Research on Fault Prediction Method of VHF Radio Station Based on L-M Algorithm

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Abstract: Aiming at the problem of intelligent detection and location of marine VHF radio station fault machine, this paper studies BP neural network algorithm, analyzes the characteristics of VHF radio stations at sea, builds fault tree model, presents an intelligent detection method of VHF radio fault using L-M (Levenberg-Marquardt) intelligent algorithm to design L-M algorithm-based automatic fault detection model for VHF stations. The feasibility and efficiency of L-M algorithm in VHF fault detection are verified by simulation. The results show that: L-M algorithm can identify fault points more quickly and accurately among VHF radio station fault detection methods. Compared with the traditional manual detection, accuracy and efficiency of L-M algorithm are greatly improved.

1. Introduction
Artificial intelligence technology is becoming increasingly closely to the economic, political and scientific activities of today's society. The integration of artificial intelligence and communication technology has significant contribution to the development of communication technology. In the new period, China has implemented the strategy of "maritime power" and "Belt and Road", which helps to continues to make fresh progress of "maritime power". It plays a key role in moving towards the sea, managing the sea and maintaining the sea rights. [1] Pursuant to GB15304-94 technical requirements for marine radio communication equipment of the Global Maritime Distress Safety System, when sailing near or far sea, ships in each area are required to be equipped with maritime voice communication equipment with ultrashort wave channels at 156.000 MHz~173.975 MHz[2], which is extremely necessary to ensure the safety of navigation and the information interaction and identification among ships. The BP neural network based on L-M algorithm in this paper can identify the fault location of VHF station and analyze the cause of the fault by training. Besides, it solves the problems of long duration of manual maintenance, difficult positioning, long maintenance period, unable to repair equipment quickly, accurately and efficiently, and saves most of the time for equipment repair. Intelligent algorithm has a certain fault tolerance ability to build fault detection model, with higher resistance to attack and damage. Even if the system can work normally when it is damaged locally. It is blessed with strong reliability and high adaptability to harsh environment.

2. L-M algorithm

2.1. BP neural networks
BP neural network topology consists of input layer, hidden layer as well as output layer. Neural networks are modeled as collections of neurons. Since loops can lead to infinite loops of forward propagation, neurons are connected in form of acyclic graph.
The hidden layer can be extended to multi-layer[3], and there is no connection of each neuron in each layer. The output layer is mostly used to represent the classification score so that it's a real number of arbitrary values, or target number of some real number. Thus, generally, there is no activation functions at neurons in the output layer. After getting the input variable, neurons will produce weight factor. [4] The weight coefficients are modified from the output layer to the hidden layer to return the input layer, reducing the error between expected and actual output. And the process of learning is completed.

2.1.1. BP model training process
To train a BP neural network is to adjust the weights and biases of the network and create a training set that includes input X and expected output output Y, to obtain the training set error through current BP model and complete the process of signal forward propagation to error back propagation, correcting weight value of each unit. For forward propagation, the direction of propagation is from input layer to hidden layer to output layer. [5] The state of each layer of neurons affects the next layer of neurons, only. In the even that there is a large error between the actual output and expected output, then the back propagation process of the steering error signal is carried out alternately by forward propagation and back propagation. The error function gradient descent strategy is performed in the weight vector space. With dynamic iteration weight vector, it minimizes the error function, and completes the acquisition and memory of information.

2.1.2. BP Neural Network Algorithm
(1) Network initialization
Given n input layer neurons, p hidden layer neurons, q output layer neurons, the weight is \( w_{jk} \), the transfer function of hidden layer is \( f_1(\cdot) \), transfer function of output layer is \( f_2(\cdot) \), while error function \( e \) is given, to calculate calculation accuracy \( \varepsilon \) and maximum learning times \( M \).

(2) Forward propagation process
\( n \) is number of layers in the network, taking \( n_t=3 \), neural network parameters is given as \((W, b) = (W^{(1)}, b^{(1)}, W^{(2)}, b^{(2)})\), \( W^{(i)}_{ij} \) = connection parameters of \( j \) element at Layer \( l \) and \( i \) element at Layer \( l+1 \), and \( b^{(i)}_i \) is bias units of \( i \) element at Layer \( l+1 \). \( a^{(i)}_i \) activation value (i.e. output value) of Unit \( i \) at layer \( l+1 \). +1 is the offset node, that is, the intercept term. For a given parameter sets \( W, b \), neural network can calculate the output results according to the function \( h_{w,b}(x) \) [6].

