Study on Fault Location for High Voltage Overhead Transmission Lines Based on Neural Network System

Xiangning Lin, Peng Mao, Hanli Weng, Bin Wang, Z Q Bo and A Klimek

Abstract-- A distributed & hierarchical NN (DHNN) system based on the integrated module architecture and hierarchy architecture is proposed in this paper. The DHNN system adequately uses the powerful function of artificial neural networks at aspects of pattern identification, nonlinear-approaching, associative memory etc. Its information processing mechanism coincides with the processing law of classification-sketchiness-accuracy in human biologic NN system. This system not only can deal with the advanced information required by fault location for HV overhead transmission lines but accurately locate the fault sites. Thus this method for fault location presented in this paper can thoroughly eliminate the disadvantages in other extant fault location methods, such as convergence to the false root or divergence in the procedure of iteration, which result in the great location error in practice. This paper pioneers a new direction to the study and application on fault location. Results from theoretical analyses and simulations by EMTP show that fault location precision of this method can completely satisfy practical requirements.

Index Terms— Neural Network (NN), Fault Location, Transmission Lines.

I. INTRODUCTION

The result of fault location for HV transmission lines is an important reference to pinpoint the trouble areas. Accurate fault location is essential for power companies to accelerate the restoration of service, which has great practical and economical value. Fault location for transmission lines emphasizes the precision and reliability, and the demand of Real-time isn't very necessary, compared with protection for transmission lines.

Approaches of fault location can be divided roughly into two types, i.e. one-terminal fault location approach and two-terminal approach. One-terminal approaches are less expensive and not dependent on the technology of communication in the power system. Further more, these kinds of approaches are widely adopted by Chinese fault location equipment. Some studies on fault location based on information from one terminal is being a focus all the while.

Representatives of these approaches include the approaches of solving differential equation, fault current's phasor angle modification[3], solving equation, and fault current modification etc.. Fault location results by solving differential equation are greatly effected by noises in the field. In the approach of fault current's phasor angle modification, iterating calculation can possibly converge to a false root or diverge. And with the increasing of infeed currents from the opposite system and the ground resistance, measure errors of fault location based on this kind of approaches will increase. Literature [1] leads to a unitary quadratic equation from the iterative formula of the fault current’s phasor angle modification. Although the approach of solving equation avoids the limitation of converging to a false root or diverging, it brings a new problem how to distinguish the real root between the two roots. The approach of fault current modification[5] is parallel to the approach of fault current's phasor angle modification in theory and precision. Now most of one-terminal approaches for fault location don't have expected results when put into service. The published literatures lately propose several novel approaches, such as the approach based on expert system and recognition on line etc. However, all of which are still at primary stage.

The measured data have different characteristics for different fault sites, and between them exits one-by-one mapping relation of $R^n \rightarrow R^r$. Where, 'n' is decided by the quantity of characteristics at a fault case. And a Feedforward NN(FNN) with $N$ input neurons and $M$ output neurons can perform $R^n \rightarrow R^m$ mathematical mapping. In this sense, fault location for transmission lines can operate in the view of mapping. Therefore, it is feasible to perform fault location using NN.

Fault location is a complicated task. Fault location for HV transmission lines operates in the sequence of fault detection, fault classification, fault site location. Faults can be subtly classified as ten types, i.e. phase-to-ground faults (A-G, B-G, C-G), phase-to-phase faults (A-B, B-C, C-A), two-phase-to-ground faults (A-B-G, B-C-G, C-A-G), three-phase faults (A-B-C-G or A-B-C). The precision of fault location is affected by many factors such as the fault site, the phase angle between EMF of two systems, the fault resistance and the internal impedance of opposite system etc.. So it is impossible to realize the fault location by any kind of existent single NN.
In consideration of the physical architecture and information processing mechanism of the biologic NN system, a DHNN system is presented in this paper, which is modular and hierarchical. The discussion in detail is as follows.

II. DHNN SYSTEM FOR FAULT LOCATION

The DHNN system consists of two sections: one is the identification NN(IDNN) sub-system for fault detection and fault classification, the other is the fault location NN(FLNN) sub-system for fault location. The overall architecture of the DHNN system is shown in Fig.1.

