The Application of Artificial Intelligence Technology in the Fault Diagnosis of Assets in Power Grid

Rongbo Pan(✉), Min Lei, Mingjie Zhang, Peifa Shan, Yaopeng Zhao, and Yangyang Li

Qingyuan Power Supply Bureau, China Southern Power Grid Guangdong Power Grid, Qingyuan 511500, China
752418439@qq.com

Abstract. This paper discusses the application of Artificial Intelligence (AI) technology in the fault diagnosis (FD) of the essential assets in power grid, introducing the importance of FD in industry and the development of AI technology in FD of power grid as well as the application of machine learning in this field. Subsequently, it outlines the specific implementation process of machine learning technology in FD of assets in power grid and elaborates on each step, while pointing out the issues that should be taken into consideration at this stage. Finally, a summary and prospect are made, which may help relevant technicians apply AI technology in FD of power grid.

Keywords: fault diagnosis · artificial intelligence · power grid · machine learning

1 Introduction

The assets in power grid such as power transformer are essential in the power system. This is necessary to ensure that the correct voltage is supplied to different types of electrical equipment. Additionally, assets in power grid are used to transfer power between networks, isolate networks, and provide protection against voltage spikes. With the rapid development of modernization and industrialization, the application of assets in power grid has witnessed an explosive growth. In order to avoid sudden faults of assets in power grid, leading to major production accidents, engineers need to formulate effective maintenance plans [1]. The maintenance of assets in power grid is a key factor in improving the competitiveness of the electrical industry. Operation and maintenance need to be considered comprehensively to ensure the availability of human and material resources and the rapid response to operational issues, thus ensuring the realization of the goal under the condition of maximizing available resources [2].

In the context of Industry 4.0, automation and digitalization of power grids can be improved by using advanced information technologies and communication tools. Data is one of the key points of such technological development. The development of Internet-of-Thing enables the better data acquisition, data processing, data storage, data analysis

D. Kumar et al. (Eds.): IEIT 2023, AHSSEH 10, pp. 1286–1294, 2023.
https://doi.org/10.2991/978-94-6463-230-9_155

and data sharing between devices and human. Besides, the cost reduction and increased reliability of sensors, data transmission and storage devices have facilitated the emergence of power transformer state monitoring systems. Meanwhile, the Internet of Things allows real-time transmission of information related to the system status captured by different monitoring devices. This progress provides a great opportunity for intelligently using state monitoring data in FD, while combining the ability to collect data with the ability to efficiently integrate and analyze data.

The potential of Artificial Intelligence technology enables us to improve system availability, reduce maintenance costs, improve operational performance and security, and improve decision-making capabilities for ideal time and ideal operation for maintenance intervention [3]. AI is a frontier science and technology that simulates and extends the theory, technology and methods of human intelligence. Part of human intelligence operations is realized by machines to replace the recognition, decision-making, cognition, classification and other functions of human beings. AI mainly focuses on data analysis. Machine learning algorithms directly learn information from data rather than using predefined formulas as models. A machine learning project begins with the establishment of strict and clear goals definition. The system can only complete very specific tasks, setting a vague goal could mean that the developed model cannot accurately predict its intent. The most important part of a machine learning project is understanding the data used, and its relation to the task we want to solve [4, 5]. Randomly selecting an algorithm, using the dataset available, and expecting good results is ineffective. Before building models, it is necessary to understand what is happening in the dataset. Machine learning algorithms and methods are only part of the complex process to solve a specific problem. Sometimes, a lot of time is spent building complex machine learning solutions, only to find that they do not address the problem at hand. With the increasing depth of machine learning technology, it is easy to overlook the goal. It is important to remember all explicit or implied assumptions when building machine learning models.

Typical machine learning algorithms such as Hidden Markov Model, Hidden Semi-Markov Model, Self-Organizing Neural Network, Support Vector Machine, k-Nearest Neighbor algorithm and Bayesian algorithm have been applied to fault diagnosis of dynamic devices, while these methods have been successfully applied to many applications, it is still difficult to know which is the best algorithm for a particular dataset. Therefore, FD strategies are being applied to the most complex devices in electrical industry, thus making machine learning techniques particularly important in FD of assets in power grid.

