Fault identification in T-connection transmission lines based on general regression neural network and traveling wave power angle

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Abstract. In order to improve the accuracy of internal and external fault identification of T-connected transmission lines, a new method for identifying internal and external faults of T-connected transmission lines based on general regression neural network and traveling wave power angle was studied. The initial voltage and current traveling wave measured by each traveling wave protection unit of T-connected transmission line are transformed by S-transform, and the single frequency power angle after fault is calculated to form the sample set of fault eigenvector of T-connected transmission line. The established general regression neural network intelligent fault recognition model is used to train and test the sample data to identify internal and external faults. The simulation results show that the algorithm can accurately identify the internal and external faults of the T-connected transmission line under various operating conditions.

1. Introduction

High-voltage transmission lines are the place where the most faults occur in the power system. Finding faults quickly through fault diagnosis and excluding faults are of great significance to the safe and stable operation of the power system [1-2]. With the continuous development of the power system, T-connection transmission lines have been widely used in power systems due to their small transmission corridors, small footprints, and other objective factors. However, these lines are often connected to large power plants and large systems. When a fault occurs, it is required to be able to diagnose the fault quickly and reliably [3-5], and then eliminate the fault.

In reference [6], faults occurred within and outside of the protection zone are identified by using the ratio of the phasor sum of T-connection transmission line three-terminal voltage fault component and the phasor sum of the current fault component. Reference [7] uses the sum of the three-terminal current fault components of the T-connection transmission line and the vector difference between the maximum current in the three-terminal current fault components and the sum of the currents of other two terminals to establish a criterion to identify internal and external faults, but the selection of the braking coefficient in the criterion will have an impact on the sensitivity and reliability of fault identification. In reference [8], in order to improve the sensitivity of the standard in case of internal fault and the reliability in case of external fault, the standard proposed in [7] is improved. The
sinusoidal angle between the maximum current in the three-terminal fault current component of the T-connected transmission line and the current at the other two ends is used as the criterion braking coefficient to identify the faults inside and outside the zone. Reference [9] combined the arrival time of transient traveling waves at each end of the line in pairs to obtain a fault branch discrimination matrix composed of fault distances. However, this method is complicated and difficult to implement.

In reference [10], a second-order Taylor-Kalman-Fourier filter is used to process voltage and current signals, and the positive sequence impedance information to obtained from the voltage and current signals is used to identify internal and external faults.

This article is based on the study of the fault power angle when T-connection transmission line occur internal and external fault, proposes a new fault identification method for T-connection transmission line based on general regression neural network and traveling wave power angle. The algorithm uses the initial voltage and current traveling wave sampling point data of the three-terminal traveling wave protection unit in the T-connection transmission line after the S-transformation, obtain the power angle of each traveling wave protection unit at a single frequency and form them into a T-connection transmission line fault characteristic sample set in a specific order, combined with the general regression neural network to realize the identification of the faults internal and external the T-connection transmission line.

2. Fault traveling wave characteristic analysis

2.1 The theory of fault traveling waves

Fig 1 shows a 500-KV T-connection transmission line. The three branches AO, BO and CO in Fig. 1 are defined as the internal branches of the T-connection transmission line, and the remaining branches are the external branches.

\[
\begin{align*}
\Delta u(x,t) &= \Delta u_0(x - vt) + \Delta u_0(x + vt) \\
\Delta i(x,t) &= \Delta i_0(x - vt) + \Delta i_0(x + vt) \\
v &= 1 / \sqrt{LC}
\end{align*}
\]

In the equations above, \( t \) is the observation time; \( L \) and \( C \) are the inductance and capacitance of the transmission line per unit length; \( \Delta u_0, \Delta u_0 \) are the voltage and current forward (backward) traveling wave propagating along the positive (negative) direction of \( x \).