A. IDNN Sub-system

Self-Organizing NN(SONN) is adopted to perform the functions of fault detection and fault classification in the IDNN sub-system. Based on Ref. [4], some improvement is made in this paper to enhance the SONN’s reliability and precision.

In Ref. [4], the fundamental components of voltages and currents are used as the SONN's input vectors in one of the two approaches presented. In order to improve the classification sensitivity of the SONN, the zero sequence component of current \( I_0 \) and the two characteristic parameters (amplitude and damping time constant) of exponentially damping dc-offset\[7\] are added to the input vector.

IDNN system's output layer is a 3*4 two-dimension matrix, that is, twelve neurons, eleven of which are corresponding to 10 types of faults and the normal state respectively.

Using EMTP, independent training and testing sample sets are acquired. And testing results show that the percentage of correct fault detection and fault classification reaches 100%.

B. FLNN Sub-system for Fault Location

General introduction: FLNN sub-system for fault location is composed of four parallel and independent modules, one of which is responsible for one of the four fault classes(phase-to-ground faults, phase-to-phase faults, two-phase-to-ground faults, three-phase faults). As we know, FNN using BP algorithm has the capabilities of the accurate nonlinear approaching and the powerful generality. So FNNs are adopted in these four modules of FLNN sub-systems.

Structure of modules: In order to improve the precision of the trained FNNs for fault location, we should consider all kinds of factors, such as fault sites, intermediate fault resistances at fault sites, phase angles between EMF of two systems, loads and the opposite system impedance etc.. Thus a large number of training sample set should be available. The training procedure will easily diverge, or the morbid structure (the number of neurons in hidden layer is huge) will appear if a single FNN is used to perform the fault location, which will result in the low fault location precision of the trained FNN.

To solve the above problem, the following approach is proposed. Every fault location module comprises of three serial elements shown in Fig. 2.

1. Sketchy fault location element

One FNN is used in this element, whose output layer has only one neuron representing the fault distance between the recording terminal and the fault site. When the training sample set is constructed for this network, the following factors should be considered: fault distances \( k\Delta l \) \((k=0,1,\ldots,L/\Delta l)\), where \(\Delta l\) represents the step size, \(L\) represents the length of the transmission line, intermediate fault resistances at fault sites, and the opposite system impedance. \(\Delta l\) is chosen relatively larger in the sketchy fault location element so that the number of training samples is relatively smaller. Based on this element the fault site can be roughly located.

Using fuzzy theory, the output of this element is processed and then taken as the control factor of the next element, that is, the accurate fault location element.

2. Accurate fault location element

The accurate fault location element is composed of several parallel FNNs. The number of FNNs is relevant to the length of the transmission line and the fault location precision required. Every FNN is respectively responsible for the fault location in a designated range. Some overlapping part exists in the boundary between the neighboring ranges. To describe clearly, a power system shown in Fig. 3 is taken as an example.
The 14th International Conference on Intelligent System Applications to Power Systems, ISAP 2007
November 4 - 8, 2007, Kaohsiung, Taiwan

\[ I = \sum (I \times \mu) \] to get the final result of the accurate fault location element.

During the FNNs’ training, the same factors as the above element discussed are considered, whereas \( \Delta t \) is chosen smaller for fault location precision.

3. Rectification element

The factor of the phase angle between EMF of two systems should also be considered for this element, which has an effect on additional voltage at the fault site in the additional network due to fault. However, the current distribution coefficients in this network are not influenced. Thereby, this factor is not as important as those factors discussed in the above two elements to the fault location precision. If it were considered in the above two elements, the number of training samples would double and redouble. Thus the factor is only considered in this element to rectify the output deviation of the accurate fault location element because of the negligence of this factor.

The output of the rectification element is the final result of the fault location.

Shown in Table 2, the different electrical quantities are used as the input vectors in each element for the four modules, based on the characteristics of each fault class.

