorological sequence $T = \{(t_{i-k}, b_{i-k}), \ldots, (t_{i-1}, b_{i-1}), (t_i, b_i), (t_{i+1}, b_{i+1}), \ldots\}$, where t is the time and b is the value of a specific micro-meteorological element. Take k to be the length of the unilateral sliding time window. For the point (t_i, b_i), the unilateral time window contains data for the previous k time points of micro-meteorological element values $(b_{i-k}, b_{i-k+1}, \ldots, b_{i-2}, b_{i-1})$. The square weighting method is used to assign the weights because the closer the time is to t_i, the greater the influence of the element value on b_i. The following equations are used to calculate the predicted values of micro-meteorological elements at the moment t_i.

$$\begin{cases} b_i' = \sum_{j=1}^{k} w_{i-j} b_{i-j} \\ w_{i-j} = \dfrac{(k-j+1)^2}{\sum_{u=1}^{k}(k-u+1)^2}, \quad j = 1, 2, \ldots, k \\ \sum_{j=1}^{k} w_{i-j} = 1 \end{cases} \tag{1}$$

where $w_{i-k}, \ldots, w_{i-1}$ are the weights corresponding to $b_{i-k}, \ldots, b_{i-1}$, and b_i' is the predicted value of the micro-meteorological element at the moment t_i.

2) Determine the acceptable range of the micro-meteorological element value at the moment t_i.

The t-distribution is satisfied by the micro-meteorological element values within the time window, and the confidence interval PCI for the predicted value b_i' can be written as

$$PCI = b_i' \pm t_{\alpha,k-1} \times \frac{S_k}{\sqrt{k}} \tag{2}$$

where S_k is the standard deviation of the micro-meteorological element data within the time window, α is the upper quantile of the t-distribution, and the confidence coefficient $P = 100(1-\alpha)\%$ reflects the probability that the actual value appears within the confidence interval.

According to PCI, the acceptable range of the micro-meteorological element value at the moment t_i is

$$[b_i' - t_{\alpha,k-1} \times \frac{S_k}{\sqrt{k}}, b_i' - t_{\alpha,k-1} \times \frac{S_k}{\sqrt{k}}] \tag{3}$$

3) Data correction

If the actual value of the micro-meteorological element b_i measured by the sensor at the moment t_i is within the acceptable range, b_i is normal data and no correction is required; if b_i is outside the acceptable range, b_i is abnormal data and b_i' is used instead.

B. CRITERIA FOR JUDGING NOISE REDUCTION

The purpose of data correction is to reduce sensor noise interference, and the length of the unilateral sliding time window k, as well as the acceptable range, which is related to the confidence coefficient P, are the two most important factors affecting the correction results. The noise reduction effect vary depending on the k and P values. The corresponding k, P values are optimal when the noise reduction effect is best.

The noise reduction effect is measured by H, which is the equal-weighted sum of the corrected data curve's curvature Q and deviation M after normalization.

The curvature Q reflects the unsmoothness of the change curve of micro-meteorological elements, which is defined as the ratio of the sum of the amplitudes when the curve exhibits non-monotonic changes to the data volume. Suppose the total amount of data is N, for a sequence of data $(\ldots, b_{i-1}, b_i, b_{i+1}, \ldots)$, there are two cases:

① If $(b_i - b_{i-1})(b_{i+1} - b_i) \leq 0$, then $q_i = |b_i - b_{i-1}| + |b_{i+1} - b_i|$,

② If $(b_i - b_{i-1})(b_{i+1} - b_i) > 0$, then $q_i = 0$.

The curvature Q can be calculated according to the equation

$$Q = \frac{\sum q_i}{N} \tag{4}$$

The deviation M indicates how far the corrected micro-meteorological element curve differs from the original curve. If the original sequence of the micro-meteorological element is $(\ldots, b_{i-1}, b_i, b_{i+1}, \ldots)$ and the corrected sequence is $(\ldots, b''_{i-1}, b''_i, b''_{i+1}, \ldots)$, then the deviation M can be calculated according to the equation

$$M = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(b_i - b_i''\right)^2} \tag{5}$$

Since Q and M have similar ability to characterize the curve, H takes the normalized equal-weighted summation value of Q and M with the following equation:

$$H = 0.5Q_{\text{normalized}} + 0.5M_{\text{normalized}} \tag{6}$$

The smoother the data, the smaller the curvature Q; the more complete the information retained, the smaller the deviation M. As a result, the data correction effect is best when H is the smallest, and k, P are the optimal values at this time.

