Journal of Electrotechnology, Electrical Engineering and Management (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/jeeem.2024.070303
ISSN 2560-6697 Vol. 7 Num. 3

Optimization of Preventive Maintenance Strategies for Electrical Equipment on Offshore Oil Support Vessels Based on Predictive Maintenance Algorithms in an Intelligent Platform

Changsheng Wang*

China Oilfield Services Limited Zhanjiang Branch, Zhanjiang, Guangdong, 524047, China
714228714@qq.com
*Corresponding author

Keywords: Predictive Maintenance; LSTM Network; Electrical Equipment Maintenance; Offshore Oil

Abstract: The electrical equipment of offshore oil support ships operates in harsh marine environments with high failure rates, posing challenges to the development of preventive maintenance strategies. To address this issue, this article proposes an intelligent platform based on Long Short Term Memory (LSTM) algorithm to optimize preventive maintenance strategies for electrical equipment. Firstly, operational data of ship electrical equipment is collected, and data preprocessing and key feature extraction are carried out; subsequently, a prediction model based on LSTM is constructed to make real-time predictions on the health status of the equipment; then, the predictive model is integrated into the intelligent platform to achieve real-time monitoring of device status and dynamic optimization of maintenance strategies. The experimental results show that the LSTM based prediction model outperforms support vector regression (SVR) and random forest methods in terms of prediction accuracy and robustness. The average monthly failure rate of the equipment is 0.67 times, and the maintenance cost for 12 months is only $4750. In the above data conclusions, the intelligent platform based on LSTM algorithm can significantly improve the effectiveness of preventive maintenance strategies for marine oil support ship electrical equipment, highlighting the advantages of the proposed method.

1. Introduction

With the increasing complexity of offshore oil extraction operations and the long-term operation of electrical equipment in harsh marine environments, the equipment failure rate remains high, and traditional preventive maintenance strategies are no longer able to meet practical needs. The high humidity, high temperature, salt spray, and load fluctuations in the marine environment exacerbate equipment wear and aging, leading to continuous increase in maintenance costs and inability to effectively avoid sudden failures. In this situation, how to improve the efficiency and accuracy of equipment maintenance through more accurate prediction models has become the focus of current research.

The main contribution of this article is the proposal and validation of an electrical equipment prediction and maintenance method based on LSTM model, particularly for the complex operating environment of offshore oil support ships. This method not only achieves high-precision device health status prediction through data preprocessing, feature extraction, and model training, but also integrates into an intelligent platform to achieve real-time monitoring and dynamic maintenance strategy optimization of devices. The experimental results show that this method can maintain high prediction accuracy and robustness in various complex marine environments, significantly improving the effectiveness of equipment preventive maintenance and demonstrating broad application prospects.

This article first introduces the operating environment of electrical equipment on offshore oil support ships and the limitations of traditional maintenance strategies. Next, the collection and preprocessing of device data, feature processing, prediction and maintenance methods based on LSTM model, and integration of intelligent platform were elaborated. Subsequently, the experimental section conducted detailed tests on the accuracy of the prediction model and the optimization effect of maintenance strategies. Finally, the research results were summarized and future application prospects and optimization directions were discussed.

2. Related Works

In order to improve the scientificity and accuracy of equipment maintenance, many scholars and researchers have conducted research in the field of electrical equipment maintenance. For example, Qiao S H I et al. analyzed newly introduced intelligent detection, live detection, power outage testing, and state analysis methods, and detailed the principles, applicable scenarios, and application conditions of these new technologies [1]. Wei W et al. studied the basic structure and training methods of convolutional neural networks in object detection, constructed a state dataset of electromechanical equipment, and trained the object detection network [2]. Mohammed N A et al. proposed an intelligent predictive maintenance system for industrial equipment monitoring. This system integrates industrial Internet of Things, message passing technology, and machine learning algorithms. By analyzing and processing the collected data, it predicts motor faults and provides maintenance recommendations[3]. Yu Hang drew inspiration from the portable electrical equipment maintenance and management method of Lancaster University in the UK, and combined it with the actual situation of domestic universities to propose a combination of risk assessment, user inspection, visual inspection, and comprehensive inspection and testing to effectively strengthen electrical equipment maintenance and management and reduce the incidence of electrical accidents[4]. Wang Jian analyzed the operation and maintenance of electrical equipment in hydropower stations, and highlighted some key aspects [5]. With the continuous improvement of specialization and automation level of port electrical equipment, equipment maintenance and management work has become increasingly complex. Regarding this, Jin Feng analyzed the current problems in the maintenance and management of port electrical equipment and proposed optimization strategies, believing that breaking through existing bottlenecks is particularly necessary [6]. Zhao Binbin outlined the ability requirements for maintenance personnel in the installation and commissioning of electrical equipment, and analyzed in depth the key work points that electrical maintenance personnel need to pay attention to in the installation and commissioning process of three article machines and their ancillary equipment that he participated in [7]. Rosales V's research aims to evaluate the acceptability of teaching trainers for the National Secondary Certificate Course in Electrical Installation and Maintenance for National High Schools in the first semester of the 2018-2019 academic year. These trainers have played an important role in cultivating students' skills in electrical installation and maintenance [8]. However, although these studies have optimized the preventive maintenance of equipment to some extent, there are still shortcomings in accuracy or inability to cope with long time series data, resulting in poor robustness of equipment state prediction.