I.Selecting input samples \( x_i = (l, x_1, x_2, ..., x_{nl}) \).
II.Calculating the input and output of each neuron in the hidden layer:
\[
a^{(i)}_i = f(W^{(i)}_{1i}x_1 + W^{(i)}_{2i}x_2 + ... + W^{(i)}_{ni}x_n + b^{(i)}_i) \\
h_{w,b}(x) = a^{(i+1)}_i = f(W^{(i+1)}_{1i}a^{(i)}_1 + W^{(i+1)}_{2i}a^{(i)}_2 + ... + W^{(i+1)}_{ni}a^{(i)}_n + b^{(i+1)}_i) 
\]
Of which weighted summation of \( i \) unit inputs at layer \( l \) is represented by \( z^{(i)}_i \), then
\[
z^{(i+1)}_i = \sum_{j=1}^{n} W^{(i)}_{ij}x_j + b^{(i)}_i 
\]
The above formula 2-1 is simplified as follows:
\[
h_{w,b}(x) = a^{(l)}_i = f(z^{(l)}_i) 
\]
(3) Back propagation process
I. Setting a sample set containing m samples \( \{ (x^{(1)}, y^{(1)}), ..., (x^{(m)}, y^{(m)}) \} \).
II. Calculating the residuals of each output unit in layer \( n_t \) (output layer):
Half variance surrogate function of single sample \( (x,y) \) is obtained as
\[ J(W, b; x, y) = \frac{1}{2} \| y - f(x) \|^2 \]  

III. Residual for each output unit at layer \( n_l \) is:

\[ \delta_i^{(n_l)} = \frac{\delta}{\partial z_i^{(n_l)}} J(W, b; x, y) = -(y_i - a_i^{(n_l)}) \cdot f'(z_i^{(n_l)}) \]  

IV. Calculate the residuals of the i node at layer l:

V. When \( l = n_l - 1, n_l - 2, \ldots, 2 \), the residual of the i node at layer l is:

\[ \delta_i^{(l)} = \left( \sum_{j=1}^{d+1} W_{ji}^{(l)} \delta_j^{(l+1)} \right) f'(z_i^{(l)}) \]  

VI. The process of successive forward derivation is "reverse conduction".[7]

VII. Through desired and actual output of the model, to calculate the partial derivative \( \delta_o^{(k)} \) of the error function to each neuron in the output layer

\[ \delta_i^{(k)} = -(d_i^{(k)} - y_o^{(k)}) f'(y_i^{(k)}) - \frac{\partial e}{\partial y_i^{(k)}} \]  

VIII. Correction of link weights \( w_{ho}^{(k)} \) using the \( \delta_o^{(k)} \) of neurons in the output layer and the output of neurons in the hidden layer.

\[ \Delta w_{ho}^{(k)} = -\mu \frac{\partial e}{\partial w_{ho}} = \mu \delta_o^{(k)} h_o^{(k)} \]  

\[ w_{ho}^{N+1} = w_{ho}^{N} + \eta \delta_o^{(k)} h_o^{(k)} \]  

Correction of link weights \( w_{ho}^{(k)} \) using \( \delta_h^{(k)} \) the of neurons in the hidden layer and input of neurons in the input layer.

\[ \Delta w_{hi}^{(k)} = -\mu \frac{\partial e}{\partial w_{hi}} = \delta_h^{(k)} x_i^{(k)} \]  

\[ w_{hi}^{N+1} = w_{hi}^{N} + \eta \delta_h^{(k)} x_i^{(k)} \]  

Global error calculation:

\[ E = \frac{1}{2m} \sum_{k=1}^{m} \sum_{i=1}^{d} (d_i^{(k)} - y_i^{(k)})^2 \]  

To determine whether the model error meets the requirements, if the error reaches the preset precision or the learning times are greater than the set maximum number, the algorithm terminates. On the contrary, to select the next learning sample and corresponding expected output for next round of learning.

