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Coordination Of Mlp Network And Distance Relay Improves Fault Location Accuracy On Transmission Line

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SUMMARY
Power transmission lines are the very important parts in power systems. The lines may encounter various incidents,... When such an incident occurs, due to the lines length, an accurate fault location will have a great impact in reducing the restoration time of the system. This paper will present a new method using the classical artificial neural networks MLP in parallel with a distance relays to correct the fault location estimation of the relay. The solution will base only on the voltage and current signals from the beginning of the lines. The training samples signals of the transient states are generated using ATP/EMTP. The numerical results will show that the solution had helped to reduce the fault location error from 0,85% to 0,39%.
Keywords: *short-circuit faults, fault location; impedance based distance relay; neural networks; transmission lines.*

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I. INTRODUCTION

Due to the great impact on the power delivery system performance, there are many proposed methods and devices to estimate the location of the faults on the lines. We can divide them into groups, such as: methods based on the input impedances, [7,14,15] vesus methods based on wave travelling effects [1,2,4,5,10],... among which, the methods basing on the input impedences are more popular. There are impedance methods, which use only the value from one lines' end [3,15], and there are also methods, which use the values from both line's endlinkes and they are usually more accurate than the methods with one end. But these methods are exposed to various noise sources [14,15]. For example in Vietnam, when testing with the 200kV lines Thái Nguyên - Hà Giang of the length 232,2km, the errors are from 1000m (~0.4%) to 2.300m (~1%). Approximately, from the real operation statistics, the distance relays may have errors up to 5%. It means that the results are still needed to improve. The development of solutions using artificial intelligence have the potential for further improvements.

In this paper we propose a solution to estimate a correction value and add it to the response from the distance relay to give a more accurate final fault location. The correction value will be estimated based only on the voltage and current signals at the beginning of the lines. When a fault occurs on the transmission lines, it will cause sudden changes in the electrical signals at both ends of the lines (with a little delay due to the time needed by the fault waves to reach those ends). These signals are monitored continuously and the sudden changes are detected by wavelet analysis of the signals to have the fault time. With that fault time, a small signal window of 60ms (40ms before and 20ms after the fault time) will be extracted.

Selected points on the frequency amplitude spectrum and selected time points of the extracted window of signals will be used as the input (features) vector into the MLP. The MLP will make the nonlinear mapping from the input vector into the distance correction. This correction value will be added to the response from the relay to give the final estimation result:

$$l_{final} = l_{relay} + \Delta l_{MLP} \qquad (1)$$

The MLP network will be trained with the data samples corresponding to the fault cases that it is targeted to work with.

II. THE SAMPLES GENERATION

2.1. The ATP/EMTP software

In this paper we will simulate the data using the ATP/EMTP software [13] with a transmission line with parameters taken from a real line. We will simulate 4 types of circuit shortages including single (one) phase shortage, two phase shortage, two phase earthed shortage and three phase shortage with 5 parameters changing: the fault type, fault location, shortage resistance, fault time and the line load. The ATP/EMTP will perform the simulation and generate the 6 signals (3 voltages and 3 currents) at the beginning of the line for further processing purposes.

2.2. The universal relay tester CMC-356

With a simulated data, in order to bring the simulations and the responses closer to the reality, we will use the universal relay tester CMC-356 from OMICRON and the real distance relay to process the signals from ATP/EMTP. The schematic of the application is shown in Fig. 1.

The responses from the 7SA522 will be read back to the computer. The difference between the estimated fault location of the relay and the location set in the ATP/EMTP is the correction value that the MLP network needs to generate for this case. One data sample for the MLP will consist of:

- Input: feature values from the 6 signals at the beginning of the line.
- Output: the correction value.

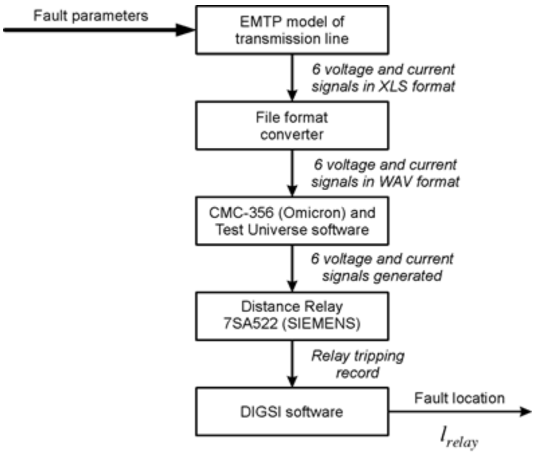

Figure 1. *The schematic of using CMC-356 to generate the signals from EMTP simulation to fed into the 7SA522 distance relay*

III. THE SIGNAL PROCESSING AND FAULT LOCATION ESTIMATION

To get the estimated fault location given by the impedance based method used by the distance relay, we use the same distance relay SIEMENS-7SA522 as the one onsite (also with the same setup parameters). By this way, the relay will receive signals similar to the real ones onsite.