Some studies have shown that LSTM has significant advantages in processing time series data, as it can better capture hidden state information during device operation. For example, Wu Y and Ma X proposed a data-driven method based on LSTM model for accurately evaluating turbine performance and diagnosing faults. This method has been successfully applied to two wind turbines, detecting gearbox bearing faults and generator winding faults respectively [9]. Cui Y et al. proposed a fault detection framework for wind turbine condition monitoring, which helps identify when the turbine deviates from normal operation by modeling and analyzing data in the monitoring and data acquisition system [10]. However, most existing research has focused on specific fields, and there has been no research on the specific application scenario of offshore oil support ships. Therefore, this article cites an intelligent platform based on LSTM to address complex issues in the maintenance of electrical equipment for offshore oil support ships.

3. Methods

3.1 Equipment Operation Data Preprocessing and Feature Extraction

3.1.1 Data cleaning and outlier handling

Equipment operation data is often affected by various uncertain factors in the marine environment, such as high humidity, salt spray, electromagnetic interference, etc., which may result in a large amount of noise and outliers in the data. Therefore, the first step is to clean the raw data. The cleaning steps include removing obviously erroneous measurement data, filling in missing values, and smoothing out data with short-term fluctuations. For missing values, interpolation is used to fill in, while for noisy data, median filters are used for smoothing to preserve the trend characteristics of the signal and eliminate excessive short-term fluctuations[11]. For missing values, this article uses linear interpolation method, as shown in formula (1):

$$\mathrm{X(t)} = \mathrm{X(t_0)} + \frac{\mathrm{X(t_1)} - \mathrm{X(t_0)}}{\mathrm{t_1} - \mathrm{t_0}} \cdot (\mathrm{t} - \mathrm{t_0}) \tag{1}$$

In formula (1), $\mathrm{X(t_0)}$ and $\mathrm{X(t_1)}$ are known adjacent data points, $\mathrm{X(t)}$ is interpolated data point, and $\mathrm{t_0}$, $\mathrm{t_1}$, and t are corresponding time points.

3.1.2 Data standardization

Due to the different dimensions of electrical equipment parameters, directly inputting them into the model may result in significant numerical differences between features, affecting the convergence speed and prediction accuracy of the model. Therefore, in the data preprocessing process, all input features were normalized to limit their range between 0 and 1, as shown in formula (2):

$$y_{pred} = f(X_{input}) \tag{2}$$

In formula (2), X_{input} is the processed device operation data, f is the LSTM model function, and y_{pred} is the predicted health status score.

3.1.3 Feature extraction

Feature extraction is a key step in improving the accuracy of prediction models, especially in the case of long time series data. By extracting representative key features, the dimensionality of the data can be effectively simplified while preserving important information. In the feature extraction process of this article, features closely related to the health status of electrical equipment were selected, including core parameters such as voltage, current, temperature, and vibration. In addition, the derivatives and rates of change of these parameters were also calculated to capture the dynamic changes in device status. The rate of change is shown in formula (3):

$$\Delta X = \frac{X(t)-X(t-\Delta t)}{\Delta t} \tag{3}$$

In formula (3), $X(t)$ is the eigenvalue at the current time point, $X(t-\Delta t)$ is the eigenvalue at the current time point, and Δt is the time interval. These rate of change characteristics often exhibit abnormal fluctuations in the early stages of a fault, making them an important basis for fault warning.

