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Fault analysis of oil-immersed transformer based on digital twin technology

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Abstract: Oil-immersed transformer is one of the important equipment to support the safe and stable operation of power system. At the same time, in the process of transformer operation, transformer failure is inevitable, this kind of failure belongs to multiple latent faults, which seriously endangers the safe operation of the transformer. Therefore, the maintenance of the transformer has played a crucial role. A fault detection method based on digital twin model is proposed to solve the problem that the internal dynamic characteristics of oil-immersed transformer are difficult to extract, and the fault detection error is large due to noise interference. The dynamic model of oil-immersed transformer is constructed, the main cause of failure is analysed, the failure time of internal insulator is taken as a linear index, and the linear correlation between failure probability and failure time is solved by Weibull distribution function. The fitting function between transformer fault residence time, operating days and fault probability variance is established, and the fitting value obtained is used as the initial data reference of the fault detection model. The digital twin model is used to establish the dynamic fault probability calculation function, and the on-site data is substituted to calculate the fault detection threshold, and then the data is compared to complete the detection.

Keywords: Oil-immersed transformer; Overheating failure; Transformer maintenance; Digital twin.

1. Introduction

Oil-immersed transformer is one of the indispensable and important equipment in the power system, its stable operation plays a vital role in the safety and reliability of the power system. With the continuous progress and development of society, the continuous improvement of people's quality of life for life and production of electricity requirements are becoming higher and higher, transformer maintenance work and plays a vital role, the current power system transformer maintenance level is still relatively low, did not form a more complete standardized management. The transformer often has various problems in the maintenance process, which seriously affects the power supply stability of the power system and hinders the sustainable development of power enterprises. Based on the occurrence of such problems, the research on the common problems and countermeasures of transformer maintenance needs to be further developed.

As a key technology connecting the physical world and the information world, digital twin technology can realize bidirectional mapping, dynamic interaction and real-time connection between physical entities and digital twins, reflect the state of physical entities in the real environment, and use relevant digital models to achieve the goal of monitoring and control of the whole life cycle of physical entities. This feature of digital twin provides technical means for the digital transformation and upgrading of real-time operation and detection of power equipment, which can promote the digitalization and virtualization of all elements of the power system, real-time and visualization of all states, coordinated and intelligent operation and management of the power grid, and realize the collaborative interaction and parallel operation of the physical power grid and the digital power grid.

Literature puts forward a method of full life cycle state assessment of electrical equipment based on digital twin technology. This method uses the full life cycle data of electrical equipment, including from design to operation, to build and simulate the electrical equipment model, and then optimizes the model, proving the feasibility of the digital twin full life cycle assessment method. Literature introduces the digital twin into the intelligent solution of the power grid system and takes the power grid vacuum circuit breaker and 35kV transformer as examples to apply the digital twin to its construction and takes the 110kV substation as an example to develop the digital twin health management system in its general simple practice and verifies the feasibility of the scheme. Literature, supported by technologies such as the Internet of Things, blockchain, and large data, integrates massive data such as power, regulatory planning, and meteorological data to build an online digital twin platform that can be planned, constructed, and operated for power grids. This platform integrates a variety of professional systems such as infrastructure, scheduling, equipment, and marketing. Access equipment ledger, operation curve, project data, space resources and other data categories, and realize the digital twin of physical power network. Literature has implemented digital twin on distribution transformers. This model can predict the voltage and current waveform on the medium voltage side in real time through the voltage and current waveform on the low voltage side of the distribution transformer and can identify most transformer faults.

By comparing the predicted value of the model with the field data, the effectiveness of this digital twin model is proved. Literature proposes a transformer fault detection system based on bionic fish. This method has poor application ability for the actual field, and requires a large number of data operations, resulting in excessive detection errors. In literature, a transformer fault detection method based on genetic optimization algorithm is established. This method cannot detect the dynamic fault change of transformer obviously and cannot detect the fault state in real time, and the detection accuracy is low.

By comparing two kinds of fault detection methods for transformers, the digital twin model proposed in this paper highlights its advantages. First of all, the digital twin model has good data simulation and dynamic data analysis capabilities and can detect and analyse the data generated by the equipment in real time. The internal load rate of the transformer, hot spot temperature, voltage and current, oil temperature and other data are imported into the digital twin model, and the pre-condition of fault is compared and analysed, to judge the operation state of the transformer. Taking the generated comparative data as a reference condition, the real-time and accuracy of fault detection can be improved, and the data generated by the analysis and calculation of the normal running time, fault residence time and fault occurrence probability of the transformer during detection is more real-time, and the number of processed data is reduced, the calculation is simplified, and the error is reduced.

