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Integration of neural network and distance relay to improve the fault localization on transmission lines

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Abstract: Power transmission lines are integral and very important components of power systems. Because of the length of these lines and the complexity of the power grids, the lines may encounter various incidents such as lightning strike, shortage, and breakage. When an incident or a fault occurs, a fast process of identification, localization, and isolation of the fault is desired. An accurate fault localization would have a great impact in reducing the restoration time of the system. One of the most popular solutions for fault detection and localization is the distance relays using the impedance-based algorithms. However, these relays are still not perfect with nonzero errors of the fault locations. This paper will present a new approach using the neural networks in addition to a distance relays to correct the fault location estimation of the relay. The solution will be based only on the voltage and current signals measured at the beginning of the lines. The training samples' signals of the transient states on the lines are generated using ATP/EMTP, and then regenerated into the relay tester Omicron CMC-356 to test with the real Siemens 7SA522 relay to improve its fault location results. The numerical results will show that the solution had helped to reduce the average fault location error from 0.92% to 0.42% for 4 types of shortage faults on the lines.

Key words: Fault location, distance relay, neural networks, transmission lines protection

1. Introduction

In Vietnam, the rapid development of power systems over the past few decades has also led to a rapid increase in the number of transmission lines, as well as the total length of these lines. According to the statistics Electricity of Vietnam (EVN), the power network of Vietnam has more than 300,000 km of transmission lines at different voltage levels up to 500 kV, where the majority lines are at 110 kV. In the last 10 years, more than 12,000 km of 110 kV lines were newly built[1].

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. They can be grouped into methods based on the input impedance [1–6], methods based on wave travelling effects [7–11]. For the methods based on the lines' impedance, the location is estimated from the values of the input impedance measured at the lines' ends. There are methods, which use only the value from one end of the lines [6, 12–14], or use the values from both ends of the lines. Usually, the methods using both ends' values are more accurate but they need more computations and

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[1]Electricity Regulatory Authority of Vietnam (2016). Vietnam 7-th National Master Plan for Electricity Development [online]. Website http://www.erav.vn/userfile/User/trungnla/files/2020/10/QD_428_QD_TTg%20nam%202016.pdf [accessed 15 Oct 2022]

require higher hardware configurations. In general, the impedance-based methods are exposed to various types of noises that affect the accuracy [4, 6, 15] such as the unknown shortage dynamic resistance, the inaccuracy of zero-sequence impedance calculation for the lines, the unbalanced configurations of the lines, the errors of instruments TU/TI, limited frequency bandwidth of the TU/TI. For example, in a practical test with the 200 kV lines Thai Nguyen - Ha Giang (Vietnam) of the length 232.2 km, the distance relay errors were from 1000 m (0.4%) to 2.300 m (1%). From the real operation statistics for the given lines, the distance relays may have errors up to 5%.

The wave travelling methods can be divided into two main groups [16, 17]. The first group consists of methods detecting the waves caused by the new fault, which travel to both ends of the lines. The other group consist of methods which actively send a new wave into the faulted lines and analyse the reflected waves (also known as time-domain reflectometer (TDR)). For the first group, an accurate synchronization of time for device from two ends of the lines is required since the difference of times the waves reaching the ends of the lines will determine the location. The popular way to synchronize the time is to use the GPS signal, but it may cause a big error since $1\mu s$ of time error may cause hundreds of meters of distance error.

With the introduction of artificial intelligence and the adaptive systems such as artificial neural networks (ANN) with learning capability, many new approaches in signal processing have been proposed to improve the accuracy of fault location problems in particular and the estimation of nonlinear problems in general. In [18], a simulated line of 345 kV, 321.86 km, a 3-phase shortage fault at 32.186 km is estimated to be at 36.997 km using the continuous wavelet transform (CWT)-based method. The work [19] uses ATP software to simulate the voltage and current signals of a 3-phase, 188-km-long line with different shortage types. The ANN is used to estimate the fault location and the maximum error was less than 11.32 km. The authors of [20] use the voltage and current signals at both ends of a single-phase, 60-km, 110-kV line simulated in EMTP. The trained ANN gave the maximum error less than 3.6 km. In [21], an ANN was trained to work on the signals of a 100 km, 230 kV line with generators at both sides. The signals were simulated in PSCAD/EMTDC for different types of shortage and other parameters. The maximum errors achieved were 0.33 km for single-phase shortage, 0.14 km for two-phase shortage, and 0.493 km for 3-phase shortage. Similar studies in [22, 23] gave the error lower than 1.35%, in [24] the error was lower than 0.23%, but it was a 300-km-long line, which means the average error was 0.7 km. The authors in [25] proposed to split the tasks and trained individual networks for each fault type. When simulating with a three-phase, two-generator, 400-kV, 100-km lines, the location accuracy results of multilayer perceptron (MLP) networks ranged from 70.47% (for single-phase-to-ground faults) to 94.9% (for two-phase-to-ground faults).

Some studies consider the transmission lines equipped with other elements like the compensation capacitors and filtering coils as in [26], where a 300-km, 400-kV line with compensating (parallel) capacitors was simulated and the authors could estimate the fault location based on the input impedance, the input and output currents with average error about 0.21% (i.e. 630 m) and maximum error about 0.35% (i.e. 1.05 km). The MLP was also used in [27] to detect several types of faults including high-impedance fault (from 150 Ohm up to 700 Ohm) and Zone 3 false trip during system stress with the accuracy of 94.8% and 95.9% for these tasks, respectively.