C. OPTIMAL CORRECTION METHOD

In this paper, data are collected every ten minutes by the micro-meteorological sensor of No. 150 of the 500 kV Ako line in Tongliao, China. The value of k is chosen as $2, 3, \ldots, 8$ to account for the effect of data from $20, 30, \ldots, 80$ minutes before a specific moment; the confidence coefficient P is chosen as 95%, 98%, 99%, 99.5%, 99.8%. The H values of the corrected curves are calculated using various parameter combinations and the optimal k, P values are obtained when H is the smallest, as shown in TABLE 1. The unilateral time window algorithm that corresponds to the optimal k, P values is the optimal correction method.

TABLE 1. The k, P values corresponding to the smallest H.

Micro-meteorological elements	H	k	P
Temperature(°C)	0.326	5	98%
Humidity(%RH)	0.401	5	95%
Barometric pressure(hPa)	0.385	6	99.5%
Ten-minute average wind speed(m/s)	0.342	4	99%
Standard wind speed(m/s)	0.355	3	99%
Extreme wind speed (m/s)	0.276	4	98%
Ten-minute average wind direction (°)	0.294	3	99.5%

III. MICRO-METEOROLOGICAL ELEMENTS INFLUENCE WEIGHTS

Multiple micro-meteorological elements influence the galloping condition of transmission lines, but different elements have varying degrees of influence. To improve the prediction effect, it is preferable to strengthen the effect of strong influencing elements while weakening the interference of weak influencing elements when constructing the model. In this paper, this is accomplished by assigning influence weights to various micro-meteorological elements.

The gray correlation analysis method is used to obtain the correlation degree between micro-meteorological elements and galloping amplitudes. Then, the correlation degree is converted into the influence weight by the specific gravity method, giving the influence weight a total value of one to clearly demonstrate the contribution of each micro-meteorological element to the galloping. The following are the specific calculation steps:

1) Identify the reference and comparison series: the reference series refers to the series that reflects the system's behavior characteristics (i.e. the galloping amplitude series); the comparison series refers to the series of factors that influence the system' behavior (i.e. the series of micro-meteorological elements). Assume the galloping amplitude series is $Y = \{Y(k)|k = 1, 2, \ldots, N\}$, and the micro-meteorological element series is $X_i = \{X_i(k)|k = 1, 2, \ldots, N\}, i = 1, 2, \ldots, 7$.

2) Dimensionless processing of variables: The factors have different magnitudes and orders of magnitude that make comparison and calculation difficult, so the data need to be dimensionless processed.

$$x_i(k) = \frac{X_i(k)}{X_i(l)}, \quad k = 1, 2, \ldots, N;\ i = 1, 2, \ldots, 7 \tag{7}$$

3) Determine the correlation coefficient.

$$\xi_i(k) = \frac{\min_i \min_k \Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_k \Delta_i(k)} \tag{8}$$

where $\Delta_i(k) = |y(k) - x_i(k)|$. $\xi_i(k)$ is the correlation coefficient between x_i and y at the moment k. ρ is the resolution coefficient, which is usually set to 0.5.

4) Determine the correlation degree. The correlation degree is the weighted average of the correlation coefficient, and the equation is as follows

$$r_i = \frac{1}{N}\sum_{k=1}^{N} \xi_i(k) \tag{9}$$

5) Convert the correlation degree into influence weight by the specific gravity method.

$$w_i = \frac{r_i}{\sum_{i=1}^{7} r_i} (\mathrm{i} = 1, 2, \ldots, 7) \tag{10}$$

TABLE 2 shows the correlation degree and influence weight of various micro-meteorological elements.

TABLE 2. The correlation degree and influence weight of various micro-meteorological elements.