2 The Implementation Process of Machine Learning in FD of Assets in Power Grid

In order to implement machine learning in FD of assets in power grid, the data should be carefully collected to ensure that it is real and reasonable. Once the data is collected, it is important to define a clear and specific target for the machine learning application. This will help to ensure that the resulting models are effective at solving the intended problem. The next step is to process the dataset and apply feature engineering techniques to create new, meaningful features. This step is crucial because it can greatly impact the

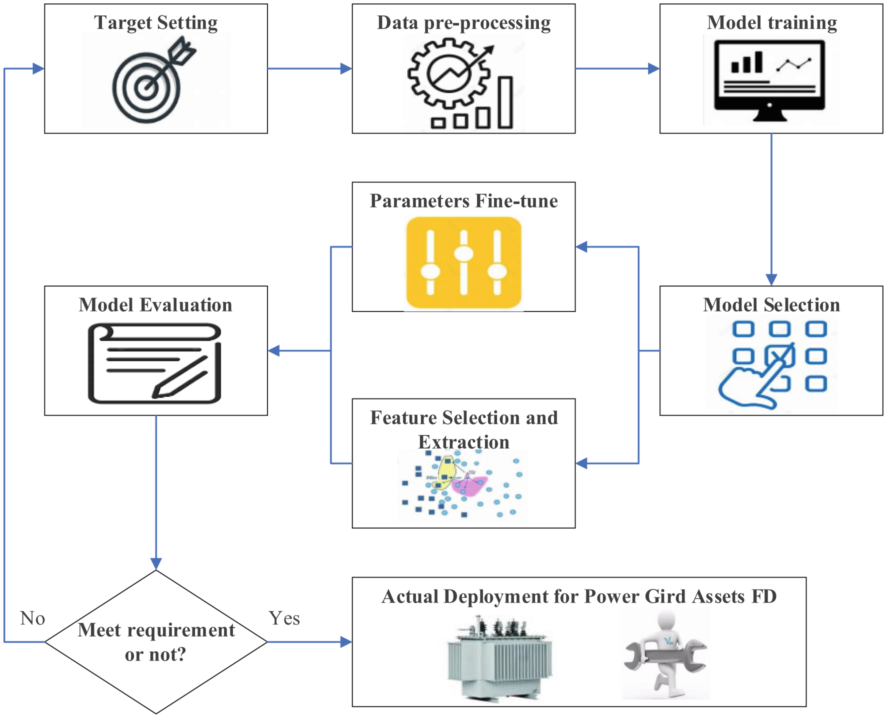

Fig. 1. The overall flowchart for implementing machine learning in FD of assets in power grid

performance of the machine learning models. The dataset used for the project is also an important consideration, and it is essential to carefully select which data to use and how to process it to achieve the best results.

After processing the dataset and applying feature engineering techniques, the next step is to divide the dataset into training, validation, and testing subsets. This allows for the machine learning algorithms to be trained and evaluated on the training subset, and the validation subset can be used to tweak the model and its hyperparameters to seek better performance. The testing subset is then used to obtain an estimate of the model's performance and to simulate its behavior with future data.Throughout this process, it is important to evaluate different machine learning algorithms to determine which performs best for the specific problem at hand. This may involve training and evaluating various models using different algorithms and comparing their results. The stages of this process are illustrated in Fig. 1, and it is important to carefully follow each step to ensure the success of the machine learning project.

2.1 Target Determination

Machine learning projects must begin with a strict and clear goal. For FD of assets in power grid, the main goal of the model used is to predict the probability of device failure within a defined time window. Then, with a specific and clear goal set, more concrete questions can be posed about the machine learning itself:

(1) should a supervised, unsupervised or reinforcement learning model be chosen, or a combination of learning models?
(2) Supervised learning, classification or regression?
(3) Is the model intended to be trained immediately upon obtaining new data (batch learning or online learning)?

Supervised learning is a widely used approach in machine learning, where the data is labelled and the model is trained to learn from the input and output data. In the case of FD of assets in power grid, supervised learning is usually the preferred approach as it can be transformed into a multi-class problem, where the machine learning model can be trained to predict the probability of device failure within a defined time window. The labelled data can be used to train and evaluate the model, and the model can be updated and improved over time as new data becomes available.

In real-world scenarios, it is often not necessary for the model to be trained immediately upon obtaining new data. Batch learning can be used to train the model over a period of time, using a large dataset that has been collected over a period of time. Batch learning allows for the model to be updated and improved over time, as new data becomes available. This is particularly useful in FD of assets in power grid, where data collection can be continuous and ongoing.

In addition, other approaches such as unsupervised learning or reinforcement learning can also be used depending on the specific problem and available data. Unsupervised learning can be used when the data is not labelled, and the goal is to uncover patterns and structure within the data. Reinforcement learning can be used when the model needs to learn how to interact with the environment to achieve a certain goal, and the model learns through trial and error. Overall, the choice of learning approach will depend on the specific problem at hand, the nature of the data, and the goals of the FD system.