Another popular task of the distance relay that the neural networks were trained for is fault type classification. For example in [28], for a 3-phase, 400-kV, 300-km transmission lines with two generators at two ends, an MLP network was trained to detect fault type with an accuracy of 78.1%. And in [29], the authors used an MLP as a part of power swing blocking algorithm to avoid incorrect operation of distance relay due to the variation in voltage and current signals during power swing. The neural network will predict voltage and current signals during power swing to estimate the input impedance, which in turn is used to distinguish the swing and fault conditions of the lines.

In this paper a solution was proposed to improve the fault location estimation of the relay by generating a correction value to be added to the estimation of the relay to form the final result. The correction value will be estimated based only on the voltage and current signals at the beginning of the lines and then added to the result from the relay. The block schematic of the proposed solution is presented in Figure 1. Similar idea of combining the operations of different systems to have a final better result can be seen in other studies such as [30, 31] because a good combination will emphasize the advantages and limit the disadvantages of the individual models.

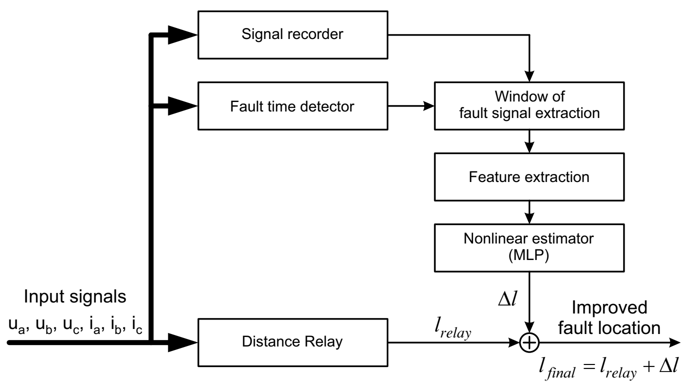

Figure 1. The schematic of the proposed solution to improve the accuracy of the distance relay.

In normal operation mode of a distance relay, when a detectable fault occurs on the transmission lines, the distance relay would react and estimate the distance to the fault denoted as l_{relay} [32, 33]. In our solution, when the relay reacts, a fault time locator algorithm will search the voltage and currents signals (measured at the begin of the lines) in a short window before and after the time the relay reacts to find a more accurate time of sudden changes in the signals, i.e. the time when the fault signals were propagated to the relay. Then a small window of signals around that estimated fault time will be extracted and the characteristic features would be generated from that signals window. Those features are used by an (nonlinear) estimator to calculate the correction amount Δl to be added to the result from the distance relay to give the final estimation result as

$$l_{final} = l_{relay} + \Delta l. \tag{1}$$

In this paper, the classic neural network MLP was selected to be the nonlinear estimator and was trained such that the final result l_{final} is more accurate than l_{relay}. The approach was selected instead of using MLP to directly estimate the fault location based on the idea that a good combination of estimators would have a better performance than each individual estimator [30, 31].

The data samples will be generated for the fault cases that the system is targeted to work with. The numerical results will show that the proposed solution manages not only to reduce the average error of fault location from 0.92 km down to 0.50 km (a more than 45% reduction) but also to significantly reduce the maximum error of fault location from 9.2 km down to 2.79 km (a 69.67% reduction).

The paper is organized as follow. In Section 1, a short overview of the problem and the proposed solution are introduced. Section 2 describes the generation process for data samples needed for training the neural network as the nonlinear estimator. In Section 3, the details of data processing algorithms including feature extractions and model training will be presented. The numerical results will be shown and discussed in Section 4. The paper ends with a conclusion section and a list of references.

2. The signal samples generation

To overcome the difficulties in field testing power system devices, and to bring the simulation results closer to the real performance on practical hardware, in this paper, a scheme for generating the data samples for training and testing the nonlinear neural network to correct the results of the distance relay was proposed as follows:

- Select a real transmission line to have its parameters and the setting of the distance relay used for that line.
- Implement an ATP/EMTP model for the lines to simulate the signals on the lines in normal conditions and in selected fault states. In these simulations, for each case the fault location l_{fault} was known for further processing.
- Use a relay tester to feed the generated signals from ATP/EMTP into the distance relay equipped with the same settings used for the real lines.
- For each test case, get the fault location generated by the relay and calculate the error $\Delta l = l_{fault} - l_{relay}$ between the fault location used in ATP/EMTP simulation and the response from the relay for that test case. These errors will be used as destination output values from the neural network.
- The signals generated by the ATP/EMTP will be used to calculate the features as the input into the neural networks.
- With the generated pairs of input and destination output, a neural network model will be trained and tested in supervised mode.

In the following subsections, more details of the above scheme will be presented and discussed.

2.1. The ATP/EMTP as a simulator of transmission lines signals

Because collecting a good data set with samples containing various fault cases with different parameters is very difficult (almost impossible) in practice, in this paper the data were generated using the ATP/EMTP software with a 3-phase transmission line with parameters taken from a real line. Different fault cases were simulated by changing 5 parameters: 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. An example of an ATP/EMTP model to simulate a 3-phase transmission line with a single phase shortage fault is shown in Figure 2. This is the model of a 118.5-km, AC-185/29 line from Yen Bai to Khanh Hoa (Vietnam), which is divided into 5-km sections (except the last one, which is 3.5 km) for easier simulation of different fault locations. With this model, the resistance of the shortage path can also be set for different values.

