A Fault Prediction Model of Adaptive Fuzzy Neural Network for Optimal Membership Function

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ABSTRACT

As an essential and challenging technology of fault prediction and health management (PHM), fault prediction technology has been a research focus in the field of fault diagnosis. However, the current model-based fault prediction technology and data-driven fault prediction technology have some limitations, and it is difficult to effectively apply them in practice. Therefore, this paper combines the advantages of two kinds of fault prediction technology, sets the fault distribution function as the membership function of the adaptive fuzzy neural network based on the full analysis of the fault mechanism. The use of the fault distribution function to highly generalize the law of fault occurrence, and the strong self-learning ability of the neural network can effectively tap the potential fault information of the fault data, thereby using the fault distribution function to fit the fault data, and forming a set of membership functions by presetting a variety of membership functions, so as to expand the applicability of the proposed model in fault prediction. The experimental results show that the fault prediction model proposed in this paper has the advantages of high prediction accuracy, fast convergence speed and good applicability.

INDEX TERMS

Adaptive fuzzy neural network, fault mechanism, fault prediction, membership function.

I. INTRODUCTION

Fault prediction starts with the status of the current equipment. It makes use of all kinds of information, such as status monitoring data, current environmental information, working conditions, previous test data and historical experience, and predict, analyze and judge the future faults of the equipment by making use of various reasoning techniques, so as to formulate reasonable and effective maintenance strategies to avoid the occurrence of failures and ensure the smooth completion of training and combat tasks [1], [2].

At present, fault prediction models can be roughly divided into two categories: the one is model-based fault prediction technology and the other is data-driven [3], [4].

Model-based fault prediction technology predicts fault through dynamically simulating the fault prediction model according to the established model [5], for example, the performance of model-based fault prediction technology is highly dependent on the characteristics of fault data sets, but this prediction model often lacks theoretical basis. To effectively solve the problem of model selection of different fault data sets based on model-based fault prediction technology, Cagatay Catal [6] constructed a fault prediction recommendation system based on logical decision tree by comparing the applicability of various algorithms of machine learning and statistical technology to the identified fault features. Considering the railway ballast system is susceptible to adverse weather and thus causes fault, Wang [7] set the weather as the variable of the fault prediction model, and constructed a causal-based Bayesian network to realize the fault prediction of the railway ballast system by reducing the dimension of the input characteristic data through the method of minimizing the entropy value. Qiao [8] used the Density Peak Clustering Algorithm (DPCA) to fit the clustering center of the fault data and fine-tuned the extracted fuzzy rule parameters based on the improved Leveberg-Marquardt algorithm, and proposed a fault prediction algorithm of adaptive fuzzy neural network based on...
density peak. The experimental results show that, compared with the existing methods, the algorithm has faster convergence speed and higher prediction accuracy. It can be seen from the above literature that the advantage of model-based fault prediction technology features high accuracy, and the parameters have practical physical significance, but its disadvantage is that it is difficult to establish a corresponding fault prediction model for the fault systems with complexity, multiplicity and correlation. Therefore, it is suitable for fault prediction of some systems with a simple system or a single fault mode.

The data-driven fault prediction technology [9] is different from the model-based fault prediction technology, which does not need to have a good understanding of the equipment fault mechanism studied, and can establish a corresponding fault prediction model by only relying on the collected fault data. Wang [10] measured the anomaly degree of the sample by introducing an anomaly index, and then proposed a data-driven fault prediction and anomaly measurement model based on the estimation of probability density by improving the constraint condition, which effectively reduced the size of the objective function and the number of solutions, greatly improving the computational efficiency of the model. Guo [11] used monotonicity and correlation to measure them by constructing eight time-frequency features into original feature sets, in order to solve the problem of predicting the remaining service life of bearings because the statistical feature range cannot be determined and the fault threshold is difficult to determine. He selected the most sensitive features as the characteristic variables of the input recurrent neural network, so that a recurrent neural network bearing life prediction model based on health indicators is constructed. Sun [12] extensively studied all environmental attributes including the cause of the fault, discussed the relationship between potential faults and environmental attributes, evaluated the impact of fault-induced fault prediction on the overall prediction performance, and proposed a fault prediction model based on environmental attributes. It can be seen from the above literatures that the data-driven fault prediction model does not need to have a good understanding of the fault mechanism of the system, as long as there is sufficient data, but the accuracy of the fault prediction is not based on the high fault prediction technology of the model, and it is affected by the error of the collected data. It can be concluded that the data-driven fault prediction technology is a fault prediction method that compromises complexity and accuracy.