According to the traveling wave propagation theory, the time at which the initial traveling wave reaches the three ends A, B, and C is \( t_m(m = 1,2,3) \), respectively, and the second time the traveling wave reaches the three ends of A, B and C after catadioptric reflection occurs is \( TR_m(m = 1,2,3) \); within the time period \( t_m - t_m \), the fault traveling wave obtained by the traveling wave protection unit
$TR_m (m=1,2,3)$ at the three ends of the branches near A, B, and C is called the initial voltage and the current traveling wave. $\Delta u_m (m=1,2,3)$ is the initial voltage traveling wave measured by the three-terminal traveling wave protection unit of the internal branch near A, B and C, respectively. And $\Delta i_m (m=1,2,3)$ is the initial current traveling wave measured by the three-terminal traveling wave protection unit of the internal branch near A, B, and C, respectively.

2.2 Initial traveling wave power distribution

2.2.1 Initial traveling wave power distribution when faults in the internal: When a fault $F_1$ occurs at the AO branch in the T-connection line, the Peterson equivalent circuit of the T-connection line is shown in Fig.2, Where $\alpha U_f$ is the additional network voltage at the point of fault, $\alpha U_A$ and $\alpha I_A$ are the measured initial voltage and current traveling wave of bus A, respectively. The wave impedances of the lines OA, OB, OC, AD, BE, CF are $Z_{c1} - Z_{c6}$. It can be known from the line wave impedance that it is approximated as a real constant [12-14], $Z_{c1} = Z_{c2} = Z_{c3} = Z_{c4} = Z_{c5} = Z_{c6} \approx R$, The equivalent impedance of bus A to ground is $Z_{c4}$.

![Fig. 2. Peterson equivalent circuit when OA branch fault in T-connection transmission line internal](image)

According to the definition of the initial traveling wave complex power [16], It can be obtained that the initial traveling wave complex power at the A end of the line bus is:

$$\Delta S = \alpha U_A \alpha I_A^*$$

(2)

When the fault in the internal OA branch, the Peterson equivalent circuit in Fig.2 shows:

$$\alpha I_A = -\frac{\alpha U_A}{Z_{c4}/Z_{c4}}$$

(3)

The complex power measured by the $TR_i$ traveling wave protection unit at the A end of the AO branch can be obtained:

$$\Delta S = \alpha U_A \alpha I_A^* = \alpha U_A \times \left(-\frac{\alpha U_A}{Z_{c4}/Z_{c4}}\right)^* = -\alpha U_A^2 \times \frac{1}{Z_{c4}/Z_{c4}} = P_A + jQ_A$$

(4)

In the formula, $P_A$ is the initial traveling wave active power of the line, and $Q_A$ is the initial traveling wave reactive power of the line.

2.2.2 Initial traveling wave power distribution when faults in the external: When a fault $F_2$ occurs at the AD branch in the T-connection transmission line, the Peterson equivalent circuit of the T-connection line is shown in Fig.3,

![Fig. 3. Peterson equivalent circuit when AD branch fault in T-connection transmission line external](image)

From Fig.3:
\[ \Delta I_1 = \frac{\Delta U_x}{Z_{c1} + Z_{c3}} \]

The complex power measured by the traveling wave protection unit TR is:

\[ \Delta S_x = \Delta U_x \Delta I_x^* = \frac{\Delta U_x^*}{Z_{c1} + Z_{c3}} \left(\frac{1}{Z_{c1}} + \frac{1}{Z_{c3}}\right) = P_x + jQ \]

In the formula, \( P_x \) is the initial traveling wave active power of the line, and \( Q_x \) is the initial traveling wave reactive power of the line.

3. Calculation of initial traveling wave power angle based on S-transform

In the three-phase transmission power system, the coupling between the phase voltage and the phase current affects the voltage and current. Therefore, the phase voltage and phase current need to be decoupled. In this paper, the phase voltage and phase current are decoupled with the implementation of Clark phase-mode transformation, and the combined modulus method is used to reflect the various fault types of the T-connection transmission line [15].

\[ \begin{align*}
\Delta u_\alpha &= 4\Delta u_x + \Delta u_\beta \\
\Delta i_\alpha &= 4\Delta i_x + \Delta i_\beta
\end{align*} \]

In the equations above, \( \Delta u_x \) and \( \Delta u_\beta \) are Clark’s \( \alpha \) - and \( \beta \)-modes voltage, respectively; and \( \Delta i_x \) and \( \Delta i_\beta \) are Clark’s \( \alpha \) - and \( \beta \)-mode current, respectively.