2. Intelligent construction method framework for oil-immersed transformer fault detection based on digital twin model

The construction of digital twins is inseparable from modelling and simulation. Traditional simulation uses offline mode to establish mathematical models of physical objects and update model parameters offline, etc., while digital twins transmit information through the interaction between physical models and realize automatic update of models and parameters. The digital twin model is unrestricted and traditional simulation only analyzes the process with large circuit and time constant, and more fully reflects the dynamic change characteristics of the multi-physical field of the field or field coupling device. In order to ensure the credibility of twin data, digital twin technology needs to learn from the perfect theoretical system and technical system in the process of modeling and simulation. There are two methods to construct the digital twin model: one is model-driven, which describes the change rule of transformer research and the relationship between input and output by solving mathematical equations; The other is data-driven, based on data modeling technology, to build correlation models such as neural network models, which can provide more prediction, identification, evaluation and other functions for physical models. The two can cooperate to better build digital twin models.

At present, the most recognized model of digital twin is the five-dimensional model of digital twin, which is composed of five parts, as shown in equation (1)

In the formula, PE represents a physical entity, VE is a virtual entity, AS represents twin support, DD represents twin data, CN represents the link of each component. The digital twin framework is not only applicable to a certain industry, it has universal applicability. The framework can be applied to most fields in most industries, especially in the application of equipment condition monitoring, and has a very broad prospect. See Figure 1.

$$M_{DT} = (PE, VE, AS, DD, CN) \tag{1}$$

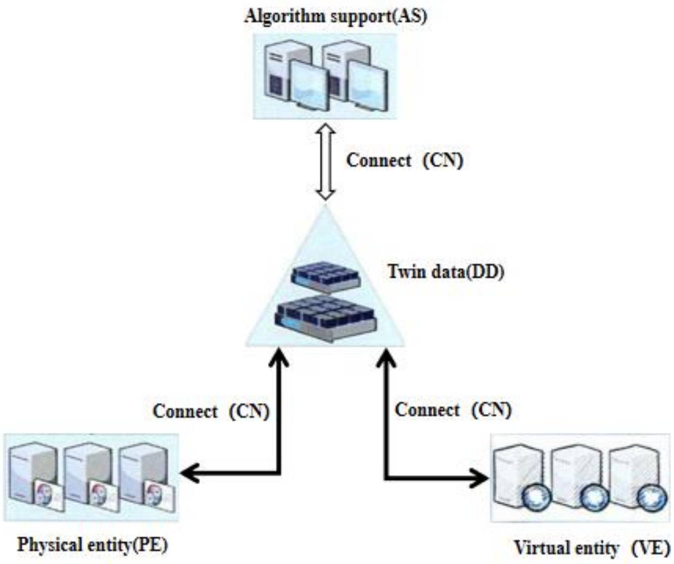


Figure 1. Digital twin structure diagram based on the five-dimensional model of digital twin.

Physical entity is the service object of digital twin technology, but also the data source of digital twin technology, accurate data collection of physical entity is the key to establish the entire digital twin system. Taking the digital twin of a power system as an example, the Unit physical entity is the smallest unit for the establishment and function realization of the digital twin model, such as transformers, circuit breakers and other equipment; System level (System) physical entity is composed of equipment, can achieve a certain function of the physical entity system, such as substation; A complex system-level physical entity is an integrated system that contains many system-level physical entities and can achieve overall planning and optimal scheduling of system-level physical entities, such as a large power grid composed of power plants, substations, and transmission systems. The level of physical entity is of great significance to the realization of digital twin function. When the digital twin realizes the function of device status monitoring and fault prediction, it needs to pay attention to the physical entity at unit level, while when it realizes the function of optimal scheduling and coordination among devices and systems, it needs to pay attention to the physical entity at system level and complex system level.

Virtual entity is the mapping of physical entity in virtual space, which can reflect physical entity from multi-time scale and multi-space scale, also known as digital twin. Virtual entities can be divided into three parts, physical model, mathematical model, and rule model. A physical model is a model that reflects the geometric parameters of a physical entity (such as device size, internal structure, etc.), which is visually close to the physical entity and must be consistent with the physical entity on a time scale.

