Temperature Prediction of High-voltage Switchgear Based on Multi-type Machine Learning Algorithm

Zuowei Pan, Xiaowei Wang*, Yan Li, Haiting Yang, Ning Wang, Guoliang Sun, Jun Wu, Bo Zhang

Inner Mongolia Jingneng Kangbashi Thermal Power Co., Ltd., Inner Mongolia, China

**Corresponding Author.*

Abstract:

High-voltage switchgear plays a crucial role in modern industrial and electrical systems, used for controlling and safeguarding electrical equipment from overloads, short circuits, and other electrical faults. However, these switchgears generate significant heat during operation, making accurate prediction and timely alerting of abnormal temperature changes essential for preventing equipment overheating and extending its lifespan. To establish an efficient temperature warning system, real-time temperature data from optic fiber temperature sensing system was studied in this work. Initially, multi-type machine learning algorithms including Lasso Regression, Random Forest, AdaBoost, SVM, KNN, and GradientBoost were tested and compared. Experimental results revealed that the Random Forest algorithm performed the best in predicting high-voltage switchgear temperatures. By combining predictions from multiple decision trees, this algorithm effectively captures complex temperature variations, providing highly precise forecasts. Leveraging the predictive capabilities of the Random Forest model, temperature warnings were generated for different time intervals. Experimental findings demonstrate that the Random Forest algorithm could effectively forecast temperature trends for 10 minutes, 2, 4, and 8 hours ahead, thereby enabling timely detection of potential overheating risks and facilitating necessary maintenance measures.

Keywords: machine learning algorithems, temperature warning, random forest, high-voltage switchgear, overheating risk detection

INTRODUCTION

With the swift advancement of industrial automation and smart grids, monitoring the operational status and predicting faults of high-voltage switchgear has become a key focus in engineering research. The temperature of high-voltage switchgear is a critical indicator reflecting its operational status and safety stability. Accurately predicting temperature changes is essential for improving equipment reliability, extending equipment lifespan, and ensuring the safe operation of power systems [1,2]. As power systems evolve towards intelligence and high capacity, higher demands are placed on temperature measurement technologies for switchgear [3]. Currently, temperature measurement techniques for switchgear mainly include contact and non-contact methods. Contact-based temperature measurement relies on independent temperature sensors installed inside the switchgear to monitor temperatures in real-time [4-6]. While simple and practical, this method is limited by factors such as sensor quantity and placement, making it difficult to comprehensively monitor internal temperature distributions. Non-contact temperature measurement techniques utilize infrared thermal imaging to monitor the surface temperature of switchgear without physical contact [7]. Although online monitoring technology enables real-time temperature monitoring, faults of switchgear have occured by the time an alarm is triggered, which affects the timeliness of maintenance efforts. Therefore, identifying potential risks to enable more proactive preventive maintenance is of utmost importance. The research on the application of artificial intelligence in switchgear will further improve the accuracy of fault prediction and the ability to identify potential risks, thereby achieving more intelligent and efficient equipment maintenance and management [8-10]. Researchers worldwide have conducted extensive studies using AI techniques to predict switchgear temperatures [11]. A model using sparrow search and backpropagation neural network algorithms were proposed to predict temperature of switchgear and humidity by collecting external temperature, humidity, and atmospheric pressure data [12]. Long short-term memory (LSTM) neural networks were harnessed to forecast busbar temperature rises in switchgear by collecting and analyzing temperature and current data [13]. A kind of improved wavelet neural network combined with neural networks were introduced for ultra-short-term prediction of high-voltage switchgear temperatures [14].

In this work, optic fiber temperature monitoring system was installed on the 6 kV switchgear in a certain power plant to collect temperature data at key locations inside the cabinet. The study compared and analyzed the effects of six artificial intelligence algorithms on the processing of temperature data, including Support Vector Machine (SVM), AdaBoost, K-Nearest Neighbors (KNN), Lasso Regression, Random Forest, and Gradient Boost. The temperature data collected were preprocessed, including data cleaning, feature selection, and standardization. Subsequently, models for predicting temperature at 10-minute intervals were established using the six aforementioned algorithms, and then trained and validated. Finally, comparative analysis of temperature prediction was conducted for the optimal algorithm at 10 minutes, 2, 4, and 8 hours. This study provided an effective solution for the early warning and potential risk analysis of the temperature in high-voltage switchgear, and held significant application value.