Table 2 Description of input vectors in four modules

<table>
<thead>
<tr>
<th>Fault module</th>
<th>Input electrical quantities</th>
<th>Fault module</th>
<th>Input electrical quantities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sketchy Element</td>
<td>( U_f, I_f, I_0 )</td>
<td>Sketchy Element</td>
<td>( U_{md}, I_{md}, I_d, I_0 )</td>
</tr>
<tr>
<td>Accurate element</td>
<td>( I_{x,f}, D_f )</td>
<td>Accurate element</td>
<td>( I_{x,d}, D_f )</td>
</tr>
<tr>
<td>Rectification on</td>
<td>( U_{gd}, I_{gd}, I_2 )</td>
<td>Rectification on</td>
<td>( U_{gd}, I_{gd}, I_d, I_2 )</td>
</tr>
<tr>
<td>element</td>
<td>( I_{x,g}, D_f )</td>
<td>element</td>
<td>( I_{x,g}, D_f )</td>
</tr>
</tbody>
</table>

All of the quantities are taken from the recording terminal. For the fault class of phase-to-ground, \( U_f, I_f, I_0 \) represent the voltage and current of the faulted phase, the zero sequence current respectively, and the faulted phase is as the reference in symmetrical component analyses. For the fault class of phase-to-phase, \( U_{gd}, I_{gd}, I_2 \) represent the differential voltage and differential current of the faulted phases, the negative sequence current respectively, and the non-fault phase is as the reference in symmetrical component analyses. For the fault class of two-phase-to-ground, \( U_{gd}, I_{gd}, I_d, I_0 \) represent the differential voltage and differential current of the faulted phases, the zero sequence current, the negative sequence current respectively, and the non-fault phase is as the reference in symmetrical component analyses. For the fault class of three-phase-to-ground, \( U_{gd}, I_{gd}, I_d, I_0 \) represent the voltages and currents respectively of the three phases. \( I_x \) and \( D_f \) represent the pre-fault current and the output of the accurate element respectively.

Fig. 3 System Model of a Transmission Line

As shown in Fig. 3, the length of the transmission line is 300km. The accurate fault location element consists of five FNNs: FNN1, FNN2, ... FNN5, which are corresponding to five ranges, respectively.

Consider that the electrical quantities (currents and voltages) are more easily affected by the changes of such factors as fault sites, intermediate fault resistances and the opposite system impedance etc., the smaller distance step is more reasonable for the fault location range of FNN1 and FNN5. Moreover, because of the output error of the sketchy element, some overlapping part exists in the boundary between the neighboring ranges to improve the fault location precision. The number of the FNNs in this element and the length of the overlapping part depend on the length of the transmission line in the practical problem.

In this paper, the fault location ranges of the five FNNs in this element are decided as Table 1. To improve the ability of error tolerance of FLNN, we process the output of the sketchy fault location element using fuzzy theory and the processed output is taken as the control factor of this element. The membership curves corresponding to the five FNNs are shown in Fig. 4.

Table 1 Ranges of the FNNs

<table>
<thead>
<tr>
<th>FNNs</th>
<th>FNN1</th>
<th>FNN2</th>
<th>FNN3</th>
<th>FNN4</th>
<th>FNN5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranges</td>
<td>0-50</td>
<td>40-120</td>
<td>110-190</td>
<td>180-260</td>
<td>250-300</td>
</tr>
</tbody>
</table>

Fig. 4 Membership Curves Corresponding to the FNNs

In Fig.4, X-axis represents the distance between the fault site and the recording terminal, and Y-axis represents the membership \( \mu \), i.e. 1, 2, ..., 5. The output of the sketchy element decides which FNN(s) the fault site belongs to and its membership \( \mu \) in the FNNs. The FNNs corresponding to nonzero \( \mu \) will run. Their outputs are processed by the formula.

All of the quantities are taken from the recording terminal. For the fault class of phase-to-ground, \( U_f, I_f, I_0 \) represent the voltage and current of the faulted phase, the zero sequence current respectively, and the faulted phase is as the reference in symmetrical component analyses. For the fault class of phase-to-phase, \( U_{gd}, I_{gd}, I_2 \) represent the differential voltage and differential current of the faulted phases, the negative sequence current respectively, and the non-fault phase is as the reference in symmetrical component analyses. For the fault class of two-phase-to-ground, \( U_{gd}, I_{gd}, I_d, I_0 \) represent the differential voltage and differential current of the faulted phases, the zero sequence current, the negative sequence current respectively, and the non-fault phase is as the reference in symmetrical component analyses. For the fault class of three-phase-to-ground, \( U_{gd}, I_{gd}, I_d, I_0 \) represent the voltages and currents respectively of the three phases. \( I_x \) and \( D_f \) represent the pre-fault current and the output of the accurate element respectively.
C. Operation Principle of DHNN

