Single-ended fault location and early warning method of transmission line based on back propagation neural network

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Abstract. For power transmission systems, accurate and reliable fault location methods can ensure rapid recovery of faulty lines and improve power supply reliability. In order to solve the problems of the structural complexity of the transmission system and the difficulty of line fault location, a single-ended fault location and early warning method of transmission line based on back propagation neural network is proposed. First, the fault line selection is performed quickly when the fault occurs. Then, the voltage fault components collected at the measuring point when the fault occurs are decomposed and reconstructed by wavelet packet to obtain the wavelet packet energy, which is used as the input sample to train through the nonlinear fitting ability of back propagation. With the help of backpropagation neural network, arbitrary complex functions can be processed, and the learning results can be accurately used for new knowledge, and circuit faults can be diagnosed conveniently and quickly. Finally, the corresponding fault distance can be output by substituting the wavelet packet energy reflecting the fault location. The simulation results show that the method has strong resistance to transition resistance and high positioning accuracy.

1. Introduction
With the gradual increase in the coverage of the grid, compared to the traditional power grid, a significant increase in the probability of failure of the transmission line and the difficulty of locating the fault[1]. Most of the faults that occur on the transmission line are transient faults, that is, the faults that can be reclosed by the automatic reclosing device[2]. Although the damage traces caused by the transient short-circuit fault are not obvious, it seriously affects the insulation strength of the line and is likely to induce more serious faults again. The rapid and accurate location of faults in long-distance transmission lines is of great significance for reducing the burden of line inspection, quickly restoring faults, and ensuring the safe operation of power systems[3]. The traveling wave method calculates the distance to the fault according to the traveling wave propagation time between the measuring observation point and the fault point [4]. Although it has a high ranging accuracy, it requires additional investment in a special primary sensor, which has poor reliability. Transition resistance is a key factor affecting fault location. It has shortcomings such as complicated operations, pseudo-roots, and high requirements for synchronization. Improving the robustness of the ranging algorithm is a key issue in fault location research.

Literature [5] is based on multi-level back-propagation neural network, data fusion of single-ended multi-dimensional electrical quantities and calculation of fault location. However, due to insufficient research on the variation characteristics of electrical quantities, there are shortcomings of large input electrical quantities, complex network training, and only suitable for small resistance faults. Literature [6] studied the structure of neural network and proposed an optimal network structure suitable for fault...
location problems. However, the training sample set in this article does not cover the complete fault mode space, and only considers the grounding of small transition resistance. Therefore, this paper presents a fault location method for transmission line based on BP neural network. First, analyze the change of electrical quantity with transition resistance. Then, a distance measurement neural network based on the classification of transition resistance is constructed. Finally, the training method is improved, and the repeated sample pairs composed of error-free and error-free samples are used as the training input samples of the BP neural network, so that the trained ranging network has a certain ability to adapt to random errors.

2. Fault traveling wave analysis and location

2.1. Fault traveling wave analysis

This paper provides a system simulation diagram of a 525 kV transmission line, as shown in Figure 1. The high-voltage transmission line is a three-phase transmission line, and there is phase coupling, so decoupling transformation is required first. This paper uses Karen Bell transform. Taking the current traveling wave as an example, if the transformation matrix of the current is Q, then Karen Bell principle of phase-mode transformation:

\[
\begin{bmatrix}
  b_0 \\
  i_w \\
  i_p
\end{bmatrix} = Q_i
\]  \hspace{1cm} (1)

\[
Q = \begin{bmatrix}
  1 & 1 & 1 \\
  1 & -2 & 1 \\
  1 & 1 & -2
\end{bmatrix}
\]  \hspace{1cm} (2)

\[
Q^{-1} = \frac{1}{3} \begin{bmatrix}
  1 & 1 & 1 \\
  1 & -1 & 0 \\
  1 & 0 & -1
\end{bmatrix}
\]  \hspace{1cm} (3)