This article refers to the method used in [16], discrete S-transformation will be performed on the phase-mode transformed fault current and voltage traveling wave modulus, select the current and voltage retrograde wave head information at a single frequency after the fault to calculate the initial traveling wave power angle.

3.1 S transform principle

Set the continuous time signal as \( h(t) \), then the continuous S transformation \( S(\tau, f) \) of the time signal \( h(t) \) is defined as:

\[ S(\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t, f) e^{-i2\pi \tau t} dt \]

\[ g(\tau-t, f) = \frac{1}{\sqrt{2\pi}} e^{-i\frac{\tau^2}{2\sigma^2}} \]

In the equations above, \( \tau \) is the parameter that controls the position of the Gaussian window on the time axis, \( f \) is the continuous frequency, \( t \) is the time, \( i \) is the imaginary unit, \( \sigma = |f| \), and \( g(\tau-t, f) \) are Gaussian windows, which are susceptible to the change of frequency.

If \( h[kT](k = 0, 1, 2, \ldots, N-1) \) is a discrete time series obtained by sampling signal \( h(t) \), T is the sampling interval, and N is the number of sampling points, then the discrete Fourier transform function of \( h[kT] \) is:

\[ h[\frac{n}{NT}] = \frac{1}{N} \sum_{k=0}^{N-1} h[kT] e^{-\frac{2\pi in}{N}} \]

In the equation, \( n = 0, 1, \ldots, N-1 \).

Then the discrete S transform of signal \( h(t) \) is:

\[ S[kT, \frac{n}{NT}] = \frac{1}{N} \sum_{k=0}^{N-1} H[kT] \frac{e^{2\pi in}}{\sqrt{\sigma}} e^{-\frac{\tau^2}{2\sigma^2}}, n \neq 0 \]

\[ S[kT, 0] = \frac{1}{N} \sum_{k=0}^{N-1} h[\frac{r}{NT}], n = 0 \]

The complex matrix after the implementation of S transformation reflects the time-domain and frequency-domain characteristics of the signal, as well as the amplitude information and phase information of the traveling wave in the time domain.
Since the S transform has good signal extraction characteristics in time-frequency analysis, therefore, this article uses S transform to extract the fault current traveling wave and fault voltage traveling wave, based on this, the initial traveling wave power angle is calculated.

3.2 S-transformed initial traveling wave power angle

S-transform is implemented on the current and voltage traveling wave data detected by the traveling wave protection unit \( T_R(m=1,2,3) \) of T-connection transmission line after fault occurs, Select the phasors \( \alpha U_m(l) \) and \( \alpha I_m(l) \) corresponding to the \( l (l=1,2,...,20) \) sampling points in the 0.1ms time period of the voltage and current initial traveling wave at the frequency of 60KHz after the S transformation. Obtain the initial traveling wave power at the corresponding frequency of each traveling wave unit according to Equation (13),

\[
S_m(l) = \alpha U_m(l) \times \alpha I_m(l) = P_m(l) + jQ_m(l).
\] (13)

Then find the initial traveling wave power angle corresponding to each sampling point,

A vector \( \alpha_a = [\alpha_{a1}, \alpha_{a2}, ..., \alpha_{an}] \) composed of the initial traveling wave power angles of each sampling point is defined as a fault characteristic vector of the traveling wave protection unit \( T_R \). The fault characteristic vectors obtained by the three traveling wave protection units are used to form a T-connected transmission line power angle fault characteristic vector according to a specific sequence, so as to characterize the T-connected transmission line fault characteristics.