As shown in Fig. 1, the processed sampled data are put into IDNN where the operation state (fault or non-fault) is decided. If non-fault, then exit; else the fault type is decided to choose the corresponding module in FLNN. The structure of each module is shown in Fig. 2. The sampled data are processed according to the description of input vectors in Table 2. In the sketchy element, the fault site is roughly decided, sequentially the FNNs in accurate element are chosen to perform. In the rectification element, the output of the accurate element is rectified and the final fault location result is achieved.

III. TRAINING OF FLNN SYSTEM

The operation experiences of the electric power systems show that phase-to-ground faults account for the majority among all types of faults, while the high impedance phase-to-ground faults appear from time to time. As we know, it is quite difficult to locate the fault site for this kind of fault. Thus the phase-to-ground fault should be taken as an example to discuss in detail. The approach can also be applied to other fault types. The power system model and its parameters used are presented in Fig.3. The long transmission line’s distributed parameters are taken into account when simulating by EMTP.

A. Formation of Training Sample Sets

Training sample sets should comprise of the full range of expected fault patterns. Hence the following factors are considered to form the training sample sets.
- Ground resistance $R_g$ (0Ω, 10Ω, 30Ω, 60Ω, 100Ω, 150Ω, 200Ω, 300Ω)
- System impedance at the opposite terminal $Z_s$ (80%, 100% and 120% of the normal impedance)
- Fault site. Step size $Δl$ is 20KM for the sketchy fault location element and 5KM for the accurate fault location element.
- Fault inception angle $θ$ (0, 45 and 90 degrees on the phase A voltage waveform)
- Phasor angle between EMF of two systems $θ$ (-45, -30, -15, 0, 15, 30 and 45 degrees).

Fundamental components are used in the input vectors. When they are extracted by using DFT, the error is relatively large because the sampled data in the field contains lots of noises, non-periodic components and damping high frequency components, all of which cannot be completely eliminated by using DFT. So wavelets filter is used to preprocess the real-time sampled data to eliminate those undesirable components in this paper. The detail algorithm can be referred to in Ref. [7].

In order to increase the convergence of NN, the input vectors and the output ones are normalized as follows. Every electrical phasor is expressed in the polar coordinates. The voltage amplitudes are normalized based on the recording terminal’s rated voltage, and current ones based on the maximum fault current amplitude at the worst case. So the normalized amplitudes are in the range of 0~1. Incipient angles of the phasors are normalized according to the following formulas.

\[ \varphi - \varphi_{ref} = \Delta \varphi, (\Delta \varphi + 2\pi) \% 2\pi = \Delta \varphi' \]  

Where, $\varphi_{ref}$ is the base angle, % is the operation to calculate arithmetical compliment, $\Delta \varphi'$ is the normalized phasor angle. So the normalized inception angles are in the range of 0~2π.

The outputs are normalized according to the formula of $y = (D_{mf} - L/2) / k$. Where, $y$ is desired output of NN, $D_{mf}$ is the fault distance, $k$ is a constant (k=30 in this paper), $L$ is the line’s length. So the desired outputs can be evenly distributed in the range of -5 ~ 5. Through the above-mentioned processing, the training sample sets for FLNN can be formed.

B. Training Results

Define the precision indexes for fault location as following.

\[ \mathcal{E}_j = \left| \frac{D_j - D'_j}{L} \right| \times 100 \% \]

\[ E_{\text{max}} = \frac{1}{N} \left( \sum_i |e_i| \right) \]  

Where, $\mathcal{E}_j$ is the relative error, $E_{\text{max}}$ is the absolute error, $D_j$ is an actual fault distance, $D'_j$ is an evaluated fault distance, $L$ is the overall length of the transmission line, and $N$ is the number of testing samples.

Training parameters of the module for phase-to-ground faults are presented in Table 3.