After transformation, we get:

\[
\begin{bmatrix}
  i_0 \\
  i_w \\
  i_p
\end{bmatrix} = \begin{bmatrix}
  i_0 + i_b + i_c \\
  \frac{1}{3}(i_w - i_b) \\
  \frac{1}{3}(i_w - i_c)
\end{bmatrix}
\]  \hspace{1cm} (5)

\( \alpha, \beta \) sequence impedance:

\[ Z_\alpha = Z_\beta = \frac{1}{\sqrt{C_i}} \]  \hspace{1cm} (6)

\( \alpha, \beta \) sequence wave velocity:

\[ v_\alpha = v_\beta = \frac{1}{\sqrt{C_i L_i}} \]  \hspace{1cm} (7)

In formula (7), \( L_i \) and \( C_i \) are the positive sequence inductance and capacitance of the unit length line respectively. Through the change of wave speed, it can be judged whether there is a fault, etc.

3. Fault location and early warning based on BP neural network

3.1. Single-ended traveling wave fault location algorithm

According to the law of traveling wave refraction and reflection, the fault area is divided into (0, L/3), (L/3, L/2) in the time range of 3~0\( \tau \) (\( \tau \) refers to the time from the initial traveling wave to the
measurement end through the fault point), (L/2, L/3), (2L/3, L) four sub-sections (L refers to the distance from the initial traveling wave to the measurement end through the fault point). Assuming that the fault occurs from the initial time \( t_0 \), the moments when the initial transient current traveling wave, the first or second type traveling wave, and the first, second or third type traveling wave arrive at the M terminal are \( t_1 \), \( t_2 \), ..., \( t_p \), etc. It can be further subdivided into this article, using about 4 moments at the M end of the measurement bus to calculate the average wave velocity \( v \) of the transient traveling wave and the fault distance \( x \), and the ranging algorithm for each section is derived as follows:

Section 1 (0, L/3):

\[
\begin{align*}
\frac{v(t_1 - t_0) = x}{v(t_2 - t_0) = 3x} & \quad (8) \\
v(t_3 - t_0) = 5x
\end{align*}
\]

In the formula, the average propagation speed of transient traveling wave \( v \), the unknown distance to fault \( x \), the first to third moments when each traveling wave head arrives at the M terminal in turn are \( t_1 \), \( t_2 \), \( t_3 \), and the maximum value of the wavelet transform is used for calculation:

\[
\begin{align*}
\frac{v(t_1 - t_0) = x}{v(t_2 - t_0) = 3x} & \quad (9) \\
v(t_3 - t_0) = 2L - x
\end{align*}
\]

Solve the equation and get the result: \( x = \frac{(t_2 - t_1)L}{-2t_1 + t_2 + t_3} \)  
(10)

Section 2 (L/3, L/2):

\[
\begin{align*}
\frac{v(t_1 - t_0) = x}{v(t_2 - t_0) = 3x} & \quad (11) \\
v(t_3 - t_0) = 2L - x \quad t \leq 3\tau
\end{align*}
\]

Solve the equation and get the result: \( x = \frac{(t_2 - t_1)L}{-2t_1 + t_2 + t_3} \)  
(12)

Section 3 (L/2, L/3):

\[
\begin{align*}
\frac{v(t_1 - t_0) = x}{v(t_2 - t_0) = 2L - x \quad t \leq \tau} & \quad (13) \\
v(t_3 - t_0) = 3x
\end{align*}
\]

Solve the equation and get the result: \( x = \frac{(t_3 - t_1)L}{-2t_1 + t_2 + t_3} \)  
(14)

Section 4 (2L/3, L):

\[
\begin{align*}
\frac{v(t_1 - t_0) = x}{v(t_2 - t_0) = 2L - x} & \quad (15) \\
v(t_p - t_0) = 3x
\end{align*}
\]

Solve the equation and get the result: \( x = \frac{(t_p - t_1)L}{-2t_1 + t_2 + t_p} \)  
(16)