Micro-meteorological elements	Correlation degree from eq (9)	Influence weight from eq (10)
Temperature(°C)	0.854 1	0.138 3
Humidity(%RH)	0.870 2	0.140 9
Barometric pressure(hPa)	0.880 4	0.142 6
Ten-minute average wind speed(m/s)	0.900 6	0.145 8
Standard wind speed(m/s)	0.899 0	0.145 6
Extreme wind speed (m/s)	0.897 7	0.145 4
Ten-minute average wind direction (°)	0.873 9	0.141 5

IV. GALLOPING PREDICTION MODEL DESIGN

A. PREDICTION PROCESS

The prediction process of transmission line galloping proposed in the paper is shown in FIGURE 1.

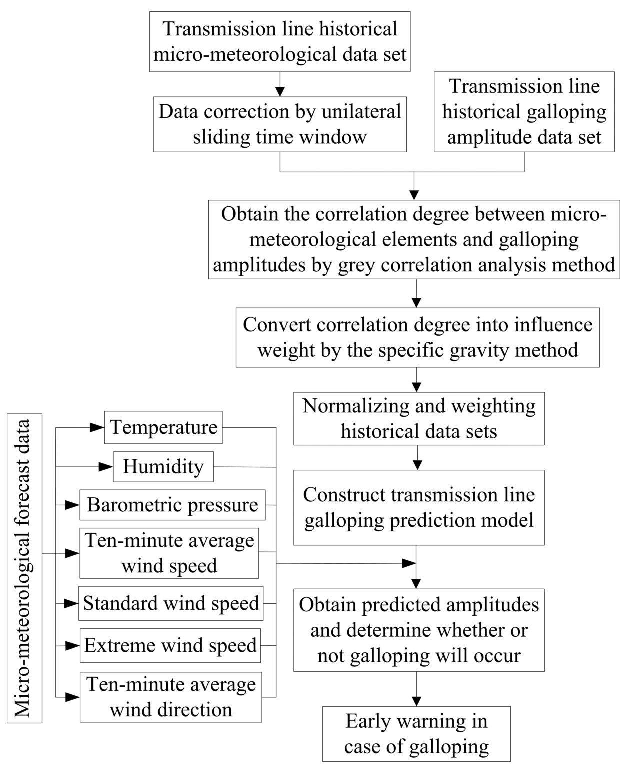

FIGURE 1. Flow chart of transmission line galloping prediction.

The historical data collected by the micro-meteorological sensors are first corrected using the unilateral sliding time window, after which the correlation degree between the micro-meteorological elements and galloping amplitudes is calculated using gray correlation analysis method, and the correlation degree is then converted into influence weight using the specific gravity method. After normalizing the historical data sets, machine learning algorithms are trained to predict transmission line galloping using weighted micro-meteorological element values as input and galloping amplitude data as output. Following the construction of the model, the predicted amplitude of the galloping can be obtained from micro-meteorological forecast data and used to determine whether or not the galloping will occur. If there is going to be galloping, an early warning will be issued.

Transmission line galloping, in contrast to aeolian vibration, which exhibits a high frequency and small amplitude oscillation, and subspan oscillation, which exhibits a medium frequency and medium amplitude oscillation [22], [23], exhibits a low frequency and large amplitude oscillation. The majority of existing studies use fieldwork or amplitude to determine whether galloping occurs because there is no universal standard for determining galloping. This paper takes into account the structure of the research line (Arco line) as well as the meteorological conditions of its location, and considers oscillation amplitudes greater than 20 times the diameter of the transmission line to be galloping, with a warning issued when the predicted amplitude reaches this threshold.

B. PERFORMANCE EVALUATION OF PREDICTION MODELS

The prediction results of the model are given in the form of a confusion matrix because the method of constructing models using past micro-meteorological and amplitude data is supervised learning.

TABLE 3. Confusion matrix of prediction results.

Actual \ Predicted	Galloping	No galloping
Galloping	*TP*	*FN*
No galloping	*FP*	*TN*

In the table above, *TP* and *TN* represent the number that prediction results match the actual situation, *FN* represents the number that actually galloping but is predicted as no galloping, and *FP* represents the number that actually no galloping but is predicted as galloping.