Based on the advantages and disadvantages of the two kinds of fault prediction techniques, this paper proposes a fault prediction model of adaptive fuzzy neural network (AFNN) for optimal membership function on the premise of fully analyzing various fault mechanisms. Firstly, based on the strong self-learning ability of neural network and the high generality, fault tolerance and robustness of fuzzy logic, this paper selects AFNN as the basic model of fault prediction; Secondly, by analyzing the fault mechanism of various equipment, the fault distribution function which can represent the fault occurrence rule is set as the membership function of the AFNN; Finally, in order to enhance the applicability of AFNN in fault prediction of various equipment, this paper optimized the membership function that can fully exploit the potential information of fault data [13] by building a set of membership functions, and constructed a fault prediction model of AFNN for optimal membership function. Through the experimental analysis, the fault prediction model proposed in this paper has the advantages of high prediction accuracy, fast convergence speed and strong applicability.

### II. ANALYSIS OF FAULT MECHANISM

Fault or failure of devices and equipment is random and unavoidable, so the time of fault or failure is also random [14]. Statistical characteristics and distribution rules of fault time of different equipment or the same equipment and devices under different conditions often show different distribution types [15]–[19], the general application scope of fault distribution types that are commonly used is shown in **TABLE 1**.

| Distribution type      | Scope of application                                                                 |
|------------------------|---------------------------------------------------------------------------------------|
| Exponential distribution | including electronic equipment, electronic components, multi-component complex systems and components with constant fault rate. |
| Normal distribution    | In the case of non-life, more than 80% of the problems are global distribution. It is suitable for the study of strength and stress distribution in mechanical products and structural engineering, wear-resistant parts and faults, the measurement of product size and performance when the quality process is stable, resistance value, semiconductor material performance index and material strength. |
| Logarithmic distribution | Life phenomena events mainly focus on top asymmetry with large dispersion of observed values, such as semiconductor devices, germanium transistors, silicon transistors, metal fatigue, fan blades, car body structure, etc. |
| Weibull distribution   | Which is mainly applicable to models with weak links, such as mechanical fatigue strength, wear life, including transmission gears, rolling bearings, engines, motors and other mechanical and electrical components. |

It can be seen from **TABLE 1** that the fault rate of the same type of equipment obeys a certain probability distribution function. If the parameter value of a certain type of equipment fault probability distribution function can be obtained,
the fault rate can be accurately characterized as shown in Fig 1.

Due to the different working environments, workload and processing techniques of equipment and devices, the probability fault distribution function of the same type of equipment and devices is often quite different [20]–[22], and the characteristics of fault often exhibit the characteristics of fuzziness [23]–[27]. Therefore, it is difficult to find a probability distributing function to accurately characterize the fault rate. Fuzzy neural network (FNN) assumes that the input data obeys a certain type of probability distribution. It uses the powerful self-learning ability of the neural network to constantly adjust the parameters of the initial membership function so as to characterize the probability distribution function of the input data. Therefore, based on the above considerations, this paper constructs an AFNN fault prediction model of the optimal membership function, introduces a membership function which can describe the fault rate of equipment, and optimizes the membership function which can best describe the fault distribution of the group of data according to the fitting effect of actual fault data on different membership functions. Finally, the fault prediction of equipment and its devices is realized.

III. CONSTRUCTION OF FAULT PREDICTION MODEL

A. AFNN

AFNN combines the self-learning ability of neural network with fuzzy system, and uses fuzzy structure of neural network to represent fuzzy processing, fuzzy reasoning and precise calculation of fuzzy systems, thereby, realizing a hybrid neural network of self-organization and self-learning of fuzzy system. Because of its strong adaptability, robustness and fault tolerance, AFNN has been widely used in the field of fault prediction [8], [28]–[30]. Its structure is shown in Fig 2.

1) INPUT LAYER

This layer is the input layer, there are n input nodes, each node represents an input variable, the output of this layer is as follows:

$$\mu_j(t) = x_j(t), \quad i = 1, 2, \ldots, n$$  (1)

wherein, $x_i(t)$ is the input value of the i-th node, $\mu_i(t)$ represents the output value of the i-th node.