According to the analysis results of the above interval, it is found that the fault distance is only related to the line length \( L \) and time \( t_p \), and has nothing to do with the traveling wave velocity \( v \). Therefore, the distance measurement method is not affected by the transient traveling wave speed, and can be directly applied to the fault location and distance measurement of high-voltage transmission lines.
Refraction and reflection occur when the faulty traveling wave reaches the bus. According to the literature, the expression of the voltage reflection coefficient $\rho_n$ is:

$$\rho_n = \frac{Z_2 - Z_1}{Z_2 + Z_1}$$  \hspace{1cm} (17)

In the case of a large transition resistance, the reflected wave at the fault point will be small, so that the direct ranging method will be affected, so it is also necessary to use the reflected wave head of the opposite bus to realize the ranging. The formula of the indirect method is as follows:

$$D_{af} = L - \frac{1}{2} v\Delta t$$  \hspace{1cm} (18)

In formula (18), $\Delta t$ expresses the time difference between the reflected wave head of the opposite end bus and the first wave head. The traveling wave line mode voltage with small dispersion is selected for fault location. Therefore, the application of fault traveling wave single-ended electrical measurement can theoretically achieve the effect of double-ended electrical measurement.

3.2. The establishment of BP neural network model

In order to make the training sample set as comprehensive as possible to include the frequency characteristics of different fault distances, the first fault point is set 5 km away from the protection installation of the distance measuring end of the rectifier station of the Yun-Guang UHV DC transmission line. After that, a fault point is set every 10 km, and the setting of the fault point continues until the 132 sets of data are trained on the BP neural network by the inverter side ranging end protection, and the remaining 10 sets of data are used to verify the BP neural network. In order to make each input component play an equally important position in the neural network operation, the sample vector is normalized, and the input amplitude of each component is adjusted reasonably, so that the variation range is generally distributed in the (0, 1) interval. Normalization processing helps to improve the convergence speed of training. After the above steps, the constructed BP neural network ranging model is shown in Figure 2:

![BP neural network ranging model](image)

The built BP neural network ranging model has 1 input layer, the number of neurons in the input layer is 5; 1 hidden layer, the number of neurons in the hidden layer is determined to be 15 by trial and error; 1 output layer, the number of neurons in the output layer is 1, and the output is the fault distance predicted by the neural network model, so the topology structure of the BP neural network ranging model built is 5*15*1. The connection strength between the $m$th neuron of the input layer and the first neuron of the output layer is represented by the connection weight $w_{ml}$. The connection strength between the first neuron in the hidden layer and the output layer neuron is represented by the connection weight $\omega_1$. 

3.3. Early warning method

The correlation model between current amplitude and echo intensity, echo peak height, and connection weight is established through data, as shown in equation (19), and then the predicted value of current amplitude is obtained according to the predicted values of these parameters.

\[ I = f(x_1, x_2, \omega) \]  

(19)

In formula (19): \( x_1 \) is the intensity of the echo; \( x_2 \) is the length of the echo.

In order to obtain the specific expression of formula (19), the historical M transmission line fault events are selected as samples for analysis and research. The input variables are three parameter values such as the echo intensity recorded when the transmission line trips. The output value is the maximum amplitude of the current at the time of tripping.

4. Simulation analysis during failure

When the model runs for 4 ms, a ground fault is added, and the fault point is set at a distance of 10 km from the head end of the rectifier side, with a step length of every 10 km. Set up single-phase ground faults in the two overhead lines until the end of the line, so that the training sample set contains the frequency characteristics of different fault distances as much as possible, and the fault grounding resistance is 0.001 \( \Omega \), 10 \( \Omega \), and 100 \( \Omega \), respectively. The fault traveling wave voltage component can obtain wavelet packet energy at different scales through wavelet packet transformation. Taking a fault 200 km away from the line measurement point and a transition resistance of 0.001 \( \Omega \) as an example, through simulation, the transient voltage component of the fault is decomposed into 8 frequency bands after wavelet packet decomposition, and each frequency band represents a different frequency range, see table 1.