Algorithm support refers to the collection of internal functions needed to realize the digital twin system and external support provided by the digital twin. The former is called internal function support, and the latter becomes external business support. The internal function support includes modelling simulation, model encapsulation, result analysis support required for virtual entity modelling, data integration and encapsulation services for twin data, and connection-oriented data transfer protocol and data interface services. External business support includes twin data operability support for terminals, visualization support for virtual entity simulation results, and optimal scheduling and decision support for decision makers. The algorithm supports all parts of the overall architecture of the digital twin and is the necessary driver for the complete operation of the digital twin technology.

Twin data is the basis of digital twins, and the establishment of digital twins cannot be separated from the support of twin data. According to different sources, twin data can be divided into physical entity data, virtual entity data, service data, rule data and comprehensive data. Physical entity data is derived from the information collection of physical entities, including the size and structure of physical entities and basic physical parameters. The physical entity data is first pre-processed and generated in the virtual entity through the constraint of regular data. The virtual entity data is then generated into the final comprehensive data for customers through the integration and scheduling of service data. The function of twin data is to reflect the running state of physical entity in virtual entity comprehensively and accurately, which is the support of digital twin.

The connection is to realize the information exchange and data exchange of each function and part of the digital twin. Specifically, the connection is responsible for real-time data acquisition on the physical entity side through sensors and other components, and the collected raw data is transmitted to the virtual entity side through a certain transmission protocol to achieve status monitoring on the physical entity side. Feedback data generated by the virtual entity side and operation instruction data generated by the algorithm support are fed back to the physical entity side to achieve optimal scheduling of the physical entity side: The twin data generated during the operation of the digital twin is transferred to the algorithm support for storage or allocation to other parts for calculation. In general, the connection is the data channel inside the digital twin.

3. Establishment of intelligent fault detection model of oil-immersed transformer based on digital twin

3.1. Construction of digital twin model of oil-immersed transformer

The model driven method is the mapping of the transformer physical entity to the multi-physical field mechanism during the transformer operation. The construction process is as follows: First, the three-dimensional geometric model of the power transformer is constructed, including the fuel tank, iron core, winding, etc. Then, a digital model of the feature parameterization during the operation of the transformer in digital space is established. The field calculation model is integrated into the geometric model and the digital twin model of transformer is realized by 3D model visualization simulation technology. In the whole process, it is necessary to characterize the physical parameters of the transformer entity and the characteristic parameters of the field calculation, and realize the multi-physical field digital twin model of the power transformer, as shown in Figure 2.

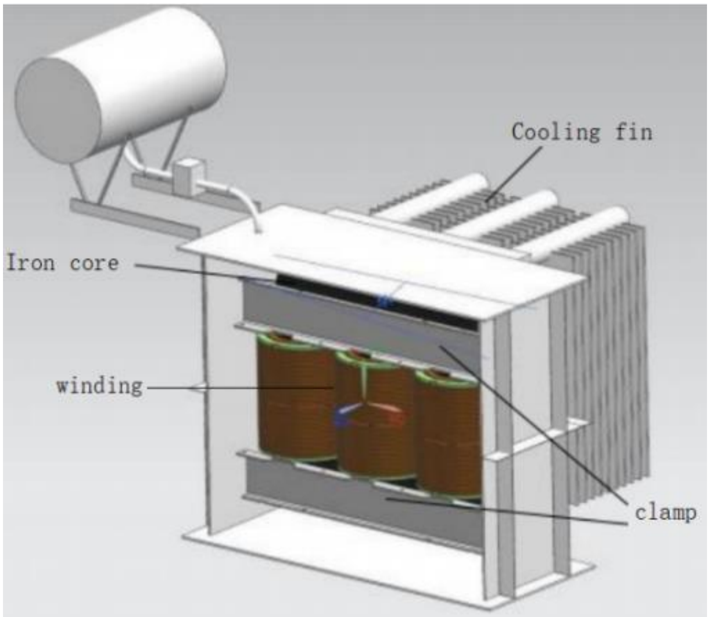


Figure 2. Multiphysics digital twin of transformer.