3.2 Construction of Health Status Prediction Model Based on LSTM Model

3.2.1 LSTM model structure design

Long term short-term memory recurrent neural network (LSTM) is a variant of recurrent neural network (RNN). LSTM has been continuously optimized and improved in subsequent applications, refining its internal structure and thus performing excellently in processing and predicting time series data. The core of LSTM consists of several gating units, mainly including update gate, forget gate, and output gate. The function of the update gate is to merge the current input information with the previous state information in order to preserve important information; the forget gate is responsible for selectively forgetting old state data that is no longer important; the responsibility of the output gate is to determine how much information to output from the current unit state to the hidden layer. These gating mechanisms enable LSTM to effectively manage information flow, thereby optimizing the learning process and prediction accuracy [12].

3.2.2 Model training and loss function

In order to ensure that the LSTM model has good predictive ability, this article conducted supervised learning training on the model. The loss function used in the training process is the mean square error, which is calculated as shown in formula (4):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

In formula (4), y_i is the actual device health status value, $\hat{y}_i$ is the model predicted value, and n is the sample size. Mean square error is used to measure the difference between the model predicted value and the actual value. The smaller the error, the more accurate the model's prediction. During the training process, this article used the Adam optimization algorithm, which combines the advantages of momentum and adaptive learning rate, and can converge quickly while preventing falling into local optima. The initial learning rate of the model is set to 0.001, and the learning rate is attenuated every 50 epochs to improve training stability. The model was trained for a total of 200 epochs, during which the model was evaluated using a validation set to prevent overfitting.

3.2.3 Time window and sequence input

In order to better capture the temporal dependence of device health status, this article adopts a sliding time window mechanism to process input data. Figure 1 shows an example of the original signal and its time window.

Each time window contains device operation data from the past period, with the specific length determined by the device's operating cycle and fault characteristics. After experimental verification, this article selected 60 time steps as the window length, which means that each input of LSTM model data contains the feature values of the past 60 time steps. This approach can help the model understand the historical operating status of the equipment, extract fault signals from it, and make health status predictions in advance. The input received by the model is a three-dimensional matrix with dimensions of. For example, if the batch size is 32, the time step is 60, and the feature dimension is 4, then the matrix size input each time is $32 \times 60 \times 4$.

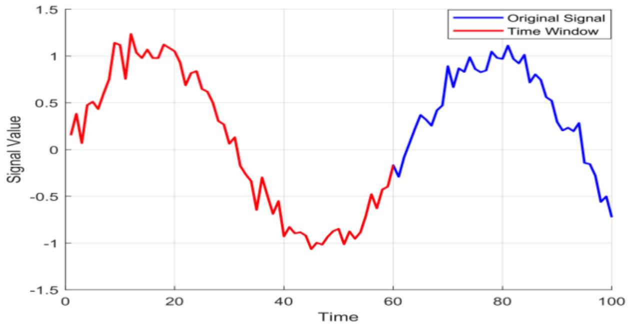

Figure 1: Example of the original signal and its time window

3.3 Intelligent Platform Integration and Real-Time Monitoring

The real-time monitoring system of the intelligent platform has the characteristics of high precision, high reliability, and high response speed. Through the dynamic prediction capability of the LSTM model, the platform can evaluate the equipment status days or even weeks before a fault occurs, and provide early warning of potential faults. The real-time monitoring system not only focuses on the current equipment status, but also conducts retrospective analysis of historical data to identify long-term trends that cause equipment aging or failure. This long-term trend analysis helps maintenance personnel identify potential problems that are gradually deteriorating, thereby optimizing long-term maintenance strategies [13].

The intelligent platform has powerful data storage and analysis functions. The platform stores operational data, predictive results, maintenance records, and other information of all devices in a cloud database for long-term analysis and trend tracking. Through in-depth mining of these historical data, the platform can identify the performance differences of devices in different marine environments and help optimize maintenance strategies in different environments. In addition, the platform also supports the use of stored data for self updating and optimization of the model, ensuring that the predictive model can gradually improve its accuracy as the device operates.

The platform also has a report generation function, which can regularly generate device health status reports and maintenance execution reports. The report contains information such as the operating history, predicted results, fault records, maintenance operations, and their effects of the equipment, which facilitates management's evaluation of the overall condition of the equipment and provides data support for further maintenance decisions. The platform system architecture diagram is shown in Figure 2.