THEORY

KNN Regression Prediction Algorithm

K-Nearest Neighbors (KNN) is a kind of versatile machine learning algorithm that classifies or predicts the value of an unknown data point based on its closest neighbors in feature space. Unlike many algorithms that require complex training, KNN stores the entire training dataset and makes predictions by analyzing the k nearest data points to a new input, typically using Euclidean distance. This lazy learning approach allows KNN to effectively handle nonlinear and complex relationships without prior assumptions. Its simplicity and effectiveness in both classification and regression tasks have made it popular in applications like image recognition, recommendation systems, anomaly detection, and bioinformatics, where it helps uncover meaningful patterns from diverse datasets [15].

Random Forest Prediction Algorithm

The Random Forest (RF) algorithm is a strong and adaptable ensemble learning technique that leverages the strengths of several decision trees to develop an exceptionally accurate predictive model. The algorithm works by generating a “forest” of individual decision trees. Each tree is cultivated using a randomly picked segment of the training dataset and a randomly chosen subset of the available features. This randomness aids in minimizing the correlation among the trees, making the overall model less prone to overfitting and better able to generalize to new, unseen data. During the prediction phase, the forest combines the results from each individual tree. The ultimate forecast is produced either by majority voting for classification tasks or by averaging for regression tasks, based on the outputs of the individual trees. The ensemble methodology of RF aids in capturing intricate, non-linear data relationships, managing high-dimensional and noisy features, and offering insightful analysis on feature significance. Additionally, the algorithm is capable of handling discrete and continuous factors, making it a flexible option for a wide range of applications. RF’s robustness, strong performance, and ability to provide interpretable results have made it a popular choice in fields Such as visual identification, language comprehension technology, medical services, economic management, and forecasting analytics, where it has proven its efficacy in tackling intricate problems. and uncovering meaningful insights from the data [16].

SVM Regression Prediction Algorithm

Support Vector Machines (SVM) represent a robust machine learning algorithm capable of handling both classification and regression assignments. The core concept of SVM focuses on determining the best hyperplane that maximizes the separation between various classes or data points. In classification problems, SVM balances model complexity and classification errors through a problem of optimization aimed at discovering the optimal hyperplane for separation. For regression tasks (known as Support Vector Regression, SVR), it aims to find the hyperplane that best fits the data with a tolerance for deviations from the true targets. The advantages of SVM encompass its capability to manage data with high dimensionality. robustness to overfitting, and adaptability in addressing both linear and non-straightforward challenges. However, the optimization procedure can be resource-intensive for extensive datasets, and the choice of kernel function significantly impacts the model’s performance [17].

Lasso Regression Prediction Algorithm

Lasso regression, also known as the Least Absolute Shrinkage and Selection Operator, is a linear regression method that uses regularization to enhance both the predictive performance and comprehensibility of the model. It accomplishes this by incorporating a penalty component into the standard least squares objective function, More precisely, it involves adding the product of a regularization parameter, lambda, and the total of the absolute values of the coefficients to the usual least squares objective. This penalty encourages sparse solutions where less important features have their coefficients shrink towards zero, efficiently carrying out attribute selection. Lasso is particularly useful in situations with high-dimensional data where many features may be irrelevant or redundant. By tuning the regularization parameter, Lasso regression balances between minimizing the residual sum of squares and shrinking coefficients, ultimately producing a simpler model that can generalize better to unseen data while highlighting the most influential predictors [18].