Figure 3 shows the implementation framework of transformer digital twin. A digital twin model is established to collect real-time data of oil-immersed transformer through sensors, and different scale models are divided. Among them, behavioural scale is used to describe the fault type of oil-immersed transformer. Physical scale damage test is carried out at each point inside the transformer. The real time running state of the regular scale model transformer; the geometric scale extracts data from the appearance and internal equipment information of the transformer.

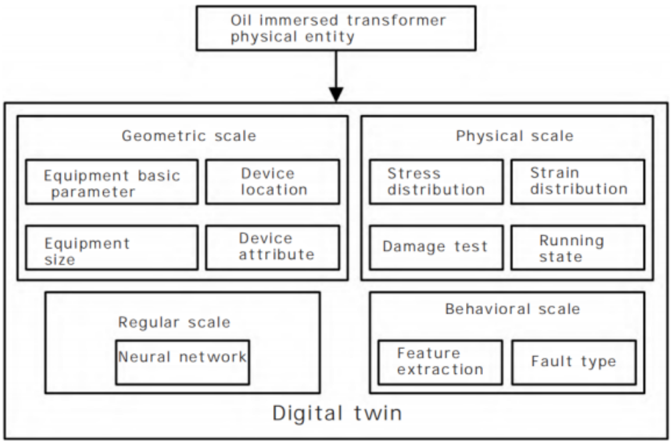


Figure 3. Schematic diagram of digital twin model.

Under normal circumstances, the reasons for the internal failure of the oil-immersed transformer include the aging of the device fault, the decline of the life of the insulator and the short circuit, which will cause the overheating of the transformer. Among them, the shortening of insulator life is the main reason leading to the high probability of overheating failure of oil-immersed transformer and the relationship between the hot spot temperature of oil-immersed transformer and the failure time of insulator is expressed by formula (2) using the Arrhenius theorem:

$$L_H(\theta_H) = C\exp\left(\frac{B^2}{\theta_H + 273}\right) \quad (2)$$

In the formula, C and B² both indicate that the internal experience parameters of the previous oil-immersed transformer can measure the internal life relationship of the oil-immersed compiler.

At the same time, Weibull distribution function is applied to the failure time of oil-immersed transformer insulator and the distribution probability in the entire time domain, and the correlation between the distribution probability and the fault function is obtained as follows:

$$\lambda = \frac{f(t)}{1 - f(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \quad (3)$$

Where: t represents the operating time when the load rate of the oil-immersed transformer is maintained at the same hot spot temperature; β represents the proportional function between failure time and failure time; $f(t)$ Representing shape parameters;η Represents life characteristics. As can be seen from formula (3), when the ratio parameter β continues to decrease, the value continues to increase, indicating that when the failure time of the oil-immersed transformer insulator increases, the failure probability also increases at the same time.

Taking the transformer load ratio as the influence factor , the load ratio value is substituted into equation (3) according to the change characteristic of β, and the expression is as follows:

$$\xi = \frac{\beta}{C\exp\left(\frac{B}{\theta_H} + 273\right)}\left[\frac{\mathrm{t}}{C\exp\left(\frac{B}{\theta_H} + 273\right)}\right]^{\beta-1} \quad (4)$$

At this time, it is necessary to use the time conversion method to convert the load rate actually generated by the transformer and the corresponding temperature curve into the following equivalent value. Based on this concept, the hot spot temperature calculation model is established, and the hot spot time change interval of the oil-immersed transformer is divided into and set when the hot spot temperature remains unchanged at this time, the equivalent running time is, and the change relationship between the hot spot temperature and the hot spot temperature is:

$$T_{eq} = \sum_{i=1}^{n}\exp\left(\frac{B}{\theta_H + 273} - \frac{B}{\theta_{Hi} + 273}\right) \quad (5)$$

Where, n represents the number of calculated point positions; θ_{Hi} Represents the current superheat temperature value of point i.

