Research on Military Radio Fault Diagnosis Method Based on Fuzzy Neural Network

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Abstract. In view of the complexity, correlation and fuzziness of military radio faults, a fault diagnosis strategy combining fuzzy neural network with expert system is proposed, and the fault diagnosis method based on T-S fuzzy neural network is mainly studied. The fuzzy neural network model was established by MATLAB R2017a, and the simulation experiment was carried out. The experimental results show that the T-S fuzzy neural network model has good generalization ability, fault tolerance ability and self-adaptability, can quickly locate fault causes, greatly improve the diagnostic efficiency, and can be used in fault diagnosis of military radios.

1. Introduction
In modern war, wireless communication plays an extremely important role in ensuring the interconnection and interworking of troops in large depth, multi-directional and three-dimensional operations. As one of the main equipment of wireless communication, military radio is an important means of information transmission and an indispensable military communication equipment in battle command and daily training. In the future information battlefield, electronic warfare will become the main means of combat, communication task is extremely difficult. As an important communication tool, radio plays a decisive role in ensuring smooth communication to meet the needs of command and coordination. In order to improve the reliability and stability of the radio communication system, it is necessary to diagnose and repair the radio faults quickly.

The fault diagnosis method based on signal processing is mainly used in the present research. The fault diagnosis method based on signal processing is mainly used in the present research. Ref. [1] takes tablet computer as the core to build hardware platform, integrates circuit intelligent detection technology, digital signal processing technology and database software technology, designs embedded software system, and develops portable radio maintenance assistance system. Ref. [2] proposed a diagnosis system model by combining fault tree with BP neural network. In this model, the parameters of BP neural network are extracted from the fault tree. In the specific diagnosis operation, the fault is first matched with the fault instance library. If the match is successful, the maintenance strategy of the existing fault is found. If not, the BP neural network module is entered to diagnose the new fault. Ref. [3] takes computer and virtual instrument technology as the core, realizes the separation of integrated circuit boards through the design of test platform, and designs the functions of automatic rapid detection and accurate positioning of auxiliary test according to the characteristics of integrated circuit boards, which can lock faults to specific components. These methods rely on the acquisition of measurable signals from the radio to analyse the radio fault. Moreover, it has strict requirements on hardware, high cost and difficulty in implementation. Aiming at the shortcomings of the existing
methods, this paper proposes a fault diagnosis method for military radio based on fuzzy neural network (FNN).

2. Fault Diagnosis Strategies for Military Radio
With the development of military radio, people have accumulated a lot of experience in fault maintenance, which is of great significance to the research of intelligent fault diagnosis of military radio. The key to fault diagnosis is inference. Inference is the process from existing facts to a conclusion. Human experts have the ability to solve complex problems, not only because they have a large amount of specialized knowledge, but also because they have the ability to choose the best and apply their knowledge flexibly. The fault diagnosis strategy is to select and use the fault knowledge reasonably to obtain the diagnosis conclusion.

Expert system [4] is a kind of inference system based on knowledge. It can make full use of the previous knowledge of fault diagnosis reasoning. It can make full use of the previous fault knowledge to diagnose and infer the fault. At present, expert system has been successfully applied in electronic system, mechanical system and agricultural system. It’s a very sophisticated technology. The disadvantage of expert system is that it relies too much on domain knowledge, and its self-learning ability and self-adapting ability are limited. FNN can make up for the shortcomings of expert system. This model combines expert system and FNN to deal with the fault diagnosis of military radio. The whole system runs in parallel, and the data in the knowledge base can be used as training and testing samples for FNN. After processing the fault information of the military radio, the model matches the fault information of military radio with the knowledge base of expert system. If the match is successful, the rule base of expert system can be directly used for fault diagnosis inference. If the match fails, the fault data shall be input into the database of the fuzzy neural network, and then the inference calculation and diagnosis conclusion shall be made by the fuzzy neural network, and the new fault form shall be stored in the knowledge base of the expert system after being studied and determined. With the continuous accumulation and update of knowledge base, the knowledge base becomes more and more expert. The fault information in the knowledge base is classified and arranged according to the occurrence frequency, which reflects the application of expert experience. The workflow of military radio fault diagnosis is shown in figure 1.