The ATP/EMTP software was used to simulate 4 types of circuit shortages including single (one)-phase shortage, two-phase shortage, two-phase earthed shortage, and three-phase shortage at different combinations of

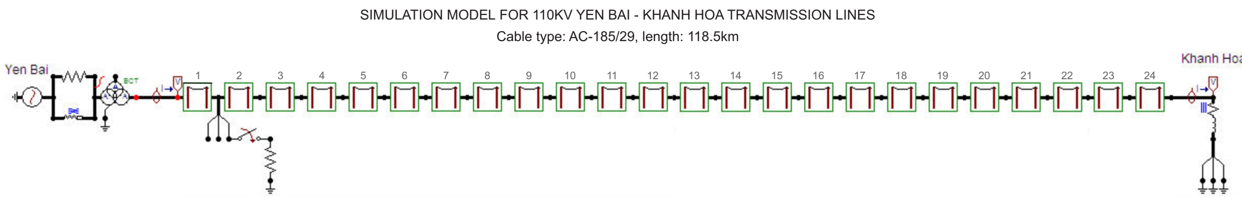

Figure 2. The ATP/EMTP model for simulating single-phase shortage fault on 3-phase transmission lines.

4 parameters: shortage resistance, fault location, actual load of the line, and the relative time (phase moment) of the fault.

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, the universal relay tester CMC-356 from OMICRON and the real distance relay were used as shown in Figure 3 to process the signals from ATP/EMTP.

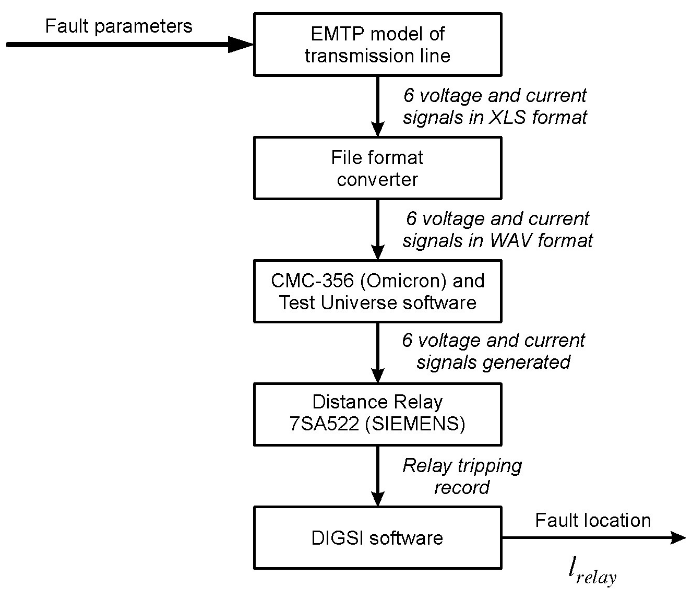

Figure 3. The schematic of using CMC-356 to regenerate the signals from EMTP simulation to input into the 7SA522 distance relay.

The CMC-356, as seen on Figure 4, is capable to generate time-dependent signals with the following parameters:

- 6 current output ports with error less than 0.05% reading plus 0.02% full scale. These ports can cooperate in the following modes: 6 × 32 A (430 VA), 3 × 64 A (860 VA), 1 × 128 A (1000 VA).
- 4 voltage output ports with error less than 0.03% reading plus 0.01% full scale. These ports can cooperate in the following modes: 4 × 300 V (100 VA), 1 × 600 V (275 VA).

The CMC-356 requires that all the data generated from ATP/EMTP should be converted into the WAV format. The data in WAV format are sent down to CMC-356 by the associated software Test Universe V2.30

on the computer. The tester will reproduce these signals into the relay connected to it. In the experiments, the 7SA522 Siemens relay, as on the real AC-185/29 line, was used and programmed with the same settings.

Figure 4. The universal relay tester CMC-356 from OMICRON.

Figure 5 shows the experimental setup with the CMC-356 tester, the 7SA522 relay and the controlling computers.

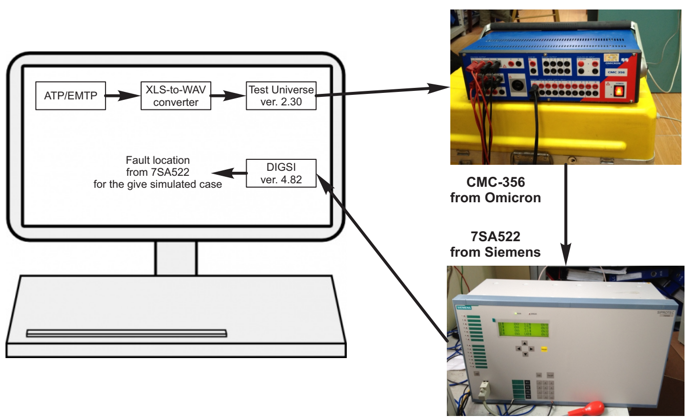

Figure 5. The setup of the experiments with CMC-356 tester, 7SA522 relay, and controlling computers.

The responses from the 7SA522 will be read back to the computer through the compatible software DIGSI 4.82. As mentioned earlier, the difference between the estimated fault location of the relay and the location set in the ATP/EMTP is the correction value, which, in turn, should be the destination output value that the MLP network needs to generate for the corresponding test case.