4. General Regression Neural Network

General Regression Neural Network (GRNN) is a nonlinear regression neural network model proposed by Donald F. Specht. It has very obvious advantages in approximation ability and learning rate. Very good classification and prediction results are obtained when the sample data is small. The algorithm has achieved good results in classification, prediction and optimization. GRNN and RBF are very similar in structure, It includes an input layer, a mode layer, a summing layer, and an output layer. The structure is shown in Fig.4.

![Fig.4. Structure of general regression neural network](image)

GRNN is based on nonlinear regression analysis [17]. Let the joint probability density function of the random variables \( x \) and \( y \) be \( f(x,y) \). The corresponding input is \( X \), the output is \( Y \) and the observed value of \( A \) is \( B \), Then the regression of \( y \) to \( X \), that is, the conditional mean is :

\[
\hat{Y} = E(Y/X) = \int_{-\infty}^{\infty} yf(X,y)dy
\]

(14)

For unknown \( f(x,y) \), the estimation obtained by Parzen nonparametric estimation can be applied [18], estimates can be obtained by calculation:

\[
\hat{Y}(X) = \frac{\sum_{i=1}^{n} Y_1 P_i}{\sum_{i=1}^{n} P_i}
\]

(15)
where \( p_i = \exp \left[-\left(\frac{(X - X_i)(Y - X_i)}{2\sigma^2}\right)\right] \) is the activation function of the neuron, \( X \) and \( Y \) are sample observations of the random variables \( x \) and \( y \), respectively, \( n \) is the number of samples, \( \sigma \) is the width coefficient of Gaussian function, estimate \( \hat{Y}(X) \) is the weighted average of all \( Y_i \).

5. Simulation and experiments

The PSCAD/EMTDC electromagnetic transient simulation software is used to establish a 500kV T-connection transmission line simulation model shown in Fig.1. The model adopts the frequency dependent distribution parameter model that can accurately reflect harmonic and transient responses. TOWER:3H5 pole tower is selected as the type of the line. Bus stray capacitance is set to \( C_n = 0.01 \mu F \). The simulation sampling frequency is 200kHz, and the length of each branch is \( AO = 300km, BO = 200km, CO = 150km, AD = 170km, BE = 150km, CF = 180km. \)

5.1 Sample data

In order to verify the reliability of the fault identification algorithm, this paper simulates four fault situations: different fault types, different fault distances, different fault initial angles, and different transition resistances. Choose 5 groups for each of the 6 branch roads internal and external each fault condition, a total of 120 sets of fault feature vectors are obtained and used as training samples for T-connection transmission line fault identification. Simulate 4 groups of faults different from the training sample for 4 kinds of fault conditions of 6 branches in and outside the T-connection transmission line area. 24 sets of fault characteristic vectors were obtained as test sample data for 4 fault conditions: different fault types, different fault distances, different fault initial angles, and different transition resistances.

5.2 Establishing a General Regression Neural Network Intelligent Fault Identification Model

The training samples of the power connection angle fault feature of the T-connection transmission line are input into the general regression neural network for training, and a trained general regression neural network intelligent fault recognition model is obtained. The training samples are then input to the model for testing, and the comparison of the prediction results is shown in Fig.5. Where, the recognition results of the generalized regression fault intelligent identification model are divided into specific branches in the case of internal faults and external AD, BE, CF faults.

As can be seen from the below figure, the test sample data is 100% correct in the general regression neural network fault intelligent recognition model.

![Fig.5. Comparison of prediction results on the training set](image-url)
5.3 Test sample test analysis

5.3.1 Testing of different fault types: The fault feature test samples of different fault types inside and outside the zone are input into the generalized regression neural network intelligent fault recognition model for testing. The prediction results are shown in Table 1.