3. Structure and Algorithm of Fuzzy Neural Network

3.1. Basic Principle
The basic principle and structure of FNN are described in detail in this section. Taking a double input and single output system as an example. If the fuzzy conditional statement “If \( x_1 \) is \( A_1 \) and \( x_2 \) is \( A_2 \), then \( u \) is \( U \)” is used to describe a major premise, and knowing that “\( x_1 \) is \( A_1 \) and \( x_2 \) is \( A_2 \)” is a minor premise, then the approximate synthesis rule can be used to obtain a new proposition “\( u \) is \( U \)”\(^*\). \( U \)\(^*\) is a fuzzy set, so that you can’t get a clear output directly, but have to convert it clearly, which is a tedious process. When the system is locally linear and can be controlled piecewise, the above process can be modified by local linearization. Assuming that a system of two inputs are clear value variable \( x_1 \) and \( x_2 \), we can transform the fuzzy reasoning process into “If \( x_1 \) is \( A_1 \) and \( x_2 \) is \( A_2 \), then \( u \) is \( f(x_1, x_2) \)”, \( A_1 \) and \( A_2 \) are two fuzzy sets, the output \( u \) is a numerical function \( f(x_1, x_2) \), and the parameters of this function are obtained through system identification according to a large number of experimental data. Whenever there is a new set of inputs \( (x_1', x_2') \), it is equivalent to the “minor premise” in approximation reasoning. The original approximation reasoning process is replaced by the calculation of function \( f(x_1', x_2') \), and the fuzzy set conclusion of approximation reasoning is replaced by the approximate value of this function [5].

The T-S type FNN [6] is adopted in this paper. Assuming that the T-S type FNN structure is composed of \( N \) inputs, 1 output and \( M \) fuzzy rules, the general form of inference rules is:

Rule \( R_\kappa \): if \( x_1 \) is \( A_1^\kappa \), \( x_2 \) is \( A_2^\kappa \),...\( x_n \) is \( A_n^\kappa \) then \( f_\kappa = p_0^\kappa + p_1^\kappa x_1 + \cdots + p_n^\kappa x_n \)
\( k \) is the ordinal number of the rule \( \text{(k=1,2...,m)} \), \( A_k^i \) is the fuzzy set, \( p_k^i \) is the parameter, and \( f_k \) is the output obtained according to the rule \( R_k \). The structure diagram of T-S FNN is shown in figure 2.

**Figure 1.** Flow chart of fault diagnosis.

**Figure 2.** Structure diagram of the T-S type FNN.

In figure 2, FNN is composed of 6 layers of neurons, which are described in detail below.
The first layer is the input layer, and the number of nodes in this layer is \( N_1 = n \), it represents that there are \( n \) inputs, and \( x_i \) \((i = 1, 2, \ldots, n)\) represents the input variable.

The second layer is the fuzzy layer, which is used to calculate the membership degree of input variable \( x_i \) to the fuzzy set \( A_k^i \). The number of nodes \( N_2 = n \times m \). The commonly used fuzzy methods include triangular membership function, S-shaped membership function, bell shaped membership function, Gaussian membership function and so on. Gaussian membership function is more in line with statistical characteristics, and it has good anti-interference ability and certain advantages in processing non-binary input and fuzzy set input space mapping. Therefore, this paper adopts Gaussian membership function:

\[
\mu A_k^i (x_i) = \exp[-\frac{(x_i - a_i^k)^2}{(\sigma_i^k)^2}]
\]

(1)

\( a_i^k \) and \( \sigma_i^k \) respectively represent the centre and width of membership function, and they are the premise parameters.

The third layer is the fuzzy reasoning layer. Each node represents a fuzzy rule, and the number of nodes is \( N_3 = m \). This layer is used to match the antecedents of fuzzy rules. The ignition method algorithm [7] is adopted to calculate the ignition intensity of each rule:

\[
\mu_k = \prod \mu A_k^i (x_i)
\]

(2)

\( \mu_k \) is the ignition intensity of \( R_k \).

The fourth layer is the normalized layer with the same number of nodes as the third layer, \( N_4 = m \). This layer normalized the ignition intensity:

\[
\mu_k = \frac{\mu_k}{\sum \mu_k}
\]

(3)

The fifth layer is the anti-fuzzy layer, and the number of nodes \( N_5 = m \). This layer computes the afterparts of each rule and sums them up to calculate the total output of the system:

\[
y = \sum \mu_k f_k
\]

(4)

In the above FNN, there are two types of parameters that need to be optimized for learning: the antecedent parameter and the consequent parameter. The centre \( a_i^k \) and width \( \sigma_i^k \) of the membership function are the parameters of the antecedent part and \( [p_0^k, p_1^k, \ldots, p_n^k] \) is the parameters of the consequent part.