3. Feature extraction for supervised learning of models

As shown in Figure 1 in Section 1, the neural network will estimate the distance correction based on the features determined from a window of signals around the fault time recorded in the relay. In this paper, the wavelet decomposition algorithms will be used to detect the moment of sudden changes in the signals due to the propagation of the fault to the relay and selected features would be computed for the window of the data around the detected time.

3.1. Wavelets and their application in fault time detection

Wavelets are very well-known tools to detect the sudden changes in a signal, which is also very typical in electrical signals when a fault occurs in the system [34].

Figure 6 shows an example of a current (phase A) and its decomposition using 3^{rd} order Daubechies into 4 first levels. It can be clearly seen that the fault moment (at 40 ms) can be easily detected from the details $\mathbf{d_1}$ of all 4 levels.

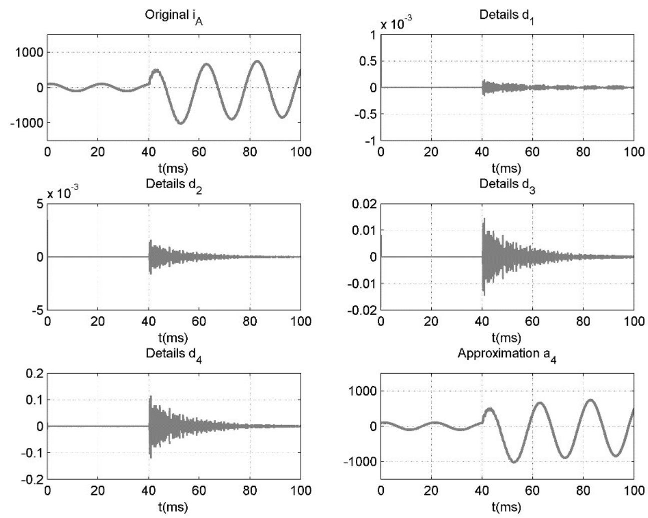

Figure 6. Wavelet decompositions to the 4^{th} level of the phase A current using the 3^{rd} order Daubechies wavelet.

The $\mathbf{d_1}$ component for detecting the fault time was used because: 1. The $\mathbf{d_1}$ contains the high frequency components from the signals, which is typical for the sudden change when an error occurs; 2. This level of detail is firstly calculated in the iterations of decomposition; therefore, the computation time needed is shortest, which is more preferable for real time solutions.

Figures 7 and 8 present the $\mathbf{d_1}$ components for all 6 voltage and current signals that the relay can collect. It can be seen that the $\mathbf{d_1}$ components clearly show the fault moments for all 6 signals, even for the phase not directly affected by the fault (like phase C in Figure 7). Later experiments showed that any of the 6 signals can be used to detect the fault time. With the help of the $\mathbf{d_1}$ component, only a simple formula is needed to detect the moment of sudden changes in the signals, in which the moment T_0 is defined as the first moment, when the amplitude of the signal is 5 times higher than the average amplitude in a 20-ms window before T_0, i.e.

$$T_0 : f\left(T_0\right) \geq 5 \times \underset{t \in [T_0 - 20ms, T_0)}{mean} f\left(t\right). \tag{2}$$

Various wavelets were proposed by different research, but no specific type was proven to be superior to others. Therefore, the "trial and error" method was applied to select the type of wavelet family to use in our experiments. The performances of 4 classical wavelets (Daubechies, Symlet, Coiflet, and Haar) were tested with formula in (2) to select the one with lowest error in fault time detection. The results of fault time detection for types of wavelet are listed in Table 1.

From the results in Table 1, the Daubechies wavelet was selected for further application in the proposed solution in this paper.

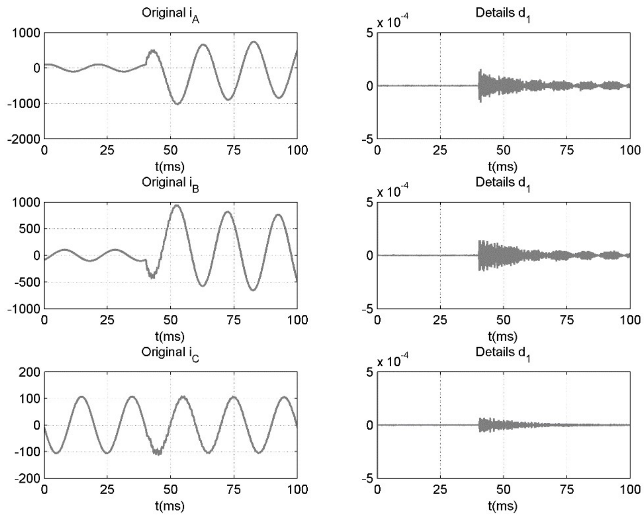

Figure 7. Wavelet decomposition $\mathbf{d_1}$ of the three phase currents using 3^{rd} order Daubechies wavelets.