| Fault branch | Fault type | Fault initial angle/degree | Fault distance O point / km | Transitional resistance / Ω | Identification result |
|--------------|------------|----------------------------|-----------------------------|-----------------------------|----------------------|
| AO           | BG         | 5                          | 125                         | 200                         | Internal fault       |
|              | ABG        |                            |                             |                             | Internal fault       |
|              | ACG        |                            |                             |                             | Internal fault       |
|              | ABC        |                            |                             |                             | Internal fault       |
| BO           | AG         | 60                         | 95                          | 300                         | Internal fault       |
|              | ACG        |                            |                             |                             | Internal fault       |
|              | BC         |                            |                             |                             | Internal fault       |
|              | ABC        |                            |                             |                             | Internal fault       |
| CO           | CG         | 45                         | 65                          | 100                         | Internal fault       |
|              | BCG        |                            |                             |                             | Internal fault       |
|              | AB         |                            |                             |                             | Internal fault       |
|              | ABC        |                            |                             |                             | Internal fault       |
| AD           | BG         | 120                        | 370                         | 50                          | external fault       |
|              | ABG        |                            |                             |                             | external fault       |
|              | ACG        |                            |                             |                             | external fault       |
|              | ABC        |                            |                             |                             | external fault       |
| BE           | CG         | 60                         | 230                         | 400                         | external fault       |
|              | BCG        |                            |                             |                             | external fault       |
|              | BC         |                            |                             |                             | external fault       |
|              | ABC        |                            |                             |                             | external fault       |
| CF           | AG         | 25                         | 260                         | 200                         | external fault       |
|              | BCG        |                            |                             |                             | external fault       |
|              | AC         |                            |                             |                             | external fault       |
|              | ABC        |                            |                             |                             | external fault       |

As can be seen from the table above, the test sample data of different fault types in the generalized regression neural network intelligent fault recognition model have 100% correct test results, so the protection algorithm is not affected by the fault type.

5.3.2 Test analysis of different fault distances: The fault feature test samples with different fault distances inside and outside the zone are inputted into the generalized regression neural network intelligent fault recognition model for testing. The output prediction results are shown in Table 2.

| Fault branch | Fault distance O point / km | Fault initial angle/degree | Fault type | Transition resistance / Ω | Identification result |
|--------------|-----------------------------|----------------------------|------------|---------------------------|----------------------|
| AO           | 260                         |                            | ABG        | 100                       | Internal fault       |
|              | 230                         |                            |            |                           | Internal fault       |
|              | 180                         |                            |            |                           | Internal fault       |
|              | 90                          |                            |            |                           | Internal fault       |
| BO           | 180                         |                            | BC         | 200                       | Internal fault       |
|              | 110                         |                            |            |                           | Internal fault       |
|              | 80                          |                            |            |                           | Internal fault       |
|              | 40                          |                            |            |                           | Internal fault       |
| CO           | 100                         |                            | BG         | 50                        | Internal fault       |
|              | 70                          |                            |            |                           | Internal fault       |
|              | 50                          |                            |            |                           | Internal fault       |
As can be seen from the above table, the accuracy of the test sample data in the generalized regression neural network intelligent fault recognition model test is 100%.

### 5.3.3 Analysis of initial angle test of different faults:
The fault feature test samples with different initial fault angles inside and outside the zone are input to the generalized regression neural network intelligent fault recognition model for testing. The prediction results are shown in Table 3.