2.2 Data Pre-processing and Feature Engineering

Data pre-processing and feature engineering are two essential steps in preparing data for machine learning models. The pre-processing step involves several sub-steps to ensure data quality and consistency. Firstly, it is necessary to integrate multiple datasets and extract the relevant features from each dataset, merging them into a single dataset. This reduces data redundancy and improves data accuracy. Secondly, irrelevant features such as time, location, latitude, and longitude are removed, as they do not contribute to the prediction of power transformer failure. Thirdly, missing values are processed by deleting features with more than 60% missing values and filling the remaining missing values with zeros, to avoid introducing bias into the model. Fourthly, the data is separated into feature data and fault types, as the model needs to learn the relationship between features and faults. Finally, data standardization is performed to scale the data to a specific range, eliminating the effects of different measurement units and facilitating model training.

Feature engineering is another crucial step in preparing data for machine learning models. It involves transforming raw data into a set of meaningful features that can better represent the underlying patterns and relationships in the data. For FD of assets in power grid, some useful features could be extracted from the raw sensor data, such as mean, standard deviation, skewness, and kurtosis. The detailed introduction of the common features in signal processing is demonstrated in Table 1.

These features can help the model capture the statistical properties of the data and identify abnormal patterns that may indicate impending faults. Feature engineering is an iterative process that requires domain expertise and creativity, as it involves selecting relevant features, transforming them, and evaluating their usefulness for the model. Overall, data pre-processing and feature engineering are critical steps in preparing data for machine learning models. They help to ensure data quality and consistency, reduce data redundancy, and extract meaningful features that can facilitate model training and improve prediction accuracy.

The purpose of feature engineering is to improve the predictive ability of machine learning algorithms by creating new features from available data [6]. Typically, feature engineering is conducted first, followed by feature selection to eliminate irrelevant, redundant or highly correlated features. Assets in power grid' datasets are usually collected from multiple sensors and information sources and applied to predictive models. Noise is often present in the collection process of industrial datasets, making the prediction task more difficult. Aggregating data in this way over time windows makes the data more "smooth" and reduces the impact of noise on the features used by the model [6]. Given the project requirements, it is important to develop a classifier that can predict failures in the given target window, for instance, failures that may occur in about two weeks. For each record, a time window of dimension N is created and lagged features are computed over the period of N time prior to the date/time of the record. N is usually measured in minutes or hours depending on the nature of the data. Li et al. [7] applied a time windowing technique to multivariate time-series data to form high-dimensional

Table 1. The features that used in Transformers FD

Feature	Expression	Feature	Expression
Max Value	$F_1 = \max(X(i))$	Standard Deviation	$F_9 = \sqrt{\frac{\sum_{i-1}^{N}(X(i)-F_4)^2}{N-1}}$
Max Absolute Value	$F_2 = \max(\lvert X(i)\rvert)$	Kurtosis	$F_{10} = \frac{\sum_{i-1}^{N}(X(i)-F_4)^4}{(N-1)F9^4}$
Minimum Value	$F_3 = \min(X(i))$	Skewness	$F_{11} = \frac{\sum_{i-1}^{N}(X(i)-F_4)^3}{(N-1)F9^3}$
Mean value	$F_4 = \frac{1}{N}\sum_{i-1}^{N} X(i)$	Clearance Index	$F_{12} = \frac{F2}{F_8}$
Peak to Peak	$F_5 = F_1 - F_3$	Waveform Index	$F_{13} = \frac{F_7}{F_6}$
Mean Absolute Value	$F_6 = \frac{1}{N}\sum_{i-1}^{N}\lvert X(i)\rvert$	Pulse Index	$F_{14} = \frac{F_2}{F_6}$
Root Mean Square Value	$F_7 = \sqrt{\frac{1}{N}\sum_{i-1}^{N} X(i)^2}$	Peak Index	$F_{15} = \frac{F_2}{F_7}$
Mean Square Amplitude	$F_8 = \left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert X(i)\rvert}\right)^2$		

feature vectors as inputs to the model to improve the predictive performance. The length of the time window usually needs to be designed based on the actual data scenario. Literature [8] suggests that reducing the width of the target window to improve accuracy is reasonable in some specific applications, however, this is usually not suitable as it can prevent the user from getting timely alerts, thus losing the chance of FD. Too narrow target windows can also have an adverse effect on the performance of the model. In order to enhance the applicability and effectiveness of predictive modeling for forecasting, Yang et al. [9] improved the existing methods and proposed a new two-stage classifier classification method that can improve the accuracy of failure time estimation without compromising the flexibility of sufficiently wide warning target windows.

