Research on Fault Prediction and Health Management of Grid-Connected Inverter based on Data Drive

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Abstract. Grid-connected inverter is the core component of photovoltaic power generation system, and its stable operation is very important to the overall performance of the system. However, the inverter is easily influenced by environmental factors and its own complexity, which leads to frequent failures and affects power generation efficiency and power grid stability. Firstly, an innovative fault prediction model of grid-connected inverter is constructed by using machine learning and deep learning technology. The prediction accuracy and robustness of the model are improved by integrating the prediction results of basic learners such as decision tree and support vector machine (SVM). The experimental results show that the integrated learning model achieves an accuracy of 0.95 and a F1 score of 0.94 under the optimal parameter configuration. At the same time, the Long Short Term Memory Network (LSTM) model is introduced to effectively capture the complex nonlinear relationship and time dependence in the data, which further improves the prediction performance, and the highest accuracy rate can reach 0.96. Based on the fault prediction model, a comprehensive health management strategy of grid-connected inverter is formulated in this paper. The strategy framework includes four links: data collection and monitoring, fault prediction and evaluation, preventive maintenance plan formulation, fault early warning and response. By monitoring the key parameters of the inverter in real time and comparing with the fault prediction model, the early warning and timely response of the fault can be realized. The experimental results show that after the implementation of health management strategy, the failure rate of inverter is significantly reduced, the response time of fault warning is significantly shortened, and the operation reliability is significantly improved.

Keywords: Data Drive; Fault Prediction; Health Management; Grid-connected Inverter.

1. Introduction

In photovoltaic power generation system, grid-connected inverter plays a key role in converting direct current into alternating current suitable for power grid, and is an indispensable component to ensure the stable operation of the system and efficient power generation [1]. However, due to various environmental factors and the complexity of the inverter itself, various faults will inevitably occur during its operation, which not only affects the power generation efficiency, but also may pose a threat to the stability of the whole power grid [2-3].

In order to meet these challenges, in recent years, data-driven methods have been widely concerned in the field of fault prediction and health management. By collecting and analyzing a large number of data generated during the operation of the inverter, the potential faults can be accurately predicted, and maintenance measures can be taken in time, thus significantly improving the reliability and operation efficiency of the system. In this study, advanced machine learning and data analysis technology will be used to deeply mine the hidden information in inverter operation data, build an efficient fault prediction model, and formulate targeted health management strategies. Promote the wide application of photovoltaic power generation technology and help the development of global green energy.

2. Research on Fault Prediction Model of Grid-connected Inverter

An innovative fault prediction model of grid-connected inverter is constructed by using machine learning and deep learning technology. The model will combine the historical operation data, environmental parameters and the working state of the inverter, and predict potential faults through data analysis and pattern recognition.

The method of ensemble learning is used to construct the fault prediction model. By combining the prediction results of decision trees of multiple basic learners and support vector machines (SVM), the overall prediction accuracy and robustness are improved [4]. Each basic learner will learn from different feature subsets and give its own prediction results. Finally, the final prediction output is obtained by means of weighted average.

The basic idea of random forest in ensemble learning is to improve the prediction accuracy by constructing multiple decision trees and combining their prediction results [5-6]. The output of random forest can be expressed as:

$$H(x) = frac1\,T\;sum_{t\text{-}1}^{T} h_t(x) \tag{1}$$

Among them, $H(x)$ is the final prediction result of random forest, T is the number of decision trees, and $h_t(x)$ is the prediction result of the t decision tree. Each decision tree is trained based on different training sample sets and feature subsets, thus increasing the diversity and generalization ability of the model.

To capture complex nonlinear relationships in data, a deep learning model, Long Short Term Memory Network (LSTM), will be introduced. The LSTM model can automatically learn feature representations from data and handle temporal dependencies in sequential data [7].

LSTM, The internal calculation process involves multiple gating units and cell state updates, and LSTM captures long-term dependencies in sequence data by introducing gating mechanisms and cell states. Its output can be simply expressed as:

$$h_t = LSTM(x_t, h_{t-1}, c_{t-1}) \tag{2}$$

Where h_t is the hidden state at the current moment, x_t is the input at the current moment, and h_{t-1}, c_{t-1} is the hidden state and cell state at the previous moment respectively.

3. Research on Health Management Strategy of Grid-connected Inverter

Based on the completion of the fault prediction model of grid-connected inverter, this study will further explore the health management strategy of grid-connected inverter. By making reasonable preventive maintenance plan and fault early warning mechanism, the purpose is to reduce the probability of faults and improve the operation reliability and overall performance of inverters. Construct a comprehensive health management strategy framework, which includes four main links: data collection and monitoring, fault prediction and evaluation, preventive maintenance plan formulation, and fault early warning and response (Figure 1). Systematically manage the health status of inverters to ensure that potential problems are found and handled in time.