**Table 3. Simulation results of initial angle test set for different faults**

| Fault branch | Fault initial angle/degree | Fault type | Distance of fault from point O / km | Transitional resistance / Ω | Identification result |
|--------------|----------------------------|------------|------------------------------------|-----------------------------|-----------------------|
| AO           | 5                          | BG         | 115                                | 200                         | Internal fault        |
|              | 45                         |            |                                     |                             | Internal fault        |
|              | 90                         |            |                                     |                             | Internal fault        |
|              | 120                        |            |                                     |                             | Internal fault        |
| BO           | 5                          | ACG        | 125                                | 400                         | Internal fault        |
|              | 60                         |            |                                     |                             | Internal fault        |
|              | 100                        |            |                                     |                             | Internal fault        |
|              | 120                        |            |                                     |                             | Internal fault        |
| CO           | 25                         | CG         | 50                                 | 100                         | Internal fault        |
|              | 45                         |            |                                     |                             | Internal fault        |
|              | 60                         |            |                                     |                             | Internal fault        |
|              | 120                        |            |                                     |                             | Internal fault        |
| AD           | 5                          | BC         | 370                                | 200                         | external fault        |
|              | 45                         |            |                                     |                             | external fault        |
|              | 60                         |            |                                     |                             | external fault        |
|              | 100                        |            |                                     |                             | external fault        |
| BE           | 25                         | BCG        | 290                                | 100                         | external fault        |
|              | 60                         |            |                                     |                             | external fault        |
|              | 90                         |            |                                     |                             | external fault        |
|              | 100                        |            |                                     |                             | external fault        |
| CF           | 5                          | ABG        | 250                                | 300                         | external fault        |
|              | 45                         |            |                                     |                             | external fault        |
|              | 90                         |            |                                     |                             | external fault        |
|              | 120                        |            |                                     |                             | external fault        |

As can be seen from the above table, the test sample data is 100% accurate in the test of the generalized regression neural network intelligent fault recognition model, so the protection algorithm is basically not affected by the initial angle of the fault.

### 5.3.4 Different transition resistance test analysis:
The fault characteristic test samples of different transition resistances inside and outside the region are input to the generalized regression neural network intelligent fault recognition model for testing.
### Table 4. Simulation results of different transition resistance fault test sets

| Fault branch | Transition resistance / Ω | Fault initial angle/degree | Fault distance O point / km | Fault type | identification result |
|--------------|--------------------------|---------------------------|---------------------------|------------|----------------------|
| AO           | 0                        | 25                        | 160                       | BG         | Internal fault Internal fault Internal fault |
|              | 100                      |                           |                           | Internal fault Internal fault Internal fault |
|              | 300                      |                           |                           | Internal fault Internal fault Internal fault |
|              | 400                      |                           |                           | Internal fault Internal fault Internal fault |
| BO           | 100                      | 45                        | 75                        | BCG        | Internal fault Internal fault Internal fault |
|              | 200                      |                           |                           | Internal fault Internal fault Internal fault |
|              | 300                      |                           |                           | Internal fault Internal fault Internal fault |
|              | 400                      |                           |                           | Internal fault Internal fault Internal fault |
| CO           | 30                       | 60                        | 55                        | ACG        | Internal fault Internal fault Internal fault |
|              | 200                      |                           |                           | Internal fault Internal fault Internal fault |
|              | 400                      |                           |                           | Internal fault Internal fault Internal fault |
|              | 300                      |                           |                           | Internal fault Internal fault Internal fault |
| AD           | 50                       | 100                       | 365                       | AC         | external fault external fault external fault |
|              | 100                      |                           |                           | external fault external fault external fault |
|              | 300                      |                           |                           | external fault external fault external fault |
|              | 400                      |                           |                           | external fault external fault external fault |
| BE           | 100                      | 90                        | 245                       | CG         | external fault external fault external fault |
|              | 200                      |                           |                           | external fault external fault external fault |
|              | 300                      |                           |                           | external fault external fault external fault |
|              | 400                      |                           |                           | external fault external fault external fault |
| CF           | 50                       | 45                        | 265                       | ABG        | external fault external fault external fault |
|              | 100                      |                           |                           | external fault external fault external fault |
|              | 200                      |                           |                           | external fault external fault external fault |
|              | 400                      |                           |                           | external fault external fault external fault |

As can be seen from the above table, the test sample data is 100% accurate in the test of the generalized regression neural network machine intelligent fault recognition model, so the fault recognition algorithm is not affected by the transition resistance.

### 6. Summary

This paper proposes a fault identification method for T-connection transmission lines based on generalized regression neural network and traveling wave power angle. The feasibility of the fault identification method is verified through a large number of simulation experiments. Simulation results show that the algorithm works in various operating conditions. Both can accurately identify the internal and external faults of the T-connection transmission line, and basically overcome the influence of factors such as the transition resistance and the initial angle of the fault.

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