The intelligent platform constructed in this article has strong scalability. With the increase of device types and quantities, the platform can support more device access and real-time monitoring by expanding data collection modules and computing resources. In addition, the platform's prediction module supports the integration of other machine learning models or algorithms, which can switch or combine different models according to different application needs, improving the flexibility and accuracy of predictions.

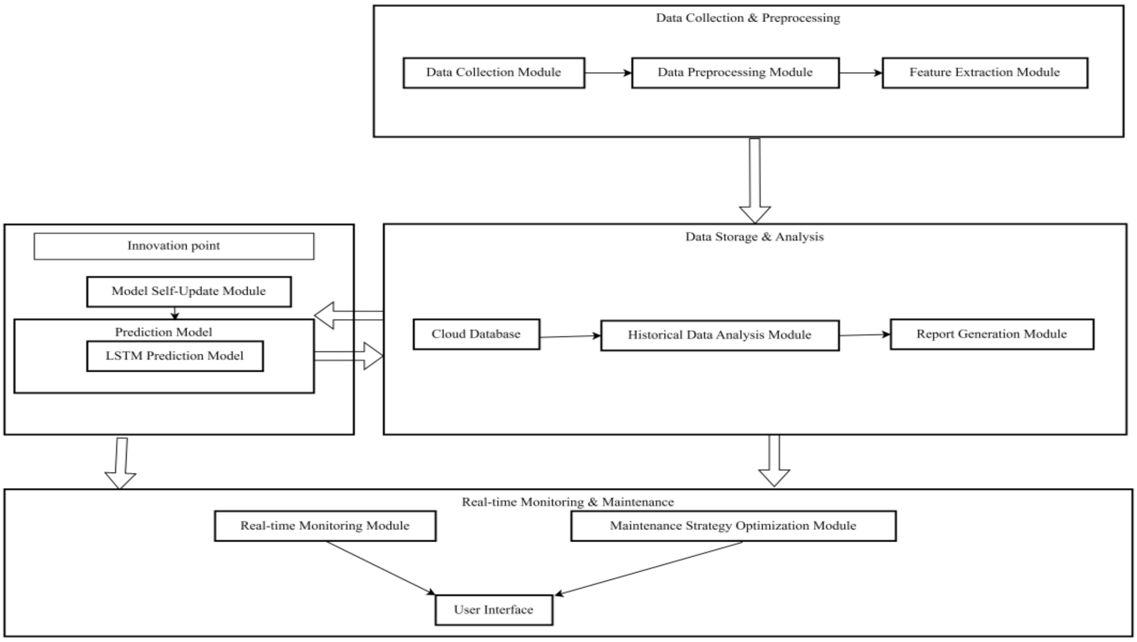

Figure 2: System architecture diagram

4. Results and Discussion

4.1 Experimental Preparation

1) Experimental equipment and data

The equipment used in the experiment is the electrical equipment on the offshore oil support ship, including key components such as generators, distribution boards, transformers, etc. Each device is equipped with sensors that are responsible for real-time monitoring of parameters such as voltage, current, temperature, and vibration. These sensor data will serve as inputs for the LSTM model, including long-term operational data and real-time status information of the equipment. Historical data is used for model training and validation, while real-time data is used to test the predictive ability and maintenance optimization effectiveness of the model.

2) Experimental environment setup

The experiment is conducted in the actual operating environment of offshore oil support ships to ensure the authenticity of data and the feasibility of results. Sensors monitor the operating status of devices in real-time, and the intelligent platform integrates LSTM models to predict and optimize maintenance strategies for the health status of devices in real-time. The experiment was conducted under different environmental conditions, including high temperature and high humidity environments, low temperature environments, and environments with frequent load changes, to evaluate the robustness of the model.

3) Evaluation indicators and statistical methods

In order to comprehensively evaluate the predictive performance and maintenance optimization effect of the model, the following evaluation indicators will be used in the experiment:

Prediction accuracy evaluation: it uses Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to measure the accuracy of LSTM models in time series prediction. The smaller the RMSE and MAPE, the better the predictive performance of the model.

Optimization effect of maintenance strategy: it compares the equipment failure rate and maintenance cost between the experimental group and the control group, calculates the percentage decrease in failure rate and cost savings rate, and verifies whether the intelligent platform based on LSTM model can effectively reduce the equipment failure rate and maintenance cost.