AdaBoost Prediction Algorithm

AdaBoost, an abbreviation for Adaptive Boosting, is a potent ensemble learning technique that integrates numerous weak classifiers to form a robust classifier. It works iteratively by adjusting the weights of incorrectly classified instances, allowing subsequent weak learners to focus more on the challenging examples. During each iteration, AdaBoost increases the weights of misclassified instances, encouraging the subsequent weak learner to focus on these more challenging cases. The final prediction is then made by a weighted combination of all weak learners, where each learner contributes according to its accuracy in the training process. AdaBoost is particularly effective in improving the accuracy of classification tasks, often outperforming single classifiers by leveraging the diversity and collective wisdom of multiple weak learners, such as decision trees with limited depth, to achieve robust generalization on complex datasets [19].

GradientBoost Prediction Algorithm

Gradient Boosting represents a collective learning methodology that constructs a robust predictive model by iteratively incorporating predictors into the ensemble, each subsequent predictor aims to rectify the errors made by the previous ones, thereby enhancing the ensemble's predictive capability. Unlike AdaBoost, which adjusts the weights of instances, In Gradient Boosting, each new model is trained to predict the residuals, or errors, left by the preceding model in the sequence. It optimizes a loss function using gradient descent or other optimization methods, which allows it to handle various types of predictive tasks such as regression and classification. By iteratively minimizing the residuals, Gradient Boosting builds a potent model by integrating the capabilities of multiple weak learners, commonly in the form of decision trees, into a robust ensemble that can generalize well to unseen data. This approach often results in highly accurate predictions and is frequently utilized in machine learning contests and practical applications where predictive accuracy is paramount [20].

EXPERIMENT

Temperature Monitoring Scheme

Optic fiber grating temperature sensor system was used to measure the temperature of high-voltage switchgear, including sensor modules, fiber optic grating demodulation modules, and terminal display modules. Optic fiber grating temperature sensors were installed at critical positions inside the high-voltage switchgear for monitoring purposes. The signals of sensors were analyzed using optic fiber grating demodulator to obtain corresponding temperature data, which was then displayed via the terminal display module enabling temperature real-time display, data storage and alarm functionalities.

Process of Temperature Prediction

The temperature prediction process for high-voltage switchgear in this study was illustrated in Figure 1. Firstly, original temperature data of the switchgear as shown in Figure 2 was obtained based on the optic fiber grating temperature sensor system described in section 3.1. Subsequently, data preprocessing was conducted to clean and filter the collected data, removing missing and outlier values. The data is formatted in vector format as shown in Equations (1) and (2).

$$\vec{x}_t = [e_1, e_1, e_1, \cdots, e_t], [e_{t+2}, e_{t+3}, e_{t+4}, \cdots, e_{t+t}] \tag{1}$$

$$y_n = [e_{t+1}, e_{2t+1}, e_{3t+1}, \cdots, e_{nt+1}] \quad (2)$$

e was the sensor temperature. Feature variables were created including the current temperature, temperature variations over the past 10 minutes at monitoring points, which encompass the temperature average, maximum, and minimum values, as well as features correlating with ambient temperature. The dataset in vector format was divided into training and testing sets, with 80% for training and 20% for model testing. Prediction models of temperature were trained using machine learning regression algorithm with the training set. The data of temperatures in testing set were input to prediction models to predict the temperature of the high-voltage switchgear 10 minutes later. The optimal algorithm was selected by comparing the prediction results with the actual temperature 10 minutes later. The performance of the optimal algorithm were evaluated by analysing the prediction results of the temperatures 10 minutes, 2, 4, and 8 hours later.