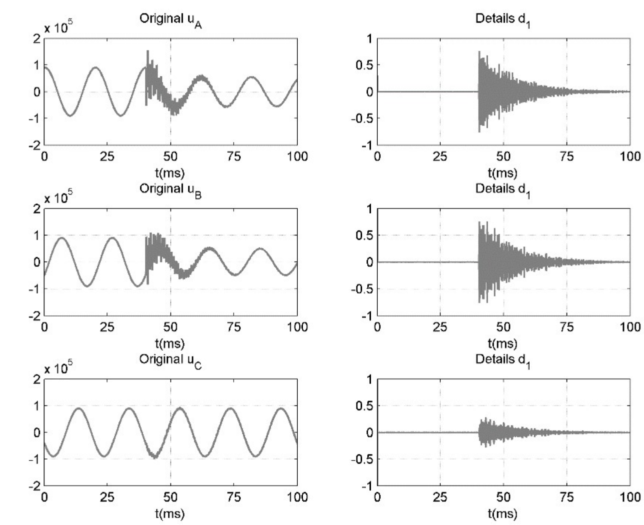

Figure 8. Wavelet decomposition $\mathbf{d_1}$ of the three phase voltages using 3^{rd} order Daubechies wavelets.

3.2. Feature extraction

After detecting the fault time (denoted as T_0), the next task is to extract the characteristic values describing the changes in the signals, which were caused by the fault. These characteristic features will form the input vector for the neural network as the nonlinear estimator. With the intention to implement the solutions in embedded systems integrated with real distance relays, features with easy extraction algorithms were selected to try first. For each signal from the six inputs (three input voltages and three input currents), with the ”trial and error” method, the following 14 values were selected as features representing the input data of each test case:

- Time-based features: 10 instantaneous values sampled with period of 1 ms from the fault time, i.e. at

Table 1. Fault time detection errors (in ms) for each signal and selected types of wavelet.

Signals	Value	Wavelet family			
		Daubechies	Coiflet	Symlet	Haar
i_A	max	0.28	0.40	0.41	155.9
	mean	0.107	0.138	0.142	0.661
i_B	max	0.28	0.37	0.37	157.9
	mean	0.108	0.139	0.143	2.371
i_C	max	0.31	0.87	0.86	160.0
	mean	0.112	0.149	0.154	17.15
u_A	max	0.25	0.33	0.33	156.0
	mean	0.096	0.118	0.118	0.597
u_B	max	0.24	0.31	0.32	158.0
	mean	0.097	0.118	0.120	1.382
u_C	max	0.28	0.47	0.48	156.0
	mean	0.104	0.127	0.131	1.812

$T_0 + k(ms)$ for $k = 0, \ldots, 9$. The sampling period of 1 ms was selected to correspond with the sampling frequency of 1 kHz that many distance relays use in their configurations.

- Frequency-based features: From amplitude spectrum based on short-time Fourier transform (denoted as $STFT(i)$), the total energy around the main frequency (50 Hz) and around its harmonics were estimated:

$$\begin{aligned}
w_1 &= \sum_{i\in[25,75]Hz} |STFT(i)| \\
w_2 &= \sum_{i\in[75,125]Hz} |STFT(i)| \\
w_3 &= \sum_{i\in[125,175]Hz} |STFT(i)| \\
w_4 &= \sum_{i\in[175,225]Hz} |STFT(i)| \\
w_5 &= \sum_{i\in[225,325]Hz} |STFT(i)|
\end{aligned} \tag{3}$$

and form the 4 features as: $\left[\frac{w_1}{\sum_{i=1}^{5} w_i}, \frac{w_2}{\sum_{i=1}^{5} w_i}, \frac{w_3}{\sum_{i=1}^{5} w_i}, \frac{w_4}{\sum_{i=1}^{5} w_i}\right]$. These relative values were proposed due to the fact that in the fault states, many signals (especially the currents) may have much higher amplitudes than in the normal states. In total, based on 6 signals, $14 \times 6 = 84$ features for each sample data were generated.

3.3. The MLP network

In the solution proposed in this paper, as the nonlinear estimator, the classical neural network MLP was selected [35]. 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 in Figure 9. For simplification, the bias inputs for neurons are coded as $x_0 \equiv 1$ and $v_0 \equiv 1$. The weights W_{ij} with $i = 1, 2, \ldots, M$; $j = 0, 1, \ldots, N$; connecting input nodes to hidden neurons form the weight matrix $\mathbf{W} \in \mathbb{R}^{M\times(N+1)}$, the weights V_{ij}, where $i = 1, 2, \ldots, K$; $j = 0, 1, \ldots, M$; connecting the hidden neurons to the outputs form the weights matrix $\mathbf{V} \in \mathbb{R}^{K\times(M+1)}$.

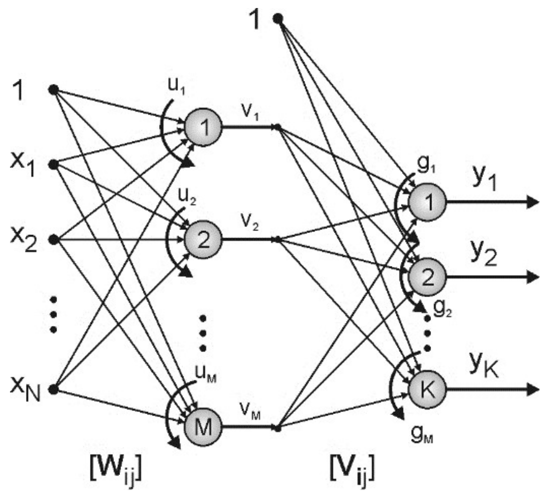

Figure 9. An MLP structure with one hidden layer of neurons.