Robustness assessment: it analyzes the predictive stability of LSTM models under different marine environmental conditions, ensuring that they can maintain high prediction accuracy in complex environments. It uses RMSE and MAPE values from different environments for horizontal comparison.

4.2 Experimental Analysis

(1) Accuracy evaluation of predictive models

The aim of this experiment is to compare the performance of three models, LSTM, SVR, and random forest, in predicting the health status of electrical equipment. By simulating multidimensional time series data such as voltage, current, temperature, and vibration, combined with introducing equipment fault points, various models are trained for health status prediction. The health status score ranges from 0 to 1, representing the risk of equipment failure. During the experiment, the same input features were used to train each model, and the prediction accuracy of each model was evaluated using RMSE and MAPE by comparing the real health status with the predicted results. The specific situation is shown in Figure 3:

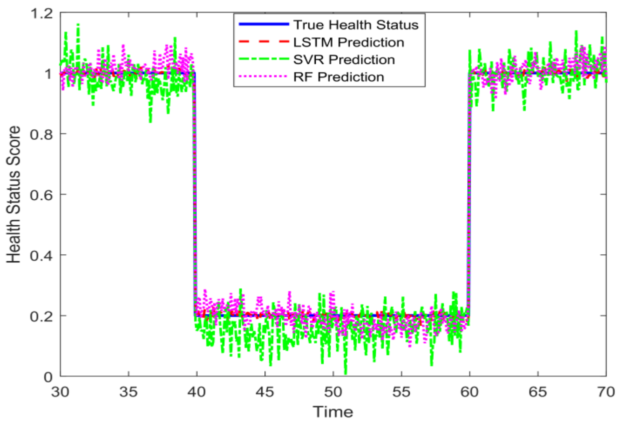

Figure 3: Accuracy evaluation of prediction model

Through experimental verification, the LSTM based prediction model has shown excellent performance in predicting the health status of electrical equipment, with significantly better prediction accuracy than SVR and random forest models. The RMSE of the LSTM model is 0.035, which is significantly lower compared to SVR's 0.082 and Random Forest's 0.071; MAPE is 2.8%, while SVR and random forest are 6.1% and 5.3%, respectively. In the above data conclusions, the LSTM model is more suitable for processing time-series data of equipment operation, which can effectively capture changes in equipment status, improve the accuracy of fault prediction, and optimize maintenance strategies.

(2) Optimization evaluation of long-term predictive maintenance

In the optimization evaluation experiment of long-term predictive maintenance, the effectiveness of the LSTM model in predicting the health status of electrical equipment on offshore oil support ships was evaluated. The experiment analyzed the impact of different model parameters on prediction accuracy. The experimental data covers six months of equipment operation records, including key parameters such as current, voltage, temperature, and vibration. The specific evaluation is shown in Figure 4:

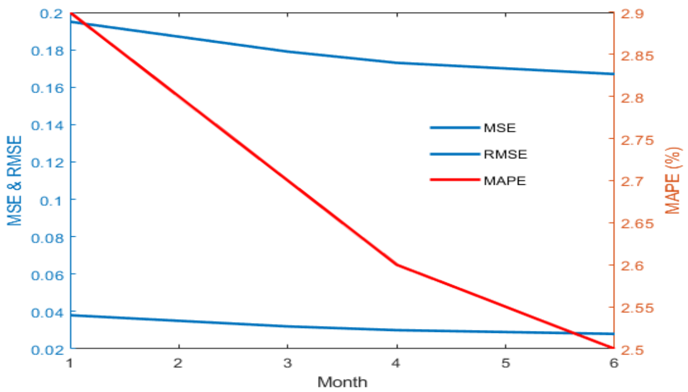

Figure 4: Optimization evaluation of long-term predictive maintenance

In Figure 4, the results show that the model performs best with a 60 step time window and 100 hidden layer units. The LSTM model of this configuration has an MSE of 0.028, RMSE of 0.167, and MAPE of 2.5% within a 6-month prediction range. In the above data conclusions, the LSTM model has good accuracy and practicality in predicting faults in electrical equipment of offshore oil support ships, providing strong data support for optimizing maintenance strategies in the future.