<table>
<thead>
<tr>
<th>Fault module</th>
<th>Number of samples</th>
<th>training error</th>
<th>training times of epochs</th>
<th>$E_{\text{max}}$</th>
<th>$E_{\text{max}}$</th>
<th>$E_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>sketchy element</td>
<td>1152</td>
<td>0.01</td>
<td>172</td>
<td>2.98KaM</td>
<td>0.59 km</td>
<td>0.995%</td>
</tr>
<tr>
<td>N1</td>
<td>792</td>
<td>0.002</td>
<td>150</td>
<td>0.61 km</td>
<td>0.21 km</td>
<td>0.205%</td>
</tr>
<tr>
<td>N2</td>
<td>1224</td>
<td>0.002</td>
<td>165</td>
<td>0.60 km</td>
<td>0.20 km</td>
<td>0.205%</td>
</tr>
<tr>
<td>N3</td>
<td>1224</td>
<td>0.002</td>
<td>166</td>
<td>0.61 km</td>
<td>0.21 km</td>
<td>0.204%</td>
</tr>
<tr>
<td>N4</td>
<td>1224</td>
<td>0.002</td>
<td>165</td>
<td>0.60 km</td>
<td>0.22 km</td>
<td>0.209%</td>
</tr>
<tr>
<td>N5</td>
<td>792</td>
<td>0.002</td>
<td>155</td>
<td>0.63 km</td>
<td>0.24 km</td>
<td>0.211%</td>
</tr>
</tbody>
</table>

From this table, we can know that the maximum location error of post-training NNs is within an accepted range along the overall line. Where, $E_{\text{max}}$ is the maximum absolute error, $E_{\text{max}}$ is the average absolute error, $E_{\text{max}}$ is the maximum relative error.

The extension to other fault types can be easily provided.

IV. TESTING AND EVALUATION OF FLNN

Some samples different from the training ones should be taken to test its fault location precision after the FLNN has been completely trained.

The testing samples should meet the following demand.
- Fault distances are selected along the overall length from the recording terminal with the step size of 2.5kM.
- Ground resistance $R_f$ (5Ω, 10Ω, 90Ω and 180Ω).
- Fault incipient angle $\alpha$ (15, 30, 60 and 80 electric degrees).
- Internal impedance of the opposite system $Z_i$ (90% and 110% of the normal impedance).
- Phase angle between EMF of the two systems $\theta$ (±20 electric degrees).

By combining above factors, we have 7744 (121\*4\*4\*2\*2) types of fault patterns. Thus a testing sample set for FLNN is formed according to the above-mentioned procedure. The location results of FLNN are presented as the followings.

The maximum absolute error $E_{max}$ =0.754kM and the average absolute error $E_{max}$ =0.2946kM. As an example, the error curves along the overall length are shown in Fig.5, where $R_f = 90\Omega$, $Z_i = 110\%$, $\alpha = 30^\circ$, $\theta = 20^\circ$.

![Fig.5 Error Curves of FLNN for Phase-to-Ground Faults](image)

The fault location results of FLNN for other types of faults are as well as those for phase-to-ground faults. The maximum absolute errors are less than 0.6kM for phase-to-phase faults, less than 0.7kM for two-phase-to-ground faults and less than 0.7kM for three-phase faults. In view of limited space, the result can’t be expounded one by one.

From the testing results, it should be understand that the post-training DHNN can accurately locate the fault sites along the overall length and the location error can satisfy the practical requirement in practice. Moreover, from fault patterns included in the testing sample set, we also know that the location results of DHNN aren’t influenced at all by such factors as the fault sites, the intermediate resistances, the fault incidence angles, the opposite system impedance and the phasor angles between EMF of the two systems, etc. The approach for fault location presented in this paper eliminates the shortcomings of false root appearing or invalidation at some fault case in other extant approaches.

V. CONCLUSIONS

A DHNN to perform accurate fault location for HV transmission lines is presented in this paper. It has been proved that this proposed approach is feasible and effective by theoretical analysis and lots of simulations and tests by EMTP. The method eliminates the shortcomings of false root appearing or invalidation at some fault case in other extant approaches and less suffers from the opposite system parameters and achieves higher precision. This paper provides a novel scheme using AI technique in fault location for transmission lines.

VI. REFERENCES


VII. BIOGRAPHIES

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