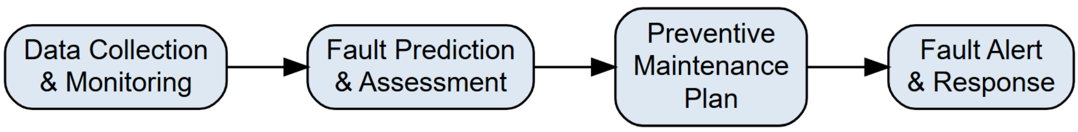

Figure 1. Health management strategy framework

Based on the output results of fault prediction model, a targeted preventive maintenance plan is formulated. It is planned to arrange the maintenance time and content reasonably according to the working state of the inverter and the predicted fault type [8-9]. For the inverter predicted to be overheated, the cooling system can be inspected and cleaned in advance to avoid the occurrence of faults. Through scientific maintenance plan, the failure rate of inverter can be reduced and its service life can be prolonged.

In order to find and deal with the potential faults of inverter in time, an effective fault early warning mechanism is designed. This mechanism monitors the key parameters of the inverter in real time and compares them with the fault prediction model. Once an abnormal situation or fault trend is found, an early warning signal will be triggered immediately. Early warning signals can be sent to relevant personnel by means of acousto-optic alarm and short message notification, so as to ensure timely response and processing. Applying these strategies in the actual operation environment and collecting relevant data for analysis can evaluate the effectiveness and feasibility of the strategies. According to the evaluation results, the strategy is adjusted and optimized to better meet the actual needs.

4. Experimental Verification

4.1 Construction of Experimental Platform

Build an experimental platform including grid-connected inverter, simulated photovoltaic panel, power grid simulator and other key components. The platform can simulate the operation state of inverter in real environment and generate corresponding operation data. At the same time, it is equipped with a data acquisition system to collect all operating parameters of the inverter in real time, in which the voltage setting range is 0-1000V, the current setting range is 0-50A, the temperature measuring range is -40°C to 125°C), the environmental parameter illumination intensity measuring range is 0-1200 w/m²) and the temperature measuring range is -40°C to 85°C).

4.2 Analysis of Experimental Verification Results

Clean, denoise and standardize the collected original data. Based on domain knowledge and statistical analysis method, the feature set related to inverter fault is extracted. The processed data are divided into training set and test set. The ensemble learning model (combined with basic learners such as decision tree and SVM) and the deep learning model (LSTM) are trained by using the training set, and the prediction performance of the models is evaluated on the test set.

Table 1 shows the accuracy, recall and F1 score of the ensemble learning model and the LSTM model under different parameter configurations. It can be seen that both the ensemble learning model and the LSTM model show high prediction performance under different parameter configurations. This shows that the fault prediction model can effectively learn the feature representation in the operation data of grid-connected inverters and accurately predict potential faults.

Table 1. Accuracy, recall and F1 score of the model under different parameters

types of models	Parameter configuration	Accuracy	Recall	F1 score
Integrated learning model	Using all feature sets, the number of decision trees is 100 and the kernel function of SVM is RBF.	0.95	0.93	0.94
	Using simplified feature set, the number of decision trees is 200, and the kernel function of SVM is linear.	0.94	0.92	0.93
	Using feature selection based on correlation, the number of decision trees is 150 and the kernel function of SVM is polynomial.	0.93	0.91	0.92
LSTM model	The number of hidden layer units is 128, the sequence length is 10, and the batch size is 32.	0.96	0.94	0.95
	The number of hidden layer units is 256, the sequence length is 15, and the batch size is 64.	0.95	0.93	0.94
	The number of hidden layer units is 64, with bidirectional LSTM, sequence length of 20 and batch size of 16.	0.94	0.92	0.93

For the ensemble learning model, under the configuration that all feature sets are used, the number of decision trees is 100, and the kernel function of SVM is RBF, the model achieves an accuracy of 0.95, a recall of 0.93, and a F1 score of 0.94, showing high prediction performance. When using simplified feature set or feature selection based on correlation, although the accuracy, recall and F1 score decreased slightly, they remained at a high level, indicating that the ensemble learning model is robust to the change of feature set.

For the LSTM model, under the configuration that the number of hidden layer units is 128, the sequence length is 10 and the batch size is 32, the model achieves the highest accuracy (0.96), recall (0.94) and F1 score (0.95), which shows that the LSTM model can effectively capture the complex nonlinear relationship and time dependence in the data under this configuration. When the number of hidden layer units, sequence length or batch size are increased, although the performance of the model decreases slightly, the overall performance remains at a high level. In addition, the attempt of bidirectional LSTM has achieved good performance, which shows that the bidirectional structure is helpful for the model to better understand the context information in the sequence data.