2) MEMBERSHIP FUNCTION LAYER

This layer is a membership function layer, with a total of $n \times r$ nodes. Among them, $n$ is the number of nodes in the input layer and $r$ is the number of nodes in the regular layer. Each node represents a certain membership function. In this paper, the membership function takes the Gauss function as an example, and its expression is as follows:

$$\mu_{ij}(t) = \exp\left(-\frac{(x_i(t) - c_{ij}(t))^2}{\sigma_{ij}^2(t)}\right)$$  (2)

wherein, $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, r$; $c_{ij}(t)$ and $\sigma_{ij}^2(t)$ represent the output value, expectation and variance of input value $x_i(t)$ on the j-th membership function respectively.

3) RULE LAYER

This layer is a rule layer, there are a total of $r$ neurons. For the output of the subordinate function layer, the output and normalized operation are carried out according to the operator. The output value of this layer represents the excitation intensity of the fuzzy rule space. For the j-th regular neuron, its output value is as follows:

$$v_j(t) = \prod_{i=1}^{n} \mu_{ij}(t) = \exp\left(-\sum_{i=1}^{n} \frac{(x_i(t) - c_{ij}(t))^2}{\sigma_{ij}^2(t)}\right)$$  (3)

$$h_j(t) = \frac{v_j(t)}{\sum_{j=1}^{n} v_j(t)} = \frac{\exp\left(-\sum_{i=1}^{n} \frac{(x_i(t) - c_{ij}(t))^2}{\sigma_{ij}^2(t)}\right)}{\sum_{j=1}^{r} \exp\left(-\sum_{i=1}^{n} \frac{(x_i(t) - c_{ij}(t))^2}{\sigma_{ij}^2(t)}\right)}$$  (4)

wherein, $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, r$; $v_j(t)$ and $h_j(t)$ represent the input value and the normalized output value of the j-th node in the rule layer respectively.
Step 1: Set NumIter & MinError, among them, NumIter is the preset number of iterations, and MinError is the preset minimum allowable error. In this step, the termination condition of the entire model is set. By setting the number of iterations and the minimum allowable error, the prediction accuracy and running time of the model are adjusted in the stage of selecting the membership function.

Step 2: Set MF & IterError, among them, MF is the pre-set membership function set, \(MF = \{MF_1, MF_2, \cdots, MF_i\}\), wherein, \(MF_i\) represents a preset membership function, IterError represents the current loop minimum error, and the initial value is set to infinity. By presetting the set of membership functions, a series of membership functions are selected in advance as pre-selected parameters. Each membership function corresponds to a fault distribution function by constantly comparing and setting the minimum error IterError of AFNN fault prediction for each membership function.

Step 3: Randomly select \(MF_i\), in the membership function set \(MF = \{MF_1, MF_2, \cdots, MF_i\}\), a membership function is randomly selected to construct the AFNN.

Step 4: Pre-training AFNN, pre-train the AFNN constructed in Step 3.

Step 5: Save e, wherein, e represents the prediction error of the current loop. The AFNN trained in Step 4 is tested and its error is saved to the variable e.

Step 6: \(e < \text{IterError}\) ?, the current loop error e is compared with the current loop minimum error IterError. When e is less than IterError, the value of e is assigned to IterError, and the membership function information of the AFNN is recorded; when e is greater than IterError, the IterError value and membership function information of AFNN are not updated.

Step 7: Delete \(MF_i\), delete the membership function \(MF_i\) corresponding to this loop in \(MF = \{MF_1, MF_2, \cdots, MF_i\}\).

Step 8: \(MF = \phi \), \(\phi\) means the collection is empty. Then judge the set of \(MF = \{MF_1, MF_2, \cdots, MF_i\}\) in the previous step is empty or not, if it is empty, all pre-set membership functions have constructed the AFNN; if not, return to Step 3 and continue the above steps to judge that the set is empty.

Step 9: Train AFNN, the fault data is put into the AFNN obtained in Step 8 for training.

IV. EXPERIMENTAL ANALYSIS

The software of MATLAB integrates 11 kinds of membership functions. Five of them are selected to establish the set \(MF = \{\text{guassmf}, \text{gbellmf}, \text{sigmf}, \text{psigmf}, \text{dsigmf}\}\) of membership functions in this paper. They are Gauss-type membership function (gaussmf), generalized bell-type membership function (gbellmf), S-type membership function (sigmf), double S-type product membership function (psigmf) and double S-type difference membership function (dsigmf), respectively. The pre-set NumIter is 20 and the pre-set MinError is 0.001. The experimental data in this paper come from the simulation results of international standard CSTV filters, as shown in Fig 4, wherein, \(R_1 = R_2 = R_3 = R_4 = R_5 = 10k, R_6 = 3k, R_7 = 7k, C_1 = C_2 = 20nf\). Considering the effect of tolerance on circuit output, resistance and capacitance are set at 5% and 10% respectively, and R5 is set as fault element. The experimental data are divided into training data and test data in the form of 4:1 through 200 times simulation analysis.
In this paper, the concrete Compressive Strength Data Set (CCS Data Set) in UCI data set is selected as the comparative data set. Through comparative analysis, the conclusion of the fault mechanism analysis in this paper is verified, as shown in Fig 5, Fig 6 and TABLE 2.