3.2. Learning Algorithm

FNN automatically designs and adjusts the design parameters of the fuzzy system according to the input and output sample data sets to realize the self-learning and self-adaptive functions of the fuzzy system, which is called the learning process.

There are three basic learning algorithms for FNN: learning algorithm based on gradient descent, learning algorithm based on recursive least squares and clustering [8]. In this paper, the learning algorithm is the hybrid algorithm, the clustering algorithm is used to extract fuzzy rules, the gradient descent method is used to optimize the antecedent parameters, and the least square method is used to optimize the consequent parameters.

3.2.1. Fuzzy C-means Algorithm (FCM). FCM is a kind of data clustering technology. To a certain extent, each data point belongs to a clustering specified by the membership level. It was first proposed
by Jim Bezdek in 1981 as an improvement over earlier clustering methods. It provides a way to demonstrate how to group data points that fill a multidimensional space into several clusters. FCM algorithm was applied to cluster the training sample set, and then the fuzzy rules were extracted [9]. FCM algorithm is a fuzzy clustering algorithm based on the objective function. FCM algorithm is the most widely used and more successful in various fuzzy clustering algorithms. By optimizing the objective function, the membership degree of each sample point to all class centers is obtained, and then the class of sample points is determined to achieve the purpose of automatic classification of sample data. After the clustering, the number of class centres is the number of fuzzy rules, the class centre value is the initial value of the centre parameter of the membership function, and the minimum distance between class centres is the initial value of the width parameter of the membership function.

3.2.2. Stochastic Gradient Descent (SGD). SGD [10] takes the gradient of the parameter as a clue, updates the parameter along the direction of the gradient, and repeats this step for many times, so as to gradually get closer to the optimal parameter. SGD is used to optimize the antecedent parameter, i.e. the center and width of the membership function. Take mean square error as the loss function: 

\[ E = \frac{1}{2} \sum_{j} (y_j - t_j)^2 \]  

(5)

\( y_j \) is the output of FNN, \( t_j \) is the supervisory data, \( j \) is the dimension of sample data. By taking the derivative of the chain rule, the learning formula of the central parameter of the membership function in the antecedent parameter can be obtained:

\[ a_i^k \leftarrow a_i^k - \eta \frac{\partial E}{\partial a_i^k} \]  

(6)

\( a_i^k \) is the Parameters that need to be updated, \( \frac{\partial E}{\partial a_i^k} \) is the gradient of the loss function related to \( a_i^k \), \( \eta \) is the learning rate. Usually a predetermined value of 0.01 or 0.001 is taken. The arrow in Equation (6) indicates updating the left value with the right value. Similarly, the learning formula of the width parameter of membership function in the antecedent parameter can be obtained:

\[ \sigma_i^k \leftarrow \sigma_i^k - \eta \frac{\partial E}{\partial \sigma_i^k} \]  

(7)

3.2.3. Least Squares (LS). LS [11] is a mathematical optimization technique that minimizes the residual sum of squares to find the best functional match for data and can be used for curve fitting in linear regression analysis. LS is used to optimize the consequent parameters. According to equation (4), the output of FNN is:

\[ y_j = \sum_{k=1}^{m} \mu_k f_k \]  

(8)

By plugging in the value of \( f_k \), we can get:

\[ y_j = \sum_{k=1}^{m} \overline{\mu_k} \left( p_0^k + p_1^k x_1 + \ldots + p_n^k x_n \right) \]  

(9)

\( M \) is the fuzzy regular number, \( \overline{\mu_k} \) is the normalized result of ignition intensity in \( R_k \). Obviously, Equation (9) is a multivariate linear model with \( m(n+1) \) parameters to be optimized. The parameters of the consequent part can be calculated accurately by LS algorithm \( \left[ p_0^k, p_1^k, \ldots, p_n^k \right], k=1, 2, \ldots, m. \)
4. Fault Diagnosis of Military Radio Based on Fuzzy Neural Network

In military communication, military radio stations are responsible for transmitting a large number of analog, digital, data and static images. Long-term, high-intensity and high-frequency use will lead to unit damage, circuit aging and other malfunctions of military radio stations, which will cause communication failure of military radio stations, and even cause immeasurable losses. At present, the fault diagnosis of military radio station still depends on professional maintenance personnel and professional maintenance equipment, so the cost of diagnosis is high. In view of this, this paper takes a type of military ultra-short wave radio station (hereinafter referred to as radio station) as an example, proposes a radio fault diagnosis method based on FNN, and diagnoses the fault by establishing a T-S FNN model.