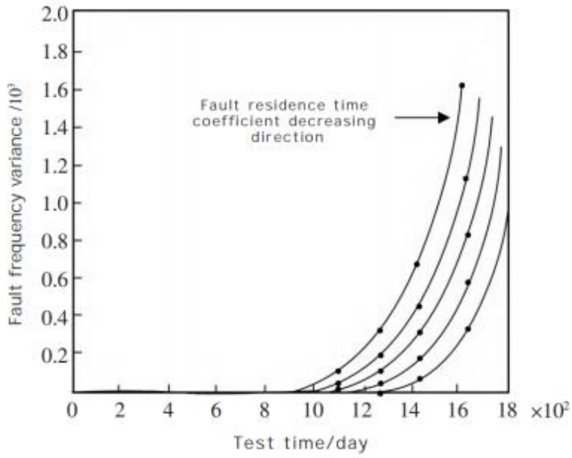
The value is brought T_{eq} into equation (4) and the value of it is obtained, that is, the probability of failure considering the change of the load rate of the oil-immersed transformer. Even under complex operating conditions, the variable voltage load ratio can be quickly obtained by substituting the data of the field transformer, which provides important help for the detection algorithm.

After the load ratio value of the oil-immersed transformer is obtained through the above process, the fitting linear relationship analysis of relevant parameters is carried out on the node data with high load ratio, and the fitting function of transformer fault residence time, operating days and fault probability variance is established. The failure time and operation reliability of the transformer are analyzed, and the measurement and obedience probability relationship between them are clarified. Taking the data of an oil-immersed transformer within 1800 days as an example, the normal distribution between the failure probability and the running time is obtained and the mean value is calculated. The distribution curve is shown in Figure 4.

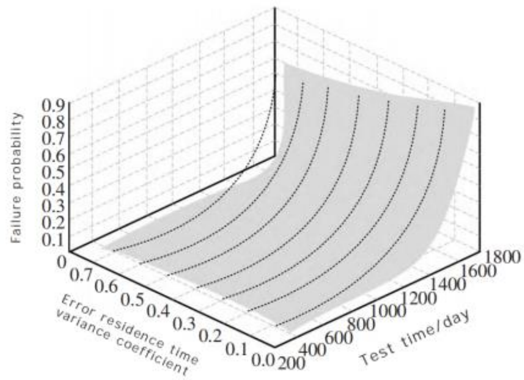
As can be seen from Figure 4, with the continuous increase of operating days, the fault variance value also increases, so it can be determined that there is a positive proportional change relationship between the two. According to the curve result of gradually reducing the residence time of failure in Figure 4(a), the fitting expression of the residence time of failure, the probability of failure and the number of days in operation is obtained, and the fitting change relationship among the three is obtained, as shown in Figure 4(b). It can be seen from the figure that there is a high fitting property among the three parameters, and the fitting function is obtained as follows:

$$\vartheta(T,\sigma^2) = a + b\exp(cT + d\sigma^2) \quad (6)$$

Where, $\vartheta(T,\sigma^2)$represents the fitting value of the failure probability of the oil-immersed transformer; σ^2 Indicates the failure residence time; T indicates the running time (days); a, b, and c represent constant terms; ϑ Represents the fitting parameter.



a) Variation of transformer failure probability under different vallance coefficient



b) Relationship between fault time variance coefficient and fault probability

Figure 4. Fitting change relationship between fault probability and time coefficient.

According to the calculation of equation, the closer the value of ϑ is to 1, the higher the fitting degree between the three parameters. Otherwise, it is smaller. Through the above process analysis, it is found that the fault probability variance has a strong correlation with the fault residence time, operation days and load ratio. The calculated linear relationship is used as the reference basis for subsequent fault detection to improve the detection accuracy.

3.2. Modeling of transformer internal fault detection

Based on the data information collected by the digital twin model, the neural network is used as the feedforward network of the digital twin fault detection model by virtue of its fast-training speed and simple structure. Set the transformer fault probability as the detection and comparison threshold, and consider the above process to obtain the correlation effect of the fault residence time, load rate and running time equivalence, and establish a node fault mapping model based on the digital twin：

$$\vartheta_{\mathrm{m}}(T_k) = \sigma^2 + \alpha e^{\beta v_t} + \lambda_0 \quad (7)$$

Where: $\vartheta_{\mathrm{m}}(T_{\mathrm{k}})$ represents the fault prediction probability function of the oil-immersed transformer after k days of operation at time m, where m= (1,2,3), 1 indicates good operation, 2 indicates normal operation, and 3 indicates poor operation; λ_0 Indicates the state to be predicted; $\mathrm{e}^{\beta v_t}$ Indicates the random probability of failure. The fault detection probability density function is derived as follows:

$$f(x) = \frac{1}{(2\pi)^{p/2} e^{\beta v_t}} \frac{1}{m} \sum \exp\left[-\frac{(x - x_{v_1})(x + x_{v_1})}{2\xi} \right] \quad (8)$$