| Node | Frequency band/Hz | Node | Frequency band/Hz |
|------|------------------|------|------------------|
| 1    | 0-1250           | 5    | 5000-6250        |
| 2    | 1250-2500        | 6    | 6250-7500        |
| 3    | 2500-3750        | 7    | 7500-8750        |
| 4    | 3750-5000        | 8    | 8750-10000       |

In the Matlab sequence, set up and run 10 networks. After the training is completed, save the most accurate data of the results. The remaining 6 sets of data are used to verify the effect of neural network training. The final fault location results are shown in Table 2. In the same way, if the fault is on the right side of the T-connected busbar, 6 groups of data can be selected for verification after neural network training. The distance measurement results are shown in Table 3.

| Fault distance /km | Measured value/km | Transition resistance/\( \Omega \) | Absolute error/km | Relative error% |
|--------------------|-------------------|----------------------------------|-------------------|-----------------|
| 31                 | 30.9567           | 0                                | 0.0433            | 0.0014          |
| 89                 | 89.0234           | 10                               | 0.0234            | 0.0003          |
| 135                | 134.8416          | 0                                | 0.1584            | 0.0012          |
| 239                | 237.2394          | 10                               | 1.7606            | 0.0074          |
| 364                | 362.0287          | 100                              | 1.9713            | 0.0054          |
| 569                | 571.1286          | 100                              | 2.1286            | 0.0037          |
Table 3 Fault location results on the right side of the T-connected busbar

| Distance from busbar /km | Fault distance/km | Measured value/km | Transition resistance/Ω | Absolute error/km | Relative error% |
|-------------------------|-------------------|-------------------|-------------------------|------------------|-----------------|
| 85                      | 1025              | 1026.2542         | 100                     | 1.2542           | 0.0012          |
| 289                     | 1235              | 1233.1279         | 0                       | 1.8721           | 0.0015          |
| 335                     | 1289              | 1286.7524         | 100                     | 2.2476           | 0.0017          |
| 439                     | 1377              | 1374.9854         | 100                     | 2.0146           | 0.0015          |
| 464                     | 1435              | 1438.0157         | 10                      | 3.0157           | 0.0021          |
| 569                     | 1538              | 1540.2567         | 10                      | 2.2567           | 0.0015          |

When the fault is on the right line of the T-connected busbar, it is verified in combination with Table 2 and Table 3. The results show that this method can also be accurately located with high accuracy. Through experiments, it can be seen that as the traveling wave head travels farther and farther, the traveling wave head is smoother; the greater the transition resistance, the smaller the initial traveling wave amplitude, which makes the wavelet packet affect the wave head recognition and the ranging accuracy. Through a large number of simulation analysis, it is found that line length changes and error factors do not reduce the effectiveness of wavelet packet energy spectrum analysis, and have a small impact on the positioning accuracy, and the ranging accuracy meets the requirements.

5. Conclusion
This paper studies a single-ended fault location and early warning method for transmission lines based on back-propagation neural network. The wavelet packet energy spectrum is used to extract the fault frequency band. Because the frequency band is rich in fault information, the spectrum energy is easier to extract than the natural frequency, and the operation is simpler, which is more effective when used for fault location. BP neural network has non-linear fitting ability. The energy of each layer obtained by wavelet packet decomposition of fault voltage is used as the input sample of BP. After training and fitting, the output is the fault distance. In the transmission line fault location, the sample set of this method is small and clear, and the convergence is good, which greatly improves the accuracy of fault location. In this paper, the simulation data obtained by establishing the simulation model is used for method verification, and the simulation model and the influencing factors considered are relatively simple. The number, type, noise and other simulation examples of bus outlets should be increased to make it closer to the actual situation.

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