2.2. L-M algorithm principle

L-M algorithm, a nonlinear neural network learning algorithm, has improved BP neural network, which is in combination of the local fast convergence property of Newton method and the global property of gradient method. As a multi-layer forward network algorithm, it not only avoids the ill-conditioned Jacobian matrix and false convergence in Gaussian Newton method but also avoids the disadvantages of low approximation accuracy and slow convergence around extreme points in gradient...
descent method. The convergence of the results is enhanced by ensuring that the weights and thresholds are adjusted each time, which avoid network shocks. L-M the algorithm requires more computation in each iteration, but as the number of iteration steps is reduced and the overall convergence is faster.

L-M algorithm steps:

F maps the parameter vector \( p \in \mathbb{R}^m \) as a function of estimating the observation vector \( \hat{x} = f(P), \hat{x} \in \mathbb{R}^n \).

1. The initial estimator is \( P_0 \) and the observed vector is \( x \), to find the optimal parameter \( \hat{p} \).

\[
P^+ = \arg \min_p n e^T \varepsilon
\]

\[
\varepsilon = x - \hat{x}
\]

\[
\hat{x} = f(P)
\]

II. With the neighborhood Taylor expansion \( f(P + \delta_p) \approx f(P) + J\delta_p \), of which \( J \) is Jacobian matrix \( \frac{\partial f(P)}{\partial P} \).

III. To find the step size for each step of the iteration and make \( \delta_p \) minimized.

IV. \( \|x - f(P + \delta_p)\| \approx \|x - f(P) - J\delta_p\| = \|e - J\delta_p\| \), proving that \( J^T(J\delta_p - \varepsilon) = 0 \), to obtain \( J^TJ\delta_p = J^T\varepsilon \) and this is the incremental normal equation of the GN method.

V. Damping term \( \mu \) is introduced by LM on this basis and the incremental normal equation becomes \( (J^TJ + \mu I)\delta_p = J^T\varepsilon \).

VI. If the obtained \( \delta_p \) at present reduces the error, to accept the update and reduce the damping term \( \mu \); Conversely, if the current increment increases the function value, then the damping term is increased, and then to solve the normal equation again until an increment that reduces the value of the function is obtained

(2) Conditions of termination

I. The gradient size, for instance, \( J^T\varepsilon \) is lower than threshold \( \varepsilon_1 \).

II. Change of step size \( \delta_p \) is lower than threshold \( \varepsilon_2 \).

III. Maximum number of iterations \( k_{\text{max}} \) is reached.

IV. If covariance matrix \( \sum_X \) of observation vector \( x \) can be obtained, the question is amended as \( J^T\sum_X^{-1}J\delta_p = J^T\sum_X^{-1}e \). The formula is a weighted normal equation.

3. The design of VHF radio station fault model based on L-M algorithm

3.1. VHF radio station fault detection model

In the construction of VHF radio fault tree model, according to the elements of this article, it is dixed as power amplifier, receiver, audio structure, transmitting circuit, logic structure, PLL circuit, receiving circuit, audio circuit, main board. According to the fault factor, the cause index of the fault is obtained, which is corresponding to RF output power, frequency offset measurement results, frequency, quiet noise single tone measurement results, receiver sensitivity, as well as audio output level. The model is shown in Figure 3, where setting fault code from \( X_1 \) to \( X_9 \), which represents unqualified RF output power, unqualified frequency offset measurement results, poor frequency
accuracy, unqualified noise single measurement results, unqualified sensitivity of receiver, unqualified audio output level, unqualified input VSWR, unqualified output VSWR and phase offset. Setting code from $Y_1$ to $Y_8$ represents unqualified RF output power, unqualified frequency offset measurement results, poor frequency accuracy, unqualified noise single measurement results, unqualified sensitivity of receiver, unqualified audio output level. $Y_9$ is set to be normal system.

The ultrashort wave radio fault tree is shown in figure 1.

![Fault Tree Map of Ultra-S Wave Radio.](image)

In Table 1, it shows the eligibility range for each element. Now a fault diagnosis system of BP neural network based on L-M algorithm is established. Applying L-M algorithm to train fault diagnosis system make the system can locate the fault parts more accurately and quickly.