To visually assess prediction performance, Accuracy, Precision, Recall, and F1-score are calculated as model performance metrics based on the confusion matrix using the following equations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{12}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{13}$$

$$\text{F1-score} = \frac{2^{*}\text{Precision}^{*}\text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

According to the definition of the confusion matrix in this paper, Accuracy refers to the probability that the prediction result matches the actual situation. Precision refers to the probability of correct prediction when predicted as galloping. Recall refers to the probability that the actual galloping can be predicted. F1-score is a comprehensive evaluation index that considers both Precision and Recall. The higher the value of these four performance metrics in this paper, the more ideal the model.

V. MODEL CONSTRUCTION AND ANALYSIS OF PREDICTION RESULTS

A. SINGLE ALGORITHM MODEL PREDICTION RESULTS

Current machine learning-based galloping prediction methods mainly include support vector machines, neural networks, integration algorithms, and cluster analysis [24]–[27]. To determine a more suitable prediction method, this paper constructs galloping prediction models using BP neural network, GA-BP neural network, RBF algorithm, AdaBoost algorithm, support vector machine (SVM), and extreme learning machine (ELM), and compares the performance of different models based on the prediction results.

The data for this paper was provided by the Mengdong Maintenance Company of the State Grid Corporation of China's Northeast Division. The 1920 valid data sets collected from the Tongliao 500 kV Ako Line No.150 sensors over two time periods, November 2018 to April 2019 and August 2019 to November 2019, are divided into two parts, the training set, and the test set, which accounts for 85% and 15% of the total. The model was trained separately using the above 6 algorithms to predict the test set, with the weighted micro-meteorological data as the input and the amplitude data as the output, and the prediction results are shown in FIGURE 2.

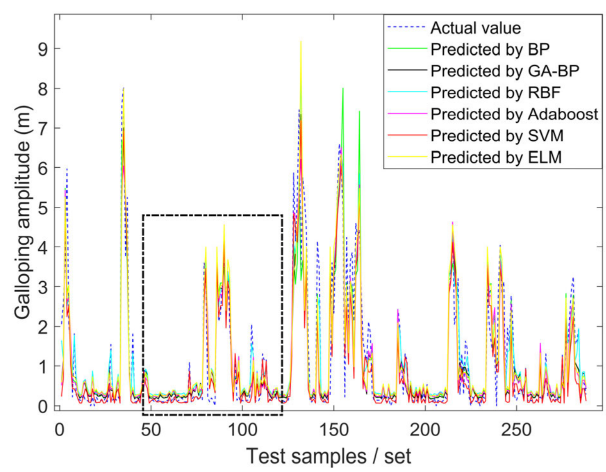

FIGURE 2. Prediction results of different algorithm models.

FIGURE 2 is partially enlarged into FIGURE 3 to show the prediction results more clearly. The contents of FIGURE 2's black dashed box correspond to the contents of FIGURE 3's black dashed box.

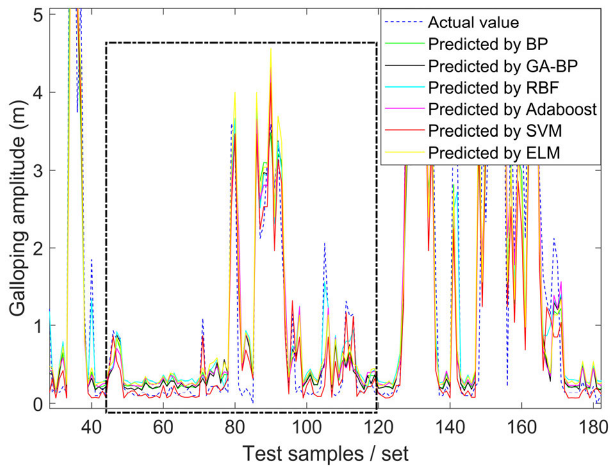

FIGURE 3. Partial enlargement of FIGURE 2.

TABLE 4. Confusion matrices for the prediction results of each model.