With this structure, when an input vector $\mathbf{x} = [x_1, x_2, \ldots, x_N] \in \mathbb{R}^N$ is presented, the output is calculated with the following formula [35]:

$$y_i = f_2\left(\sum_{j=0}^{M} v_j V_{ij}\right) = f_2\left(\sum_{j=0}^{M} f_1\left(u_j\right) V_{ij}\right) = f_2\left(\sum_{j=0}^{N}\left[f_1\left(\sum_{k=0}^{N} x_k W_{jk}\right) V_{ij}\right]\right) \tag{4}$$

The MLP is trained to fit a nonlinear problem with the popular approach of supervised training with two data samples sets: the training set and the testing set. Assume that the training set contains p pairs of input vector and its corresponding output vector $\{\mathbf{x}_i, \mathbf{d}_i\},\ i = 1, \ldots, p$, and the parameters of the MLP are tuned to minimize the error function defined as:

$$E_{learn} = \frac{1}{2}\sum_{i=1}^{p}\left\|MLP\left(\mathbf{x}_i\right) - \mathbf{d}_i\right\|^2 \rightarrow \min. \tag{5}$$

After training, the MLP was tested with the testing set, which contains q samples, not presented in the learning set, $\{\mathbf{x}_i^{test}, \mathbf{d}_i^{test}\},\ i = 1, \ldots, q$, where the test error is calculated as:

$$E_{test} = \frac{1}{2}\sum_{i=1}^{p}\left\|MLP\left(\mathbf{x}_i^{test}\right) - \mathbf{d}_i^{test}\right\|^2. \tag{6}$$

According to [35], the MLP networks were tried with single hidden layer with different number of hidden neurons. The network with lowest testing error was selected as the best.

4. Simulations and numerical results

4.1. Sample data sets

As mentioned in Section 2, the ATP/EMTP software was used to simulate an actual transmission line, which was the 118.5-km, 110-kV line (EVN code name E12.3) from Yen Bai to Khanh Hoa province (in Vietnam). The scenarios of the faults to create the data samples are as follow:

- Fault location: one of $N = 23$ positions on the line (at 5, 10, ..., 115 km distance from the beginning of the line),
- Shortage resistance R_{fault}: one of $K = 6$ values $(0, 1, 2, 3, 4, 5\Omega)$,
- Types of faults: one of $P = 4$ shortage types (single phase, two phase, two phase earthed, three phase),
- Load of the lines: one of $Q = 3$ cases (the load equals 30%, 50%, and 100% nominal load of the line).

In total, this gave $N \times K \times P \times Q = 23 \times 6 \times 4 \times 3 = 1656$ cases. Additionally, in order to check the effect of the fault time (relative phase) to the results, cases were generated for the shortage resistance $R_{fault} = 1\Omega$ at positions (10, 40, 80, 110 km) and $M = 10$ fault time stepped at 2 ms (to cover the whole period of 20 ms of the 50 Hz signals). That means:

- Fault location: one of $N = 4$ locations (10, 40, 80, 110 km),
- Shortage resistance R_{fault}: 1Ω,
- Fault types: one of $P = 4$ shortage types (as above),
- Load of the lines: one of $Q = 3$ cases (as above)
- Fault time: one of $M = 10$ values (+00ms, +02ms,..., +18ms)

As results, this gave additional $N \times P \times Q \times M = 4 \times 4 \times 3 \times 10 = 480$ cases. A total of $1656 + 480 = 2136$ scenarios were generated by ATP/EMTP.

4.2. Fault location using distance relay

With the data simulated from ATP/EMTP, firstly, the tester CMC-356 was used to regenerate them to feed into the selected 7SA522-V4.7 (the same one being used on the real line) and the fault location detected by the relay was checked. The results from the relay were read back to the computer using DIGSI software and compared with the locations set in the corresponding test cases in ATP/EMTP. Some statistics of these comparisons are listed in Table 2. It can be seen that the average error of the relay 7SA522 was $E_{mean} = 1.09(km)$ or 0.92% of the line length.

Table 2. The results from the distance relay 7SA522.

Type of faults	Mean of location error (km)	Mean of relative location error(%)
1-phase shortage	0.18	0.15%
2-phase shortage	1.57	1.33%
2-phase-to-earth	1.94	1.64%
3-phase shortage	0.56	0.47%
Average	1.09	0.92%

4.3. Fault location correction using MLP

For each simulated case, with the generated 3 voltages and 3 currents signals, the first step is to detect the time of the fault. When using wavelet Daubechies (3^{rd} order) for all 2136 simulated cases and 6 signals for each case, the achieved results are listed in Table 1. As it can be seen, the results for 6 signals are similar and the error reaches a maximum of 300 µs, which is very accurate for practical application. Because of this, further steps would be based on the time detected on current of phase A for simplification. With the time T_0 detected, for each of 6 signals in each simulated case, a 60-ms window (from $T_0 - 20ms$ to $T_0 + 40ms$) was extracted to find the time-based and frequency-based features as described above. Those features will form the inputs in the samples pairs used in the supervised learning and testing mode for MLP. As described earlier in Eq. (1), the corresponding destination output of each case is the difference between the fault location set in ATP/EMTP for the given case and the fault location returned by the distance relay for that given case.

To train an MLP network for the problem, the total set of 2136 samples was randomly divided into 2 sets: 1424 samples (2/3 of total data set that were generated) are used as the training set, the rest (712 samples) are used as the testing set. In Table 3, the detailed numbers of samples grouped by the type of faults are given for the two sets.