(3) Maintenance strategy optimization effect evaluation experiment

This experiment compared the performance of dynamic maintenance strategy based on LSTM model and traditional fixed time interval maintenance strategy within 12 months, and evaluated the performance of the two maintenance methods by simulating equipment failure rate and maintenance cost. The experimental group uses an LSTM prediction model to monitor equipment status in real-time and dynamically adjust maintenance plans; the control group undergoes routine maintenance at fixed intervals. Recording the number of failures and maintenance costs for two groups every month, as shown in Figure 5.

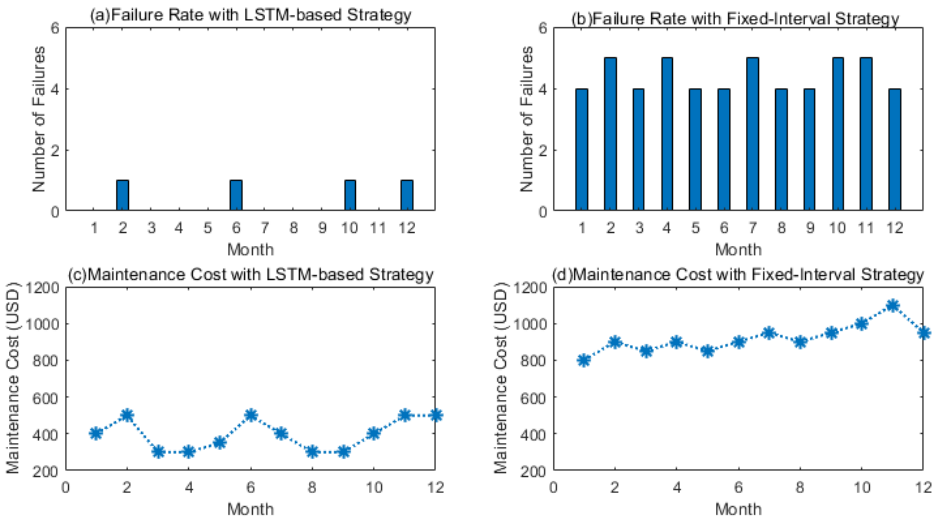

Figure 5: Evaluation of maintenance strategy optimization effectiveness

In Figure 5, (a) represents the failure rate of the LSTM strategy, (b) represents the failure rate of the fixed strategy, (c) represents the maintenance cost of the LSTM strategy, and (d) represents the maintenance cost of the fixed strategy. Through a 12-month experimental comparison, the dynamic maintenance strategy using LSTM prediction model significantly reduces equipment failure rate and maintenance costs. The experimental results show that the average monthly failure rate under the LSTM strategy is 0.67 times, much lower than the 4.25 times under the fixed time interval strategy. Within 12 months, the total maintenance cost of the LSTM strategy is $4750, while the total cost of the fixed time interval strategy is $11200. In the above data conclusions, the LSTM prediction model can effectively reduce the number of equipment failures and lower maintenance expenses.

(4) Robustness testing in different marine environments

In robustness testing experiments in different marine environments, the robustness of LSTM, SVR, and RF models for predicting equipment health status was evaluated in different marine environments. The experiment set up three typical marine environments: high temperature and humidity, low temperature, and frequent load changes. The operating data of the equipment were generated and the three models were trained and tested. The specific situation is shown in Tables 1 and 2:

Table 1: RMSE value evaluation under different environments

Model	High Temp & High Humidity	Low Temp	Frequent Load Variations
LSTM	0.045	0.085	0.075
SVR	0.065	0.095	0.09
Random Forest	0.06	0.09	0.085

Table 2: Evaluation of MAPE values in different environments

Model	High Temp & High Humidity	Low Temp	Frequent Load Variations
LSTM	0.031	0.04	0.038
SVR	0.062	0.055	0.06
Random Forest	0.051	0.048	0.05

In Table 1-2, the LSTM model shows the highest prediction accuracy in all three environments, with the lowest RMSE and MAPE values. In high temperature and high humidity environments, the RMSE of LSTM is 0.045 and the MAPE is 3.1%, which is significantly better than the predicted results of SVR and RF. In environments with frequent load changes, the RMSE of LSTM is 0.075, while the RMSE of SVR and RF are 0.090 and 0.085, respectively. Overall, the RMSE and MAPE values of the LSTM model are lower than those of SVR and RF in all environments, indicating that it has stronger robustness and higher prediction accuracy in different environments.