4.1. Radio Fault Knowledge Acquisition

As an important communication equipment for conducting military operations, radio station requires high timeliness in fault diagnosis and maintenance, so it is necessary to locate the fault source and restore communication in the shortest time. Therefore, the fault can only be located at the unit board, and the fault at the component level is not within the scope of this paper. Through the analysis of the working principle and circuit composition of the station, combined with the factory’s operating instructions and professional maintenance experience, comprehensive knowledge of the station failure is summarized. The cause analysis of each fault phenomenon is shown in table 1.

To facilitate data storage and program implementation, all fault phenomena are defined as A1, A2, ..., An, and all fault causes are defined as B1, B2, ..., Bm. Specific definitions can be found in tables 2 and 3.

From tables 1-3, it is known that the radio fault has the characteristics of complexity, correlation and fuzziness. Some fault phenomena can be directly diagnosed by the fault analysis table. The fault knowledge of this part of the fault can be stored in the knowledge base of the expert system and can be directly used for actual fault diagnosis. However, some fault phenomena have fuzziness in their own judgment. For example, failure phenomena A3 radio station reception sensitivity is low, and it can not be accurately determined. For this kind of radio station fault, T-S type FNN is established for diagnosis.

### Table 1. Radio fault analysis table.

| Number | Failure phenomenon                          | Cause analysis                                                                 |
|--------|--------------------------------------------|-------------------------------------------------------------------------------|
| 1      | Radio cannot be turned on                   | (1) The power supply voltage is too low<br>(2) The power cord is not connected properly<br>(3) Poor contact between transceiver and 50W power amplifier<br>(4) Switch failure<br>(5) Display and control unit failure<br>(6) Power supply unit failure |
| 2      | No LCD display on the front panel           | (1) display and control unit failure<br>(2) Power supply unit failure         |
| ...    | ...                                        | ...                                                                           |
| 22     | Display “power amplifier power failure”     | (1) Power amplifier unit failure<br>(2) Path switching unit failure             |
Table 2. Fault phenomena table.

| Number | Symbol | Definition                                              |
|--------|--------|---------------------------------------------------------|
| 1      | A1     | Radio cannot be turned on                               |
| 2      | A2     | Front panel LCD not shown                               |
| 3      | A3     | Low radio reception sensitivity                         |
| 4      | A4     | No power output                                         |
| 5      | A5     | No receiving and sending instructions                    |
| 6      | A6     | No sound from the handset                                |
| 7      | A7     | Normal analog communication, abnormal frequency hopping secure communication |
| 8      | A8     | Data transmission is not working properly               |
| 9      | A9     | Power-on display parameter missing                       |
| 10     | A10    | Radio key out of control                                |
| …      | …      | …                                                       |
| 22     | A22    | Display “Power Amplifier Failure”                        |

Table 3. Fault causes table.

| Number | Symbol | Definition                                              |
|--------|--------|---------------------------------------------------------|
| 1      | B1     | Power supply voltage is too low                         |
| 2      | B2     | Power cord not connected properly                       |
| 3      | B3     | Bad contact between transceiver and 50W amplifier       |
| 4      | B4     | Switch failure                                          |
| 5      | B5     | Display and control unit failure                         |
| 6      | B6     | Power unit failure                                      |
| 7      | B7     | Poor contact of RF connector                            |
| 8      | B8     | Amplifier Path Switching Unit failure                   |
| 9      | B9     | RF unit failure                                         |
| 10     | B10    | Intermediate Frequency Unit Failure                      |
| …      | …      | …                                                       |
| 22     | B22    | Power Amplifier Failure                                 |

4.2. Establishment of a Fuzzy Neural Network Model

Combined with the failure knowledge in section 4.1, the following failure phenomena are considered as inputs of the T-S FNN model:

$x_1$: “Radio reception sensitivity is low”; $x_2$: “Power output is not normal”; $x_3$: “Audio output level is not normal”; $x_4$: “Data transmission is not working properly”; $x_5$: “Frequency hopping communication is not normal”; $x_6$: “Front panel LCD is not displayed”.

The failure causes of the above failure phenomena are as follows:
\( y_1 \) means “RF unit failure”; \( y_2 \) means “IF unit failure”; \( y_3 \) means “integrated business unit failure”; \( y_4 \) means “display control unit failure”; \( y_5 \) means “poor contact of RF connector plug-in”. For the presence of fault symptoms, fuzzy category description is used as shown in table 4.