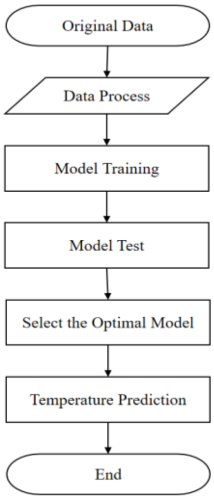

Figure 1. Process of temperature prediction

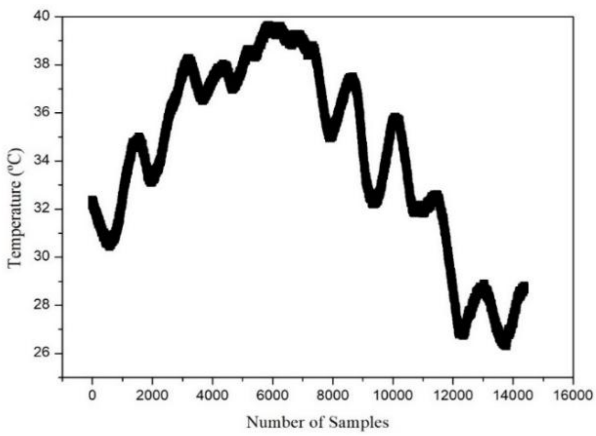

Figure 2. Original temperature data of the switchgear

Comparison of Prediction Results

In this study, six kinds of machine learning algorithms were employed, including SVM, RF, KNN, Lasso Regression, AdaBoost and GradientBoost, to predict and warn of temperatures of high-voltage switchgear. For the SVM model, the penalty coefficient was set to 1.0 and Gaussian kernel function was used. For the RF model, established the count of decision trees at 100, with the default value of the maximum number of features. For the KNN model, the value of k was set to 5, the threshold for stopping subtree growth was set to 30, and the default Minkowski distance was adopted. For the Lasso regression model, the regularization strength was set to 1.0. For the AdaBoost model, 50 training models were specified. For the Gradient Boosting model, the threshold for the minimum number of samples at internal nodes was established at 2, Leaf nodes were required to have at least 1 sample, the number of trees was 100, and the value of maximum depth of each tree was set to 3. The performance of temperature prediction for each machine learning algorithms were illustrated in Figure 3. Assessment criteria encompassed Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE)[21] were adopted and the corresponding results were presented in Table 1. The calculation of RMSE was shown in the Equation (3), the calculation of MAE was shown in the Equation (4), and the calculation of MSE was shown in the Equation (5) [22].

$$RMAS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

Where y_i represented the actual temperature, and $\hat{y}_i$ represented the predicted temperature.

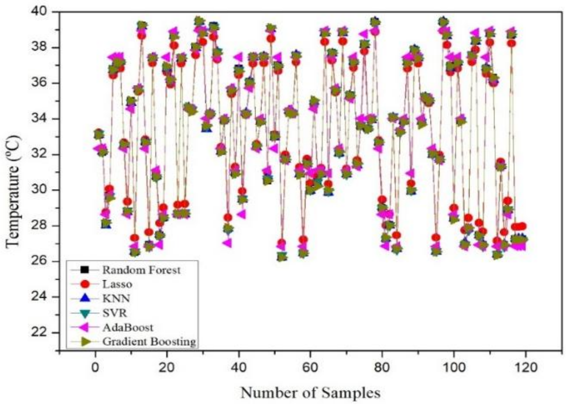

Figure 3. The performance of temperature prediction for each machine learning algorithms

Table 1. The evaluation metrics for each machine learning algorithms

Algorithms	RMSE	MAE	MSE
KNN	0.105	0.083	0.011
AdaBoost	0.341	0.265	0.116
SVM	0.106	0.085	0.011
GradientBoost	0.104	0.083	0.011
Lasso	0.428	0.368	0.183
RF	0.101	0.079	0.011

The calculation method for MSE involves squaring the differences and dividing the sum by the number of samples, which represents the predictive accuracy of the model. with smaller values indicating less deviation between predicted and actual values, thus indicating better model performance. MAE reflects the average absolute error, with lower values suggesting higher prediction accuracy. MSE is the square of RMSE; a smaller value also reflects greater forecast precision. As shown in Table 1, the RF algorithm outperforms all other algorithms across all evaluation metrics, with an RMSE of 0.101, MAE of 0.079, and MSE of 0.011. Gradient Boosting and KNN also perform well, ranking second and third with RMSE values of 0.104 and 0.105, respectively. In contrast, Lasso regression exhibits the poorest performance, with RMSE, MAE, and MSE values of 0.428, 0.368, and 0.183, respectively, indicating its limited effectiveness for the specific task of temperature prediction. These results underscore the importance of selecting an appropriate regression model to enhance predictive accuracy, wherein the RF model is identified as the preferred algorithm for the current task.