4.3 Experimental Summary

The experimental results show that the LSTM model performs well in various evaluation indicators. In terms of prediction accuracy, LSTM' s RMSE and MAPE are significantly better than SVR and random forest, indicating that it can more accurately predict the health status of devices. In terms of maintenance strategy optimization, the LSTM dynamic maintenance strategy has successfully reduced the occurrence rate of failures and maintenance costs. Within 12 months, the average number of failures and maintenance costs were significantly lower than traditional fixed time interval maintenance strategies. In addition, robustness tests conducted for different marine environments further support the stability of LSTM: in extreme environments with high temperature, high humidity, low temperature, and frequent load changes, LSTM exhibits the lowest prediction error, demonstrating its good environmental adaptability.

5. Conclusion

This article proposes an intelligent platform based on LSTM network for optimizing the preventive maintenance strategy of electrical equipment in offshore oil support ships. By collecting time series data of equipment operation, LSTM model effectively captures the change trend of equipment health status, and adjusts the maintenance plan in advance through real-time prediction. Compared with traditional SVR and random forest models, LSTM model significantly reduces the equipment failure rate and maintenance cost. The experimental results have verified that the LSTM model has strong robustness and adaptability in complex marine environments such as high temperature, high humidity, low temperature, and frequent load changes. Despite achieving good results, this study still has limitations. Data collection is limited to certain specific environments, and in the future, broader scenarios can be considered. In addition, the real-time computational efficiency and resource consumption of the model also need to be further optimized. Future work will focus on expanding data scale, optimizing algorithm performance, and exploring more adaptive maintenance strategies to further improve the intelligence level and application breadth of the system.

References

[1] Qiao S H I, Youwei L I U, Yanhong F, et al. Interpretation of the New Edition of "Code of Condition-Based Maintenance & Test for Electric Equipment"[J]. Modern Electric Power, 2022, 39(5): 623-630.

[2] Wei W, Xue-feng H, Song-gui L E I. Intelligent inspection and maintenance of mechanical and electrical equipment based on MR[J]. Journal of Graphics, 2022, 43(1): 141-157.

[3] Mohammed N A, Abdulateef O F, Hamad A H. An IoT and machine learning-based predictive maintenance system for electrical motors[J]. Journal Européen des Systèmes Automatisés, 2023, 56(4): 651-656.

[4] Yu Hang. Analysis and Insights on Maintenance and Management of Portable Electrical Equipment at Lancaster University [J]. Laboratory Research and Exploration, 2022, 41 (7): 153-156.

[5] Wang Jian. Research on the Operation and Maintenance of Electrical Equipment in Hydropower Stations [J]. Hydropower and Water Resources, 2021, 5 (4): 104-106.

[6] Jin Feng. Discussion on Maintenance and Management of Port Electrical Equipment [J]. Intelligent Buildings and Engineering Machinery, 2023, 5 (9): 55-57.

[7] Zhao Binbin. Key Points for Electrical Maintenance Personnel in Electrical Equipment Installation and Debugging [J]. Paper Equipment and Materials, 2023, 52 (7): 66-68.

[8] Rosales V. Acceptability of Electrical Installation and Maintenance Instructional Trainer[J]. Asia Research Network Journal of Education, 2022, 2(2): 84-101.

[9] Wu Y, Ma X. A hybrid LSTM-KLD approach to condition monitoring of operational wind turbines[J]. Renewable Energy, 2022, 181(1): 554-566.

[10] Cui Y, Bangalore P, Bertling Tjernberg L. A fault detection framework using recurrent neural networks for condition monitoring of wind turbines[J]. Wind Energy, 2021, 24(11): 1249-1262.

[11] Ukato A, Sofoluwe O O, Jambol D D, et al. Optimizing maintenance logistics on offshore platforms with AI: Current strategies and future innovations[J]. World Journal of Advanced Research and Reviews, 2024, 22(1): 1920-1929.

[12] Zhang P, Gao Z, Cao L, et al. Marine systems and equipment prognostics and health management: a systematic review from health condition monitoring to maintenance strategy[J]. Machines, 2022, 10(2): 72-84.

[13] Babayeju O A, Adefemi A, Ekemezie I O, et al. Advancements in predictive maintenance for aging oil and gas infrastructure[J]. World Journal of Advanced Research and Reviews, 2024, 22(3): 252-266.