Actual \ Predicted by **BP**	Galloping	No galloping
Galloping	82	24
No galloping	32	150

Actual \ Predicted by **GA-BP**	Galloping	No galloping
Galloping	96	10
No galloping	15	167

Actual \ Predicted by **RBF**	Galloping	No galloping
Galloping	79	27
No galloping	25	157

Actual \ Predicted by **Adaboost**	Galloping	No galloping
Galloping	86	20
No galloping	28	154

Actual \ Predicted by **SVM**	Galloping	No galloping
Galloping	85	21
No galloping	7	175

Actual \ Predicted by **ELM**	Galloping	No galloping
Galloping	84	22
No galloping	32	150

TABLE 4 shows the prediction results of each model as confusion matrices.

Accuracy, Precision, Recall, and F1-score of each model are calculated as performance metrics using confusion matrices, and the results are shown in TABLE 5.

TABLE 5. Performance metrics of each model.

Algorithm	Accuracy	Precision	Recall	F1-score
BP	0.806	0.719	0.774	0.745
GA-BP	**0.913**	0.864	**0.906**	**0.885**
RBF	0.819	0.760	0.745	0.752
AdaBoost	0.833	0.754	0.811	0.781
SVM	0.889	**0.924**	0.802	**0.859**
ELM	0.813	0.724	0.792	0.756

As shown in TABLE 5, the GA-BP algorithm model has the highest Accuracy and Recall values, indicating that it has the highest prediction accuracy, fits the data best, and has the lowest probability of missing a warning when the galloping occurs. The SVM algorithm model has the highest Precision value, indicating that it has the highest probability of correct prediction and the lowest probability of false warning when the predicted result is galloping. Furthermore, these two algorithm models have the highest F1-score values of the six algorithms. After considering the performance metrics of each model, it is possible to conclude that the GA-BP algorithm and the SVM algorithm are more effective in galloping prediction.

B. GA-BP-SVM COMBINED MODEL PREDICTION RESULTS

We want to construct a prediction model that has the highest Accuracy, Precision, Recall, and F1-score values, indicating that it is the most ideal model. As shown in TABLE 5, a single algorithm model does not meet this requirement. To achieve this goal, we are considering constructing a combined algorithm model. The GA-BP algorithm and the SVM algorithm, both of which have good prediction effects, are chosen for the combined prediction using the variance-covariance weight dynamic assignment method, with the following calculation steps.

First, the variance of the GA-BP and SVM algorithm models are calculated separately using the equation below.

$$\delta_i = \frac{1}{n} \times \left[(e_1 - \bar{e})^2 + (e_2 - \bar{e})^2 + \cdots + (e_n - \bar{e})^2 \right], \quad i = 1, 2 \tag{15}$$

where n is the number of test samples for each model; $e_1, e_2, \ldots, e_n$ is the absolute percentage error of test samples for each model; and $\bar{e}$ is the average absolute percentage error of test samples for each model.

The weights for each model are then calculated using the following equation based on the variance.

$$\omega_1 = 1/\left[\delta_1(1/\delta_1 + 1/\delta_2)\right] \tag{16}$$

$$\omega_2 = 1/\left[\delta_2(1/\delta_1 + 1/\delta_2)\right] \tag{17}$$

The prediction result of the GA-BP-SVM combined model is

$$f = \omega_1 f_1 + \omega_2 f_2 \tag{18}$$

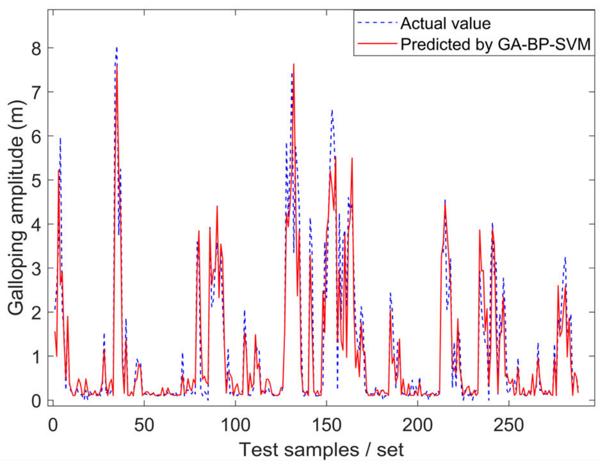

FIGURE 4. GA-BP-SVM combined model prediction results.

where f_i is the prediction result of the single algorithm model.