2.3 Model Training and Deployment

When dealing with related date and time data, it is important to carefully divide the training, validation and test sets to ensure that the evaluation obtained reflects the expected actual performance of the model. This is due to the inherent temporal correlation between the data, which is the high degree of similarity between data that is close in time. In FD problems, the best choice is to divide the data according to time, i.e. by selecting a point in time and using all the records prior to that point to train the model and all records after that point to validate the model. This approach also allows comparison of the actual behavior of the model in practice.

Use the validation set to understand the behavior of various models and to find the adjustment of hyperparameters for certain models. It is not possible to determine which algorithm is best suited for a given problem right at the beginning. During the early stages of training and evaluating various models, one can see which models have the maximum potential, but in order for this step to be successful, one must select the evaluation metric for the model according to the predetermined goal. When dealing with related date and time data, it is necessary to carefully divide the training set, the validation set and the test set in order to ensure that the evaluation obtained meets the expected performance of the model. This is because there is an inherent time-relatedness between the data, that is, a high degree of similarity between data that are close in time.

It is important to check the performance of the model on the test set. Generally, the performance of the evaluation metrics on the test set will decline. As mentioned before, in FD, the most important thing is the number of actual failures that the model can predict, which is the value of the model's recall rate. This parameter is very important because the consequences of false negatives outweigh those of false positives, which is the consequences of the model not being able to predict real failures are much greater than those of incorrect failure predictions. In practical applications, more information about the FD of assets in power grid such as cost, location in the device, degree of replacement., which are helpful in model training.

3 Deep Learning in FD of Assets in Power Grid

Deep learning is an emerging approach in machine learning, initially used for computer vision, speech, image recognition and natural language processing. Recently, it has also been applied in health monitoring, creating many fault diagnosis technologies based on deep learning. The limitations of traditional machine learning methods, such as poor performance and generalization capacity and difficulty in representing complex functions, have spurred the exploration of deep networks to extract features and represent complex functions [10]. Deep learning provides an effective method to analyze complex mechanical big data without requiring domain knowledge and expert experience.

The implementation process of deep learning in FD of assets in power grid is similar to that of machine learning. However, it combines fault feature extraction and classifier together, which has good universality. In addition, compared with the traditional shallow diagnosis method, the multi-layer model of deep learning can fully avoid the problems of dimensional distortion and insufficient diagnostic ability. Typical deep learning algorithms include: Convolutional Neural Networks (CNN), Autoencoders (AE) and its variants Stacked Autoencoders (SAE), and Recurrent Neural Networks (RNN) [11, 12].

In FD, failures are much less common than normal operation, causing an imbalance between different types of failures. This can lead to false algorithm performance, where algorithms prioritize classifying the most common examples at the expense of less common labels, aiming to reduce incorrect classifications. Typically, there are three approaches to address the class imbalance problem, namely data augmentation based, transfer learning based and model based approaches. These three approaches are aimed at solving small sample problems in different ways, all of which attempt to enlarge the data size. Data augmentation based approach can fully utilize synthetic data while the transfer learning strategies use data obtained from other domains. In [13], a novel data augmentation method based on original data is proposed, which decomposes a single sample into multiple entities, and then rearranges them to increase the sample size. Guo et al. proposed a deep convolution transfer learning network (DCTLN) based on transfer learning, including a condition identification and a domain adaptation two modules, and verified its effectiveness by six speed governors fault diagnosis experiments. Model-based strategies try to simplify the neural networks, such as compact model building algorithms, and Generative Adversarial Networks (GAN) are the most widely used technologies among the three strategies. For example, Li et al. [14] first use an improved auxiliary classifier to generate GAN to generate fault data before inputting the data into the model for training to predict the fault state, and then do data augmentation before input into the neural network for training. Zhao et al. [15] proposed a multi-scale attentional adversarial network (MSANA) in the transfer learning field, where the multi-scale model can acquire abundant features through different internal perception scales, the attention mechanism determines the weights of different scales, which improves the dynamic adjustment performance and adaptive ability of the model, and employs decision boundary auxiliary adversarial learning strategy to obtain domain invariant features.