TEMPERATURE PREDICTION OF RF ALGORITHM

As observed in the preceding section, the RF algorithm was suitable for the data of this study, so we will use the RF algorithm to predict the temperature of the switchgear in the next 2,4,8 hours.

Construction Process

The data collected by temperature sensors may contain random errors, and the accumulation of these errors can affect the accuracy of predictions. To address this issue, a method for evaluating feature importance was employed to perform dimensionality reduction on the feature data. To achieve this goal, a regression decision tree RF model based on a binary tree structure was constructed. In this regression decision tree, the internal nodes correspond to the criteria for judging feature attributes, the branches represent the output results of the judgment conditions, and the leaf nodes store the continuous values used for predictions.

In a binary decision tree, the split points are crucial to the final performance of the model. Since the prediction of switch cabinet temperature was a regression problem, we select the optimal splitting variable based on MSE. The formula for calculating the optimal split point was shown in Equation (6).

$$L(j,s)=\sum_{x_i\in R_1(j,s)}(y_i-\widehat{c_1})^2+\sum_{x_i\in R_2(j,s)}(y_i-\widehat{c_2})^2 \tag{6}$$

where y_i represented the true value at that point, j denoted the j-th variable, s indicated the s-th split point, $R_1(j,s)$ refered to the left region after the split, $R_2(j,s)$ refered to the right region after the split, $\widehat{c_1}$, $\widehat{c_2}$ represented the optimal output values for the regions $R_1(j,s)$ and $R_2(j,s)$ respectively.

Based on the determination of the optimal splitting variable, a decision tree was recursively constructed by setting an appropriate threshold for node depth. In the construction of a RF, the generation process of each decision tree was independent, meaning that each tree was constructed using the aforementioned process, but the selected features and split points for each tree were different, which increases the diversity of the model. To achieve the final feature importance analysis, feature importance ranking was performed using out-of-bag (OOB) data based on the RF model. By sampling certain samples from the dataset with replacement, a CART tree can be constructed. The samples that were not selected were referred to as OOB and can be used for internal model evaluation. The OOB error offers an impartial evaluation of the prediction error, while the final model's prediction result was determined by the average of the results from all individual tree models. This method was used for the predictions of the RF regression model. The integration of the bagging algorithm with random feature subspaces boosts the generalization power of the decision regression tree within the RF regression framework. The predictive prowess of the RF regression model is influenced by crucial parameters such as the count of decision trees and the minimum leaf node requirement.

Applying the RF algorithm for predicting the temperature of switchgear to solve the problem of nonlinear complex relationships involves the following steps:

1. Sample Set: Select the original variable data that affects the temperature of the switchgear as input variable X, while the temperature data of the switchgear serves as the output variable Y, thus forming the original sample set.

2. Sampling Set: Employ the Bootstrap technique to conduct sampling with replacement on the initial sample set, yielding multiple sample subsets, with the unselected portions forming the OOB data.

3. Growth Phase: During the construction of each individual decision tree, randomly select a subset of the input variables X and perform feature splitting by selecting the optimal input variable, which promotes the growth of the tree.

4. Validation Phase: Use the OOB data to evaluate the model's performance and accuracy, calculating the importance gain (IG) of features through the variation in the OOB error rate. The larger this value, the higher the correlation of the feature with the prediction result and the greater its influence weight. The calculation formula was shown in the Equation (7):

$$IG_j=\frac{1}{n}\sum_{i=1}^{n}OOB1_e^i-OOB2_e^i \tag{7}$$

where n represented the number of samples, $OOB1_e^i$ denoted the OOB error calculated using the OOB data corresponding to each decision tree, and $OOB2_e^i$ represented the OOB error calculated after adding noise, $i=1,2,\dots,n$.