Table 3. The number of samples grouped by the type of faults in training and testing sets.

Type of faults	Samples in training set	Samples in testing set
1-phase shortage	370	164
2-phase shortage	356	178
2-phase-to-earth	358	176
3-phase shortage	340	194
Total	1424	712

As mentioned above, a number of MLP networks with single hidden layer were randomly generated and trained with 1424 samples in the learning set. After that, the networks were tested with the testing set. The network with lowest testing error was selected as the best. The best result was achieved with the MLP with 12 hidden neurons as follows:

- Average learning error: $E_{mean} = 0.49(km)$ or 0.41% line length.
- Average testing error: $E_{mean} = 0.5(km)$ or 0.42% line length.

The detailed errors of the corrected fault locations (l_{final}) for each type of faults are given in Table 4.

The investigation of results also showed that our solution significantly reduced the maximum error as seen in Table 5.

The results have proven our assumption that the application of an MLP neural network to correct the result of a distance relay can significantly reduce the inaccuracies, both for mean error and for maximum error of location.

5. Conclusions and further development

This paper has presented a proposed method using an MLP neural network to effectively correct the final estimation of the fault locations of a distance relay. A sophisticated solution using ATP/EMTP for generating

Table 4. The results from the distance relay 7SA522 corrected with MLP.

Type of faults	Location error for training set (km)	Rel. location error for training set (%)	Location error for testing set (km)	Rel. location error for testing set (%)
1-phase shortage	0.27	0.23%	0.55	0.46
2-phase shortage	0.21	0.18%	0.49	0.41
2-phase-to-earth	1.01	0.85%	0.31	0.26
3-phase shortage	0.47	0.40%	0.65	0.55
Average	0.49	0.41%	0.50	0.42

Table 5. The maximum errors from the distance relay 7SA522 and after correction with MLP.

Method	Maximum error (km)	Rel. maximum error (%)
7SA522 only	9.2	8.23
7SA522 with MLP	2.79	2.49

electrical signals in normal and fault states of the transmission lines and using Omicron CMC-356 relay tester to test with a real 7SA522 distance relay was shown. The proposed system was tested with 4 shortage types shortage resistance varies from 0 to 5Ω, line load varies from 30% to 100% nominal load, different time moment of the faults, different locations of the fault along selected 110 kV, 118.5 km, 3-phase lines, resulting a total of 2136 test cases. The simulation results showed that a well-trained MLP can effectively correct the results firstly given by the relays to generate a final location of the fault with much smaller error levels (the mean value of testing errors was reduced from 1.09 km to 0.50 km, the maximum of testing errors was reduced from 9.2 km to 2.79 km).

Despite initial promising results, the proposed solution can be further improved in different ways:

- Test with more cases with other types of line faults, including more practical elements on the lines like power transformers, compensating devices.
- Test with wider ranges of fault parameters such as range of loads on the lines, range of the fault resistance including dynamic resistance cases.
- Test with other configurations of the transmission lines,
- Implementing of a hardware device realizing the whole proposed algorithms to work online with the distance relay and test it in the field;

The solution was also tested with 480 cases of different signal phases at the fault time only because of the exponential growth of the number of cases. This part of experiments still need to be continued with more samples to test the generalization capability of the proposed solution. More tests are also needed for further checking of the influence of the load on the error in fault location.

Another interesting problem that the actual solution can be extended is to recognize the occurrences of multiple faults concurrently in the transmission lines. In this scenario, one of the biggest problems would be the number of test cases because the total combination number of cases increases with the product function.

References

[1] Cook V. Fundamental aspects of fault location algorithms used in distance protection. Proceedings of IEE Conference 1986; 133 (6): 359-368.

[2] Djuric MB, Radojevic ZM, Terzija VV. Distance Protection and fault location utilizing only phase current phasors. IEEE Transactions on Power Delivery 1998; 13 (4): 1020-1026.

[3] Saha MM, Izykowski J, Rosolowski E. A two-end method of fault location immune to saturation of current transformers. In: Developments in Power System Protection Proceedings, Amsterdam; 2004. pp. 172–175.

[4] Waikar DL, Elangovan S, Liew AC. Fault impedance estimation algorithm for digital distance relaying. IEEE Transactions on Power Delivery 1994; 9 (3): 1375–1383.

[5] Ziegler G. Numerical Distance Protection. Principles and Applications, Siemens AG, Erlangen, Germany: Publicis MCD Verlag, 2006.

[6] Zimmerman K, David Costello. Impedance-based fault location experience. Schweitzer Engineering Laboratories, Inc. WA USA: Pullman, 2010.

[7] Aggarwal RK, Coury DV, Johns AT, Kalam A. A practical approach to accurate fault location on extra high voltage teed feeders. IEEE Transactions on Power Delivery 1993; 8: 874-883.

[8] Aurangzeb M, Crossley PA, Gale P. Fault location using high frequency travelling waves measured at a single location on transmission line. In: Proceedings of 7th International Conference on Developments in Power System Protection (DPSP 2001) 2001; 403-406.

[9] Bo ZQ, Weller G, Redfern MA. Accurate fault location technique for distribution system using fault-generated high-frequency transient voltage signals. IEE Proceedings - Generation, Transmission and Distribution 1999; 146 (1): 73-79.

[10] Bouthiba T. Fault location in EHV transmission lines using artificial neural networks. International Journal of Applied Mathematics and Computer Science 2004; 14 (1): 69-78.