Where: x_{v_t} represents the t detectionv_t sample vector of the fault type; p indicates the dimension of the test sample. In order to improve the accuracy of fault detection and the application ability in the actual environment, during the selection of the initial fault comparison threshold, three fault type x_{p1}, x_{p2}, x_{p3} samples were randomly selected from the population, p1≠p2≠p3 was set, and the final fault determination threshold was obtained by substitution of the field environmental data of the oil-immersed transformer:

$$h_{ij}(t+1) = x_{p1ij}(t) + f\left(x_{p2ij} - x_{p3ij}(t)\right) \quad (9)$$

4. Performance test

4.1. Oil immersed transformer fault detection results

The field environmental monitor is used as the carrying device of the fault detection algorithm, and the detection results are obtained through the output data of the monitor. In order to ensure the quality of the experiment and improve the comparability and referability of the detection results, the external manual input is adopted to simulate three kinds of fault conditions: good, warning and dangerous, and a high-intensity continuous fault input is set. The actual fault results of the oil-immersed transformer are shown in Figure 5, and the visual distribution of the detection results in three cases is shown in Figure 6 - Figure 8.

It can be seen from Figure 5 that the proposed method detects transformer fault results, in which the fault sample points in good condition have a small content and low overall distribution. The number of sample points in warning state is more and increases gradually with the increase of running time. The samples at risk were the most distributed of the three states. It can be seen from Figure 5 to Figure 8 that the discretization of fault detection sample points in good condition is strong, indicating that the transformer system is in normal operation at this time. However, the discreteness of warning and danger state samples is very poor, indicating that there are faults in most sample points detected. Comparing the result with the actual situation, the proposed method can accurately detect the real-time state change of the transformer fault point with high accuracy.

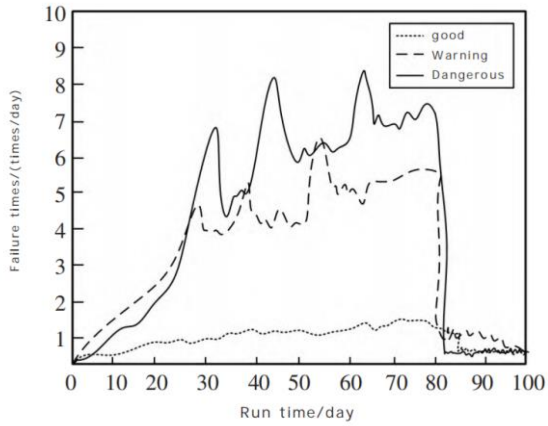


Figure 5. Fault results of oil immersed transformer.

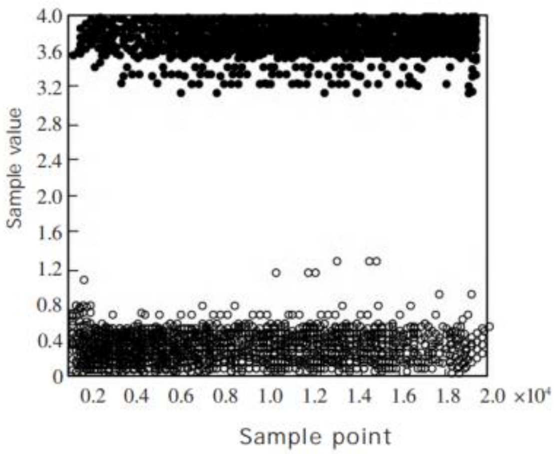


Figure 6. Sample distribution of fault points in good condition.

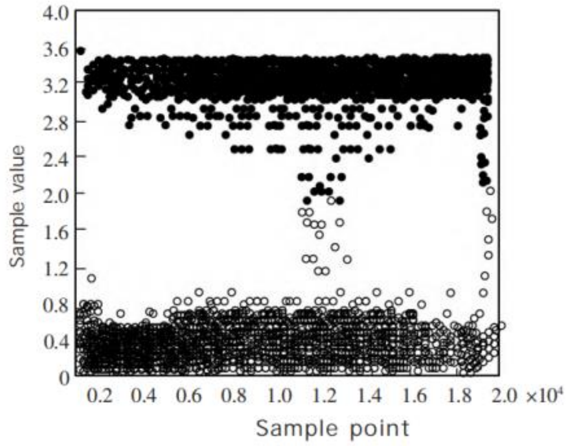


Figure 7. Sample distribution of fault points in warning state.