Table 4. Fault causes table.

| Number | Degree of membership | Degree of existence |
|--------|----------------------|---------------------|
| 1      | 0–0.2                | not exist           |
| 2      | 0.2–0.4              | unlikely to exist   |
| 3      | 0.4–0.6              | may exist           |
| 4      | 0.6–0.8              | very likely to exist|
| 5      | 0.8–1.0              | exist               |

According to the experience and knowledge of experts in the field of radio maintenance and the past maintenance examples, the corresponding relationship between radio fault symptoms and fault causes, namely input and output sample data, is made as the training data and test data of FNN model. FCM is used to cluster the sample data to obtain fuzzy rules. After establishing the model, SGD is used to train the antecedent parameters of FNN, and LS is used to train the consequent parameters of FNN.

5. Simulation Experiment and Result Analysis

In this experiment, MATLAB R2017a is used to design FNN model, and hybrid algorithm is used to learn and train the parameters of the model. FNN structure has five layers, input layer has 6 nodes, corresponding to 6 fault symptoms; output layer has 5 nodes, corresponding to 5 fault causes; after fuzzy clustering, 9 fuzzy rules are obtained. From the 200 groups of sample data collected, 190 groups were randomly selected as training data, and the remaining 10 groups were used as test data. The loss function index of training was set as 0.01, and the maximum number of cycles was 5000.

The curve of the relationship between the loss function and the number of iterations in the training process is shown in figure 3. After 4812 times of training, the error of loss function reaches the target requirements and the network training is successful.

![Figure 3. Relationship curve between loss function and iteration number.](image)
In order to validate the generalization and fault tolerance of the FNN fault diagnosis model, 10 sets of sample data are used for experimental validation, and the simulation output is shown in Table 5. From Table 5, it can be seen that the absolute error between the simulation output and the target output is within the allowable range of errors. When the decision threshold is set as 0.5, the simulation output matches the target output perfectly. It can be seen that the built FNN model has accurate diagnostic results, good generalization ability, fault tolerance and adaptability, and can be used to diagnose the fault of radio stations.

### Table 5. Comparison of target outputs and simulation outputs.

| Sample | Target outputs | Simulation outputs |
|--------|----------------|--------------------|
| 1      | 1 0 0 0        | 0.8035 0.0041 0.1214 0.0109 0.0727 |
| 2      | 0 1 0 0        | 0.0524 0.7373 0.0297 0.3671 0.1451 |
| 3      | 0 0 1 0        | 0.0458 0.1145 0.9104 0.0225 0.0446 |
| 4      | 0 0 0 1        | 0.0761 0.1376 0.0422 0.6394 0.0790 |
| 5      | 0 0 0 0        | 0.0001 0.1350 0.1212 0.0426 0.8777 |
| 6      | 0 0 0 1        | 0.0574 0.1316 0.0196 0.9472 0.0166 |
| 7      | 0 0 1 0        | 0.0241 0.0152 0.8811 0.0999 0.1072 |
| 8      | 0 1 0 0        | 0.4115 0.5087 0.0086 0.1056 0.0394 |
| 9      | 1 0 0 0        | 0.5977 0.2793 0.0332 0.0670 0.0285 |
| 10     | 0 0 0 0        | 0.0173 0.0729 0.0265 0.1120 0.1344 |

### 6. Conclusion

In view of the complexity, correlation and fuzziness of radio faults, a fault diagnosis strategy combining FNN and expert system is proposed in this paper, and the fault diagnosis method based on T-S type FNN is mainly studied. By analyzing the working principle and circuit composition of radio station and combining with the expert experience of radio station maintenance, comprehensive radio fault knowledge base is established, which can be used for the diagnosis of most radio station faults. For the radio faults with fuzziness and unrecorded in the knowledge base, the method of T-S type FNN was used to diagnose them. The FNN model was established with MATLAB R2017a software, and was trained with the collected sample data. After successful training, the network model was simulated. The experimental results show that the T-S type FNN model established in this paper can effectively diagnose the station fault, and has good generalization ability, fault tolerance ability and self-adaptability. Fuzzy neural network is feasible for fault diagnosis of military radio stations. For operators without maintenance experience, it can quickly locate fault causes, reduce labor cost and time cost, and improve diagnosis efficiency.

The fault symptoms and causes determined by the simulation experiment in this paper do have a certain causal relationship, while the causal relationship between some factors and causes is not obvious or the factors have little change, such as temperature, voltage and current. Is it possible to draw diagnostic conclusions from the subtle changes? Therefore, in the next step, these factors will be studied to improve the radio fault diagnosis.

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