[11] Kezunovic M, Rikalo I, Sobajic DJ. Real-time and Off-line Transmission Line Faulty Classification Using Neural Networks. Engineering Intelligent Systems 1996; 10: 57-63.

[12] Ayyagari SB. Artificial neural network based fault location for transmission line. PhD, University of Kentucky, 2011.

[13] Chen Z and Maun JC. Artificial neural network approach to single-ended fault locator for transmission lines, IEEE Transactions on Power Systems 2000; 15 (1): 370-375.

[14] Takagi K, Yamakoshi Y, Yamaura M, Kondow R, Matsushima T. Development of a new type fault locator using the one terminal voltage and current data. IEEE Transactions on Power Apparatus and Systems 1982; 101 (8): 2892-2898.

[15] Edmund OS. A Review of Impedance-Based Fault Locating experience. In: Fourteenth Annual Iowa-Nebraska System Protection Seminar 1990. pp. 1-31.

[16] Aggarwal RK, Blond SL, Beaumont P, Baber G, Kawano F et al. High frequency fault location method for transmission lines based on artificial neural network and genetic algorithm using current signals only. In: 11th International Conference on Developments in Power Systems Protection (DPSP 2012); 2012. pp. 1-6.

[17] Brahma SM. Iterative Fault Location Scheme for a Transmission Line Using Synchronized Phasor Measurements. International Journal of Emerging Electric Power Systems 2007; 8 (6); https://doi.org/10.2202/1553-779X.1733.

[18] Sajedi S, Khalifeh F, Khalifeh Z, Karimi T. Application Of Wavelet Transform For Identification Of Fault Location On Transmission Lines. Australian Journal of Basic and Applied Sciences 2011; 5 (12): 1428-1432.

[19] Silva JACB, Silva KM, Neves WLA, Souza BA, Costa FB. Sampling frequency influence at fault locations using algorithms based on artificial neural networks. In: 4th World Congress on Nature and Biologically Inspired Computing (NaBIC); 2012. pp. 15-19.

[20] Teklié L, Filipovié-Greié B. Artificial neural network approach for locating faults in power transmission system. EuroCon 2013, Zagreg, Croatia 2013; 1425-1430.

[21] Hagh MT, Razi K, Taghizadeh H. Fault classification and location of power transmission lines using artificial neural network. In: International Conference on Power Engineering (IPEC 2007) 2007; 1109-1114.

[22] Jain A, Thoke AS, Koley E, Patel RN. Fault classification and fault distance location of double circuit transmission lines for phase to phase faults using only one terminal data. In: 2009 International Conference on Power Systems, Kharagpur, USA; 2009. pp. 1-6.

[23] Joorabian M. Artificial neural network based fault locator for EHV transmission system. In: 10th Mediterranean Electrotechnical Conference (MELECON 2000) 2000; 3: 1003-1006.

[24] Xiangning L, Mao P, Weng H, Wang B, Bo ZQ, Klimek A. Study on Fault Location for High Voltage Overhead Transmission Lines Based on Neural Network System. In: 2007 International Conference on Intelligent Systems Applications to Power Systems; 2007. pp. 1-5; doi: 10.1109/ISAP.2007.4441662

[25] Hosseini K, Tayyebi SA, Ahmadian MB. Double circuit transmission lines short circuit fault location using wavelet transform and MLP. In: Iranian Conference on Electrical Engineering (ICEE); 2017. pp. 1336–1342; doi: 10.1109/IRANIANCEE.2017.7985249

[26] Saha M, Rosolowski E, Izykowski J. ATP-EMTP investigation of fault location algorithm applying signals of current differential relays of double-circuit series-compensated transmission line. In: 17th Power Systems Computation Conference, Stockholm, Sweden, 2011.

[27] Yin T, Lian J, Buckheit J, Fan R. Bridging Power System Protection Gaps with Data-driven Approaches. Pacific Northwest National Laboratory Report, USA, 2021. pp. 1 - 42; doi:10.2172/1771797.

[28] Jamil M, Sharma SK, Singh R. Fault detection and classification in electrical power transmission system using artificial neural network. SpringerPlus 2015; 4 (334): doi: 10.1186/s40064-015-1080-x

[29] Koteswara Rao AV, Soni KM, Sinha SK, Nasiruddin I. Tracking of impedance trajectory for distance protection using neural networks, In: 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON) 2017; 289-294 doi: 10.1109/UPCON.2017.8251062

[30] Madsen PP. Neural Network for combining Linear and Non-Linear modelling of Dynamic Systems. Neural Networks, In: IEEE World Congress on Computational Intelligence 1994; 7: 4541-4546.

[31] Siwek K, Osowski S. Short Term Load Forecasting Model in the Power System Using Ensemble of Predictors. Instrumentation and Measurement Technology Conference Proceedings (IEEE-IMTC 2007) 2007. pp. 1 – 6.

[32] Horowitz SH, Phadke AG. Power System Relaying, 3rd edition, West Sussex, England: Wiley, 2008.

[33] Tran Dinh Long. Power System Protection. Hanoi, Vietnam: Science and Technology Publisher, 2000.

[34] Daubechies I. Ten lectures on wavelet. SIAM: Society for Industrial and Applied Mathematics, USA, 1992.

[35] Haykin S. Neural Networks - A Comprehensive Foundation. NJ, USA: Prentice-Hall, 1999.