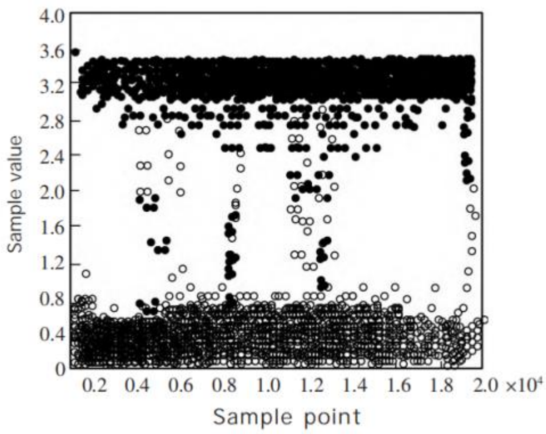


Figure 8. Sample distribution of hazardous state fault points.

4.2. Comparative analysis based on training fitness

In order to verify the practical application ability of the algorithm, the training fitness is taken as the test index to verify the practical effect of the algorithm, and the experimental results are obtained by comparison analysis with the fault detection algorithm based on genetic fault detection algorithm and bionic robot fish fault detection algorithm, as shown in Figure 9.

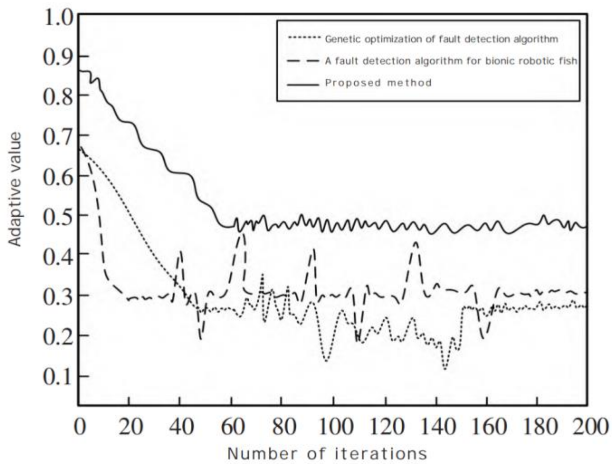


Figure 9. Comparison of fitness curves for trainers of different algorithms.

As can be seen from Figure 9, the training fitness curves proposed by the three methods are the highest and the performance is relatively stable, indicating that the proposed methods can complete the fault detection faster and more accurately under the same detection conditions. In contrast, the fitness values of the other two methods are low, and there are some differences with the proposed results, and the practical ability of the algorithm is not strong.

5. Conclusions

A digital twin model for fault detection and analysis of oil-immersed transformer is presented. Through the preliminary mathematical model of transformer fault, the correlation between the load rate, running time and fault residence time and the probability of fault occurrence is analysed. The subsequent detection efficiency can be greatly improved by using the correlation value. Considering the large amount of data inside the transformer, a digital twin model is established, and the detection scale is divided into behavioural, physical, regular and geometry through preliminary numerical comparison. According to the field data, the corresponding scale is monitored according to the transformer operating state, and the detection results are highly accurate and consistent with the actual situation. Experimental data show that the proposed method has high accuracy in fault detection, can guarantee detection results under various environments, and has strong robustness.

The established digital twin model provides real-time feedback and regulation to the whole construction process through constantly updated real-time construction data and accumulated historical data, which improves the information utilization rate in the detection operation and reduces the error. The realization method of intelligent construction based on digital twin is verified. However, due to the limited equipment of information collection, the data collection of total elements cannot be achieved. The future in big data in the integrated environment, it is necessary to analyse the whole element information of the detection process to realize the real mapping of the physical world.

It provides quality assurance for internal fault detection and reduces the rework caused by "empirical" practices in traditional detection. This example can provide reference for the research and application of equipment intelligent construction based on digital twin in the future. However, as this paper is a preliminary attempt to integrate emerging technologies into traditional construction industry, only some functions have been developed, and other functions are limited by time and technical level and need to be adjusted later.

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