The combined prediction method can dynamically adjust the weights of each prediction model based on each test result, resulting in more accurate and adaptable prediction results. FIGURE 4 shows the prediction results of the GA-BP-SVM combined model.

TABLE 6 shows the prediction results of the GA-BP-SVM combined model in the form of a confusion matrix.

TABLE 6. Confusion matrix for the prediction results of GA-BP-SVM combined model.

Actual \ Predicted by GA-BP-SVM	Galloping	No galloping
Galloping	98	8
No galloping	5	177

The performance metrics of the GA-BP-SVM combined model are calculated using the confusion matrix and compared to the performance metrics of the single algorithm models that comprise the combined model, as shown in TABLE 7.

TABLE 7. Comparison of performance metrics between GA-BP-SVM combined model and single algorithm models.

Algorithm	Accuracy	Precision	Recall	F1-score
GA-BP	0.913	0.864	0.906	0.885
SVM	0.889	0.924	0.802	0.859
GA-BP-SVM	**0.955**	**0.951**	**0.925**	**0.938**

As shown in TABLE 7, the GA-BP-SVM combined model outperforms the GA-BP and SVM models that comprise it. Each of the performance metrics for the combined model is the best. The model's Accuracy value of 0.955 indicates that it can predict both galloping and non-galloping states with 95.5% accuracy; Precision value of 0.951 indicates that the probability of correct prediction, when predicted as galloping is 95.1%; Recall value of 0.925 indicates that the actual galloping can be predicted with 92.5 percent accuracy. Meanwhile, the combined model's F1-score value reaches 0.938, indicating that it has the best prediction effect.

Based on the data presented above, it is possible to conclude that the GA-BP-SVM combined model has the highest prediction accuracy, fits the data best, has the lowest probability of missing warnings when gallopings occur, and has the lowest probability of false warnings, making it the most ideal model for predicting transmission line gallopings.

VI. CONCLUSION

This paper corrects the micro-meteorological data using the unilateral sliding time window, and determines the influence weights of micro-meteorological elements using the gray correlation analysis method and the specific gravity method. The galloping prediction models are then constructed using various machine learning algorithms, and after analyzing the prediction results, a GA-BP-SVM combined prediction model is proposed. The following conclusions are drawn from this paper.

1) The unilateral sliding time window algorithm is used to correct micro-meteorological data. The predicted values and acceptable ranges of the micro-meteorological elements are obtained, resulting in the correction of abnormal data while retaining normal data. The noise reduction effect is then measured using the normalized equal-weighted sum value H of the curvature and deviation, and the optimal values of the k and P parameters in the algorithm are determined. The method is practical and general, and it can produce correction results that retain information while having no abnormal mutation points, effectively completing the data noise reduction work.

2) The gray correlation analysis method and the specific gravity method are used to calculate the influence weights of micro-meteorological elements. Weighting the micro-meteorological elements can result in input data that highlights galloping patterns more clearly and assists in the training of galloping prediction models.

3) The galloping prediction models are constructed based on various algorithms, and the GA-BP algorithm model and SVM algorithm model are determined to have better prediction results based on the performance metrics. To achieve more ideal prediction results, the GA-BP-SVM combined model is constructed. This model outperforms all others in every performance metric, with the highest prediction accuracy, the lowest probability of missing galloping warnings, and the lowest probability of false warnings, demonstrating that the model has the most ideal prediction effect.

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YING WEI received the B.S. degree from the School of Electrical and Electronic Engineering, North China Electric Power University, in 2019, where she is currently pursuing the master's degree. Her current research interests include transmission line operation and maintenance and transmission line galloping prediction research.

XUELIAN GAO received the Ph.D. degree from the Institute of Semiconductors, Chinese Academy of Sciences, in 2005. From 2009 to 2010, she was a Visiting Scholar with Strathclyde University, U.K. She is an Associate Professor with the School of Electrical and Electronic Engineering, North China Electric Power University. Her current research interests include artificial intelligence algorithms and applications, integrated circuit, and system-on-chip design and applications.