Furthermore, the proposed health management strategy is verified by experiments. The preventive maintenance plan and fault early warning mechanism are applied on the experimental platform. According to the output results of the fault prediction model, the maintenance time is reasonably arranged and the corresponding maintenance measures are implemented. At the same time, the key parameters of the inverter are monitored in real time, and the early warning mechanism is triggered immediately once the abnormal situation is found.

By comparing the inverter operation data before and after implementing the health management strategy, the actual effect of the strategy is evaluated. The experimental results show that after the implementation of health management strategy, the failure rate of inverter is obviously reduced and the operation reliability is significantly improved. In the form of double histogram comparison, Figure 2 shows the distribution changes of fault early warning response time before and after the implementation of health management strategy.

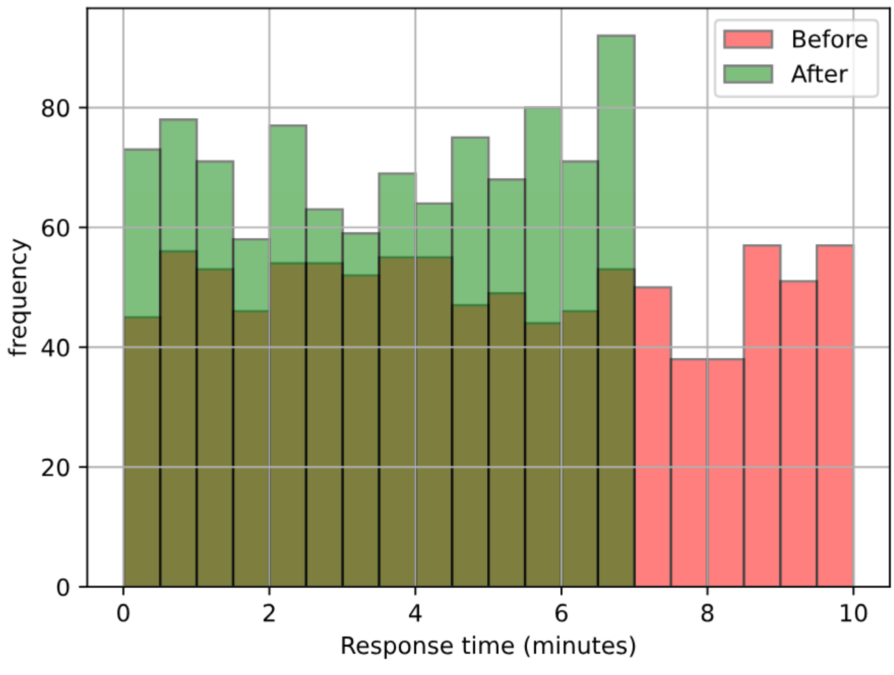

Figure 2. Response time distribution of fault early warning

As can be seen from the figure, the response time distribution before the implementation of the strategy is relatively broad and the peak value is relatively high, indicating that the fault early warning response is relatively concentrated in a long-time range, and the response time is long. After the implementation of the strategy, the distribution of response time is obviously shifted to the left, and the peak value is shifted to the left, and the overall distribution is more concentrated in a short time range, which indicates that the overall response time of fault early warning is reduced and the response is faster. After the implementation of health management strategy, the response time of fault early warning was significantly shortened, and the efficiency and timeliness of response were significantly improved. This not only reflects the effectiveness of the strategy, but also shows that the health management strategy has an important impact on improving the reliability of inverter operation.

5. Conclusion

In this study, a fault prediction model based on integrated learning and deep learning technology is successfully constructed by deeply exploring the operation data of grid-connected inverters. The model combines decision tree, SVM and LSTM, which can effectively extract key features from historical operation data and accurately predict potential faults. The experimental results show that both the ensemble learning model and the LSTM model show high prediction performance under different parameter configurations, which proves the effectiveness of the fault prediction model in capturing complex nonlinear relationships and time dependence. Furthermore, the study also puts forward a set of comprehensive health management strategies, including preventive maintenance plan and fault early warning mechanism. The implementation of these strategies significantly reduces the failure rate of the inverter and improves the reliability and efficiency of the system. In particular, the significant shortening of fault early warning response time reflects the important influence of health management strategy on improving the reliability of inverter operation. This study not only provides a strong guarantee for the stable operation and efficient power generation of photovoltaic power generation system, but also promotes the wide application of photovoltaic power generation technology and makes a positive contribution to the development of global green energy.

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