5. Prediction Phase: For each new input variable x_i (i = 1, 2, … , k), each tree produces a predicted value y_i (i = 1, 2, … , k). The final prediction of the RF was the mean of the forecasted values from all the trees. In a RF, each tree uses only a subset of the features from the original sample set for modeling. This approach increases model diversity and reduces correlation among the trees. The model structure was shown in Figure 4.

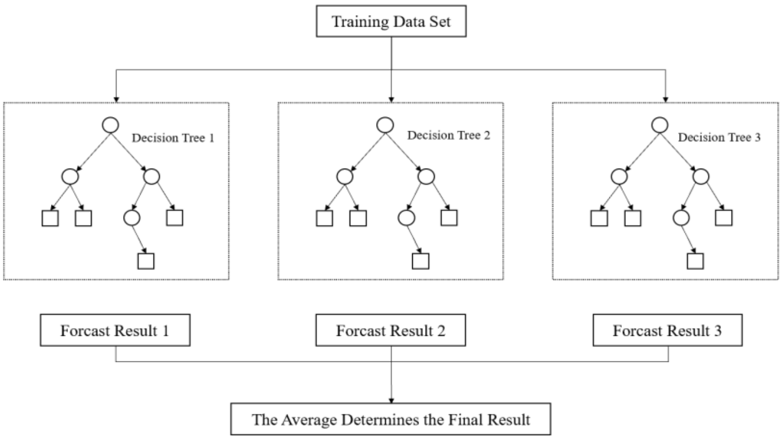

Figure 4. The model structure of RF

Construct a RF Regression Model

The overall design idea for establishing a temperature prediction model for high-voltage switchgear based on the RF algorithm was: First, it was essential to identify the feature factors related to the temperature of the high-voltage switchgear, as appropriate feature selection can significantly enhance the predictive capability of the model. Next, a dataset related to these feature factors needs to be collected and organized. Then, the RF algorithm was applied to build the prediction model. After developing the model, the next step was to continuously optimize its performance by adjusting the optimal combination of parameters. This involves systematically evaluating the impact of different parameter settings on the model results to ensure that the best parameter configuration was identified. The design flowchart was shown in Figure 5.

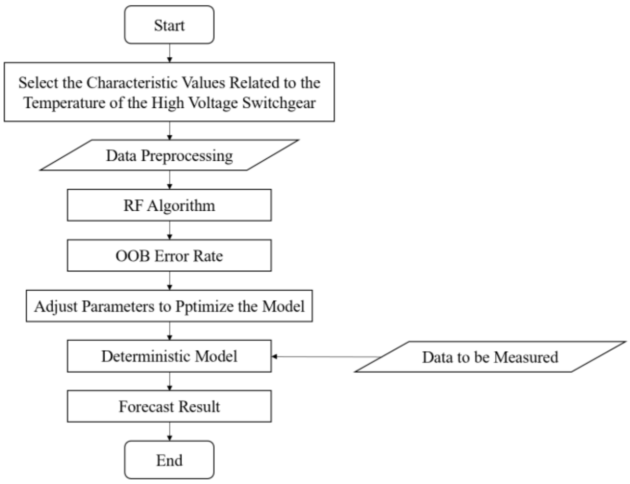

Figure 5. The flow of RF algorithm

Forecasted Temperature Outcomes of High Voltage Switchgear Based on RF Model were Realized

The trained model was verified using the test set, The performance of temperature prediction for 2, 4, and 8 hours later were shown in Figure 6, Figure 7 and Figure 8, The black square line represents the connection of the actual values at various points, with the black squares indicating the actual values. The red circle line represents the connection of the predicted values at various points, with the red circles indicating the predicted values. From the figure, it can be observed that the fitting effects of the dark square-marked line and the crimson circular line align closely. The dark square-marked line and the crimson circular line for the same temperature sample of the switchgear are also basically corresponding and close to each other, indicating that the discrepancy between the model's forecasted values and the actual values in the test set was minimal. respectively, with the evaluation metrics presented in Table 2.