It can be seen from Fig 5, Fig 6, Fig 7 TABLE 1 and TABLE 2:

1) From Fig 5, Fig 6 and TABLE 2, it can be seen that when the data set is experimental simulation data and the membership function selects Gauss function, the prediction accuracy of the AFNN is 99.84%, which can better fit the test data set of simulation experiment. But when the input of the AFNN is a non-Gauss membership function, its maximum prediction accuracy is only 85.33%, which is 14.51% less than the highest prediction accuracy. This proves that the membership function has a high contribution to the fault prediction ability of the AFNN. Therefore, the experiment positively verifies the necessity of constructing an AFNN fault prediction model with optimal membership function, and the conclusion put forward in the analysis of fault mechanism in this paper, that is, when the membership function of the AFNN is the same as the distribution function of fault data, the fault prediction ability of AFNN will be greatly improved.

2) From Fig 5, Fig 6 and TABLE 2, it can be seen that when the experimental data do not conform to the data of the fault distribution characteristics, the AFNN has a poor fitting effect no matter what membership function it takes, and its highest fitting accuracy is only 62.45%, as shown in Fig 6. The difference in fitting accuracy of AFNN of different membership functions is up to 27.46% on CCS data sets, which is higher than the difference in fault prediction accuracy of each subordinate function in the experimental simulation data. It is proved that when the prediction data are more complex or the rules are more difficult to fit, the necessity of constructing an AFNN fault diagnosis model for optimal member function is verified from the reverse side. The conclusion proposed in fault mechanism analysis of this paper is also verified.

3) It can be seen from Fig 5, Fig 6 and TABLE 1, that when the experimental data are simulation data, the fitting effect of AFNN using Gauss function as membership function is the best; when the experimental data is CCS Data Set, the fitting effect of AFNN using S-type function as membership function is the best. So we can see that although Gauss membership function is the most widely used membership function [31], [32], its fitting effect cannot be guaranteed to be the best on different data sets. Even on CCS Data Set, its fitting accuracy on the AFNN constructed by the selected five membership functions is only 61.57%, ranking second to last. Therefore, it is too arbitrary to select AFNN membership function only depending on the subjective wishes of researchers, which also proves the necessity of constructing
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4) The membership function of the AFNN is set to be Gauss function and the experimental data is the simulated data. It can be seen from the error variation diagram of the AFNN in Fig 5 and Fig 7, that the step size of the adaptive variable neural network contributes greatly to the accuracy of fault prediction in the initial iteration stage. With the decreasing of adaptive step size, the error of fault prediction of fuzzy neural network decreases rapidly. With the number of iterations increasing to about 140 times, the adaptive step-size does not reduce any more, but tends to increase. At this time, the accuracy of fault prediction of fuzzy neural network tends to be stable. Therefore, in fault prediction of more complex data, more attention should be paid to the idea of the changeable adaptive step size, which can greatly improve the fitting speed of the neural network.

V. CONCLUSION

It can be known from the experimental analysis that the fault prediction model of AFNN for optimal membership function proposed in this paper combines the characteristics of high prediction accuracy of model-based fault prediction technology and that the data-driven fault prediction technology does not need to construct a complex mathematical model, and link the membership function with the fault distribution function. By using the self-learning ability of the neural network, the potential information in the fault data is fully excavated, and a large number of fuzzy fault prediction problems can be dealt with. The model has the advantages of high prediction accuracy, fast fitting speed and strong applicability.

However, the model proposed in this paper still has the following shortcomings:

1) It is difficult to predict the failure of complex equipment, because complex equipment are affected by multiple fault distribution functions at the same time, so it is difficult to accurately describe it with a fault distribution function;

2) Model operation method is not flexible enough. When the amount of fault data is large, a large amount of computing power is wasted by comparing errors one by one.

Therefore, the fusion of multiple fault distribution functions of the same or different types according to fault data characteristics and the design of a data parallel processing framework are the focus of model optimization in this paper.

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