4 Conclusion

This paper introduces the development and application of artificial intelligence technology in the FD of assets in power grid, the specific implementation process of artificial intelligence technology in the FD of assets in power grid and the related issues to be noted in the implementation process. The modern power transformer structure is complex, and the various links are interrelated. The method based on physical model may not perform well, because the interaction in the system often occurs in a very complex way and cannot be easily captured by the physical model. Data-driven methods attempt to extract hidden knowledge from empirical data to infer the current health status of the device and predict its remaining service life. Therefore, data-driven methods are popular in FD of assets in power grid. Data-driven methods require too much human intervention and require specialized domain knowledge to extract features, which means low efficiency and high labor costs. In recent years, with the development of deep learning, data-driven methods can effectively reduce manual intervention by directly learning degradation information from raw monitoring data. Deep learning methods can automatically perform feature engineering, learn internal representation and create feature vectors from raw data without manual intervention, thus alleviating the demand for domain experts and core feature extraction. Although deep learning shows its strong ability in FD of assets in power grid. However, the industrial field often faces the problem of class sample imbalance caused by insufficient fault data, which is difficult to solve by deep learning method. In future work, we can try to solve this problem from the aspects of transfer learning and data extension.

References

1. C. Chen, Y. Liu, X. Sun, C. Di Cairano-Gilfedder, and S. Titmus, "Automobile maintenance modelling using gcforest," in 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE), (2020): IEEE, pp. 600–605.
2. K. Lu, C. Chen, T. Wang, L. Cheng, and J. Qin, "Fault diagnosis of industrial robot based on dual-module attention convolutional neural network," Autonomous Intelligent Systems, vol. 2, no. 1, pp. 1-12, (2022).
3. S. Lee, A. S. Shetty, and L. Cavuoto, "Modeling of Learning Processes using Continuous Time Markov Chain (CTMC) for Virtual Reality (VR)-based Surgical Training in Laparoscopic Surgery," IEEE Transactions on Learning Technologies, pp. 1–13, (2023), doi: https://doi.org/10.1109/TLT.2023.3236899.
4. A. Diez-Olivan, J. Del Ser, D. Galar, and B. Sierra, "Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0," Information Fusion, vol. 50, pp. 92-111, (2019).
5. T. P. Carvalho, F. A. Soares, R. Vita, R. d. P. Francisco, J. P. Basto, and S. G. Alcalá, "A systematic literature review of machine learning methods applied to predictive maintenance," Computers & Industrial Engineering, vol. 137, p. 106024, (2019).
6. F. Shen, R. Langari, and R. Yan, "Exploring Sample/Feature Hybrid Transfer for Gear Fault Diagnosis Under Varying Working Conditions," Journal of Computing and Information Science in Engineering, vol. 20, no. 4, (2020).
7. X. Li, Q. Ding, and J.-Q. Sun, "Remaining useful life estimation in prognostics using deep convolution neural networks," Reliability Engineering & System Safety, vol. 172, pp. 1–11, 2018/04/01/ (2018), doi: https://doi.org/10.1016/j.ress.2017.11.021.
8. M. Sakahara, S. Okada, and K. Nitta, "Domain-independent unsupervised text segmentation for data management," in 2014 IEEE International Conference on Data Mining Workshop, (2014): IEEE, pp. 481–487.
9. C. Yang, T. Ito, Y. Yang, and J. Liu, "Developing machine learning-based models to estimate time to failure for PHM," in 2016 IEEE international conference on prognostics and health management (ICPHM), (2016): IEEE, pp. 1–6.

10. C. Chen, C. Liu, T. Wang, A. Zhang, W. Wu, and L. Cheng, "Compound fault diagnosis for industrial robots based on dual-transformer networks," Journal of Manufacturing Systems, vol. 66, pp. 163-178, (2023).
11. C. Sun, M. Ma, Z. Zhao, S. Tian, R. Yan, and X. Chen, "Deep transfer learning based on sparse autoencoder for remaining useful life prediction of tool in manufacturing," IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp. 2416-2425, (2018).
12. Y. Liu, C. Chen, T. Wang, and L. Cheng, "An attention enhanced dilated CNN approach for cross-axis industrial robotics fault diagnosis," Autonomous Intelligent Systems, vol. 2, no. 1, pp. 1-11, (2022).
13. Z. Meng, X. Guo, Z. Pan, D. Sun, and S. Liu, "Data segmentation and augmentation methods based on raw data using deep neural networks approach for rotating machinery fault diagnosis," IEEE Access, vol. 7, pp. 79510-79522, (2019).
14. W. Li, X. Zhong, H. Shao, B. Cai, and X. Yang, "Multi-mode data augmentation and fault diagnosis of rotating machinery using modified ACGAN designed with new framework," Advanced Engineering Informatics, vol. 52, p. 101552, (2022).
15. B. Zhao, X. Zhang, Z. Zhan, and Q. Wu, "Deep multi-scale adversarial network with attention: A novel domain adaptation method for intelligent fault diagnosis," Journal of Manufacturing Systems, vol. 59, pp. 565-576, (2021).