3.1. Wavelets and their application in fault time detection

Wavelets are very well-known tool to detect the sudden changes in a signal, which is also very typical in electrical signals when a fault occur in the system. We test the performances of 4 classical wavelets (Daubechies, Symlet, Coiflet and Haar) to select the best one for further use. In Fig. 2 is an example of a current (phase A) and its decompositions using 3rd order Daubechies into 4 first levels. It can be clearly seen that the fault moment (at 40ms) can be easily detected from the details $\mathbf{d}_i$ of all 4 levels.

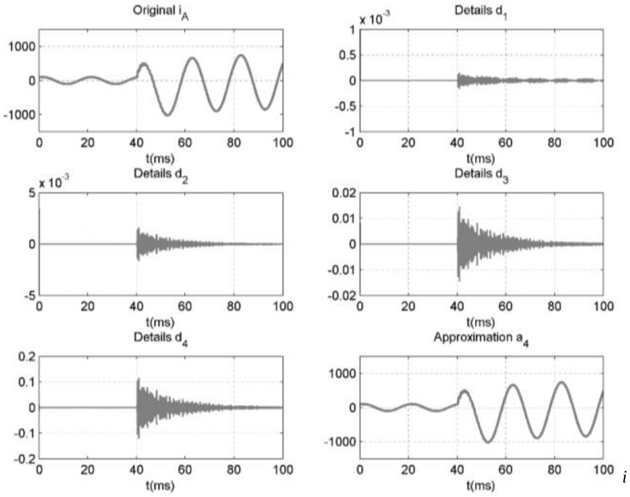

Figure 2. *Decomposition to 4th level of phase A current using 3rd order Daubechies wavelet*

Tests showed that we can use any of the 6 signals to detect the fault time and the Daubechies wavelet gives the best accuracy among the 4 listed ones [13].

3.2. Features extraction

With the fault time detected (denoted as T_0), the next task is to extract the characteristic values descibing the changes in the signals caused by the fault. These values are called the features and they will form the input vector for the MLP network. For each signal from the set of 6, we propose to use following 14 values as features:

- Time-based features: 10 instantaneous values sampled with period 1ms from the fault time.
- *Frequency-based features:* we use the total harmonic energy in 5 ranges: w_1 is the total energy for frequencies in $[25,75]\,Hz$; w_2 is for frequencies in $[75,125]\,Hz$; w_3 is for frequencies in $[125,175]\,Hz$; w_4 is for frequencies in $[175,225]\,Hz$; w_5 is for frequencies in $[225,325]Hz$. From the 5 values, we form the 4 features as:

$$\left[\frac{w_1}{\sum_{i=1}^{5} w_i}, \frac{w_2}{\sum_{i=1}^{5} w_i}, \frac{w_3}{\sum_{i=1}^{5} w_i}, \frac{w_4}{\sum_{i=1}^{5} w_i}\right]$$

Totally, based on 6 signals we have $14 \times 6 = 84$ features for each sample data.

3.3. The MLP as nonlinear mapping block

As the nonlinear mapping block, we propose the classical neural network, which is the MLP (MultiLayer Perceptron) [8]. A network with *N* inputs, one hidden layer with *M* neurons with transfer function $f_1()$ and *K* output neurons with transfer function $f_2()$ is shown on Fig. 3.

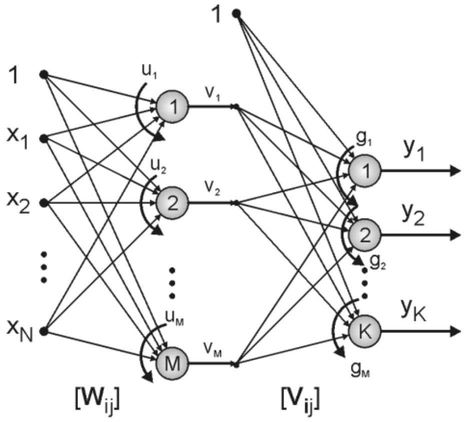

Figure 3. *An MLP structure with one hidden layer of neurons*

The main task with an MLP is its training. We will use the popular approach with two data samples sets: the training set and the testing set. The training set contains of p pairs of input vector and its corresponding output vector $\{\mathbf{x}_i, \mathbf{d}_i\}$, $i = 1,..., p$, and the parameters of the MLP are tuned to minimize the error function defined as:

$$E_{learn} = \frac{1}{2}\sum_{i=1}^{p}\left\|MLP(\mathbf{x}_i) - \mathbf{d}_i\right\|^2 \to \min \quad (2)$$