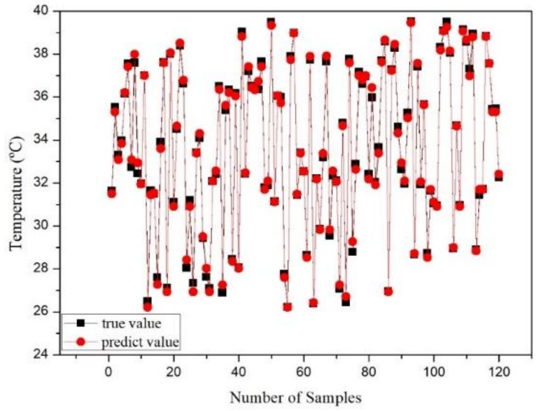

Figure 6. The performance of temperature prediction for 2 hours later

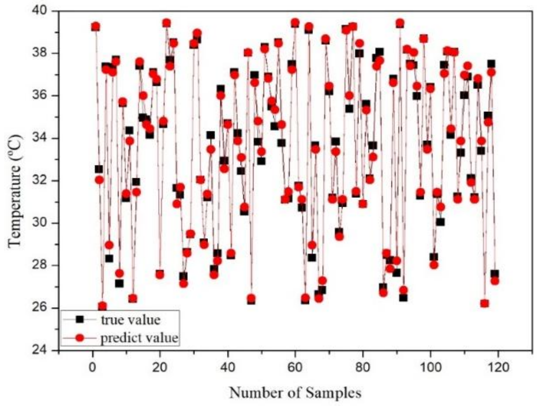

Figure 7. The performance of temperature prediction for 4 hours later

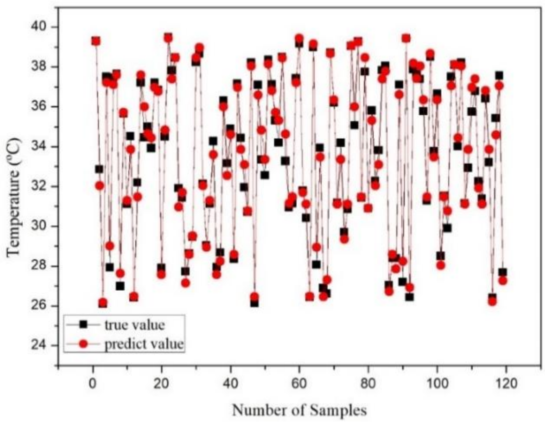

Figure 8. The performance of temperature prediction for 8 hours later

Table 2. The evaluation metrics for RF algorithm in different time periods

Evaluation index	10/minutes	2/h	4/h	8/h
MAE	0.079	0.159	0.262	0.376
MSE	0.011	0.054	0.111	0.261
RMSE	0.101	0.232	0.332	0.511

As shown in Table 2, with the increase in time intervals, MAE, MSE, and RMSE all showed an upward trend, indicating that prediction errors increased with the extension of time. The MAE value for the 8-hour temperature warning was 0.376, the MSE value was 0.261, and the RMSE value was 0.511, all of which fall within an acceptable error range. Notably, the prediction accuracy remained high, especially during the 10-minute and 2-hour time periods. Therefore, based on the results of these evaluation metrics, it can be deduced that the model demonstrates good precision and accuracy in prediction, providing a reliable reference for practical applications.

CONCLUSIONS

Temperature data of high-voltage switchgear was obtained using fiber optic grating temperature sensing system. Artificial intelligence algorithms, including SVM, RF, KNN, Lasso Regression, AdaBoost, and GradientBoost, were adopted to predicted temperature 10 minutes later. The results showed that the RF algorithm exhibited the best predictive performance. The RF algorithm was used to forecast temperatures at different time intervals and the performance of temperature prediction for 2, 4, and 8 hours later could meet the demand of temperature prediction of high-voltage switchgear, which indicated that the temperature prediction technology based on RF algorithm had important application value in the field of predictive maintenance of high-voltage switchgear.

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