Using L-M function in MATLAB to construct BP neural network fault detection system, after initializing the network, the training sample matrix is input. After completing the forward calculation, the error is judged. If the error is in the initialization range, then to output the result matrix, otherwise back propagate, to return the training matrix and make the forward calculation again until the error decision meets the output requirements.

| Element code | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ | $X_8$ | $X_9$ |
|--------------|------|------|------|------|------|------|------|------|------|
| Name of element | RF output power | Frequency offset | Frequency accuracy | Noise sensitivity | Sensitivity of receiver | Audio output level | Input VSWR | Output VSWR | Phase shift |
| Scope of qualification | $\leq 300w$ | $\leq 1KHz$ | $118.000 \-136.97$ | $5MHz$ | $\leq 1\mu V$ | $\leq 1\mu V$ | $\leq -45dBc$ | $1.5 : 1$ | $\leq 2.0 : 1$ | $\leq 5\%$ |

3.2. System validation
Input samples are based on maritime VHF radio parameters. After algorithm training, the measured data are detected by input sample matrix $P$. 
When training with L-M function, the training time is 16 min12s. Comparative figures of results is shown in Figure 2:

(1) Results Analysis
In the figure, the blue solid line represents the expected value, and the red dashed line represents the actual result value of the algorithm. As can be seen from the figure, analyzing from the cause of the failure, convergence of $Y_1$, $Y_2$, $Y_3$, $Y_5$ and $Y_6$ is sound while convergence of $Y_4$ is not very good. Analyzing from each set of data, group 3, 4, 5, 6 fluctuate greatly. The results of the other groups are basically the same as the expected value, with small fluctuation.

I. Mean square error MSE

Based on formula $MSE = \frac{1}{N} \sum (Y_n - \hat{Y}_n)^2$, the mean square error between each set of measured and predicted values is to be calculated. The greater the mean square error, the greater the training deviation.

Table 2. MSE of per group.

| SN | group1 | group2 | group3 | group4 | group5 | group6 | group7 | group8 | group9 |
|----|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| MSE | $3.60 \times 10^{-7}$ | $4.44 \times 10^{-6}$ | 0.11 | 0.13 | 0.00 | $5.44 \times 10^{-5}$ | 0.11 | 0.08 | 0.07 |

Table 3. MSE of same item between different groups.

| SN | $Y_1$ | $Y_2$ | $Y_3$ | $Y_4$ | $Y_5$ | $Y_6$ | $Y_7$ | $Y_8$ | $Y_9$ |
|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| MSE | $3.64 \times 10^{-7}$ | $3.10 \times 10^{-5}$ | 0.09 | 0.04 | 0.02 | 0.04 | 0.15 | 0.06 | 0.22 |

II. Mean absolute error MAE
Based on formula MAE: \( \Delta = (|\Delta_1| + |\Delta_2| + \ldots + |\Delta_n|) / n \), the mean absolute error of the same data between different groups is to be calculated. The actual situation of the predicted value error can be better reflected by mean absolute error.

| Serial number | \( Y_1 \) | \( Y_2 \) | \( Y_3 \) | \( Y_4 \) | \( Y_5 \) | \( Y_6 \) | \( Y_7 \) | \( Y_8 \) | \( Y_9 \) |
|---------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| MAE           | 2.22*10^{-4} | 2.26*10^{-3} | 9.81*10^{-2} | 0.10     | 0.04     | 0.07     | 0.18     | 0.09     | 0.22     |

Experimental data show that L-M algorithm runs stably with less jitter and L-M function is more fit for medium-sized networks. Its complex iterative process ensures that the step size and gradient amplitude are well selected for each iteration so that the convergence of such algorithms is fast, the results are better and the accuracy is higher.

4. Conclusion

Aiming at solving the problem of low accuracy of VHF station fault detection, this paper puts forward the fault detection method of VHF radio station based on L-M intelligent algorithm, realizes BP neural network ultrashort wave fault detection system, makes hardware as small and light as possible, makes the detection speed faster and more accurate by using intelligent algorithms and makes the test system more reliable in the complex and changeable environment of ocean. By testing the BP neural network ultrashort wave fault detection system, the simulation results show that: there is small difference between the actual training results and the expected results, which accords with the allowable error range. It is proved that it is feasible to use BP neural network for ultrashort wave fault detection.

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