After training, the MLP is tested with the testing set, which contains new samples. According to [8], we try a number of different MLP with different number of hidden neurons, the network with smallest testing error will be selected as the best one.

IV. SIMULATIONS AND NUMERICAL RESULTS

4.1. Sample data sets

As mentioned in Section 2, we use the ATP/EMTP to simulate an actual transmission line. The 135km, 110kV line has been selected. The scenarios of the faults to create the data samples are as: N = 27 positions fault location: (at 5, 10, ..., 135km); K = 9 values of shortage resistance R_{fault}: (0, 1, 2, 3, 4, 5, 10, 15, 20 Ω); P = 4 shortage types of faults (single phase, two phase, two phase earthed, three phase); Q = 3 cases of load of the lines (30%, 50% and 100% nominal load of the line).

Totally we have: $N \times K \times P \times Q \times M = 2916$ cases. Additionally, in order to check the effect of the fault time (relative phase) to the results, we simulate cases for the shortage resistance R_{fault}= 1Ω at positions (10, 50, 100, 130km) and M=10 fault time stepped at 2ms (to cover the whole period 20ms of the 50Hz signals). That means: N = 4 locations of fault (10, 50, 100, 130km); K = 1 shortage resistance R_{fault} =1 Ω; P = 4 shortage types (as above); Q = 3 cases of load (as above); M = 10 fault time values (+0ms, +2ms,..., +18ms).
As results we have $N \times K \times P \times Q \times M = 480$ cases. Totally we have 2916 + 480 = 3396 scenarios generated.

4.2. Fault time detection using wavelet

When using wavelet Daubechies (3rd order) for all 3396 simulated cases and 6 signals for each case, we have the results for 6 signals are similar and the error ranges to a maximum of 300μs [13], which is very accurate for practical application. Because of this, we will base our next steps on the time detected on current of phase A for simplification.

4.3. Fault location using distance relay

With the data simulated from ATP/EMTP, first we use the tester CMC-356 to regenerate them to put into the 7SA522-V4.7 (also used on the real line) and check the fault location detected by the relay. Some statistics of these results are listed in Tab. 2. The average error of the relay 7SA522: $E_{mean} = 1{,}15(km)$ or 0,85% of the line length.

4.4. Fault location correction using MLP

To train an MLP network for the problem, the total set of 3396 samples was divided into 2 sets: 2264 samples (2/3 of total) are used as the training set, the rest (1132 samples) are used as the testing set. Various MLP networks with different number of hidden neurons were randomly generated, trained and tested. The best result was achieved with the MLP with 12 hidden neurons: average testing error $E_{mean} = 0{,}53(km)$ or 0,39% line length.
The detailed results for each type of fault are given in Table 1.

Table 1. *The results from the distance relay 7SA522 and after correction with MLP*

Method	Average		Max	
	(km)	(%)	(km)	(%)
Error of the 7SA522	1.15	0.85%	9.4	6.96%
Learning error with MLP for correction	0.51	0.38%		
Testing error with MLP for correction	0.53	0.39%	2.84	2.10%

The results show that with the application of MLP to correct the fault locations, the results are much improved. Especially the maximum error is greatly reduced from 9.4km (6.96%) to 2.84km (2.10%).

V. CONCLUSIONS

The paper has presented following results:

- Propose and train an MLP network based on the samples data of 4 shortage types on a 110kV lines... to effectively correct the fault locating,
- The fault time occurance is detected using the wavelet decomposition of the electrical signals at the beginning of the lines. The paper uses only the $\mathbf{d}_1$ component when decomposing the signals (sampled at 100kHz) with the 3rd order Daubechies wavelet,
- Propose the application of Omicron CMC-356 simulator in combination with a SIEMENS-7SA522 digital relay to bring the results closer to the real responses in practice,

The simulation results with a datasets of 3396 fault cases has shown that the MLP can effectively correct the results firstly given by the relays to given a final location of the fault with much lower error levels.

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