Artificial Neural Network Approach for Locating Faults in Power Transmission System

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***Abstract*-- This paper presents fault location recognition in transmission power system using artificial neural network (ANN). Single phase short circuit on 110 kV transmission line fed from both ends was analysed with various fault impedances, since it is the most common fault in power system. Load flow and short circuit calculations were performed with EMTP-RV software. Calculation results including currents and voltages at both line ends were used for training ANN in Matlab in order to obtain correct fault location and fault impedance, even for those cases that ANN has never encountered before. The network was trained with back propagation algorithm. Test results show that this approach provides robust and accurate location of faults for a variety of power system operating conditions and gives an accurate fault impedance assessment.**

Keywords: Fault Location, Transmission Lines, Feed Forward Neural Network, Artificial Neural Network

I. INTRODUCTION

A transmission line is an important component of the electric power system and its protection is necessary for ensuring system stability and to minimize damage to equipment due to short circuits that may occur on transmission lines. Short circuit currents cause mechanical and thermal stresses that are potentially damaging for high voltage equipment.

Transmission-line relaying involves three major tasks: detection, classification and location of transmission line faults. Fast detection of transmission line fault enables quick isolation of the faulty line from service and, hence, protecting it from the harmful effects of the fault. Accurate fault location is necessary for facilitating quick repair and restoration of the faulty line in order to improve reliability and availability of the power supply. By accurately locating a fault, the amount of time spent by line repair crews in searching for the fault can be kept at a minimum.

However, the identification of the faults is not always an easy task. If a fault occurs, it should be isolated as quickly as possible to preserve the stability of the rest of the system. Protective relays for transmission lines normally use voltage and current input signals in order to detect, classify and locate faults in a protected line. In the case of a fault the relay will send a trip signal to a circuit breaker in order to disconnect the faulted line. In an interconnected system the rest of the network can then continue working normally or at least under close to normal conditions.

Different types of algorithms for finding fault location on transmission lines have been developed and proposed over the years. These algorithms may be broadly classified as follows:
a) computing power frequency current and voltage phasors to find impedance and hence the fault location,
b) using line differential equations and estimating line parameters,
c) travelling waves which uses one or two terminal data.

Some protection relays can have problems with detection of fault location due to high fault impedance and DC offset in short circuit current. Travelling wave approach has problems with fault detection very close to the substations and if fault inception angle is near to zero (or at zero crossing).

One of the tools recently introduced into power system protection is Artificial Neural Networks (ANN). ANN [1] is powerful in pattern recognition, classification, generalization and it is useful for power system applications because it can be trained with off-line data [2]-[5]. ANN also has excellent features such as noise immunity, robustness and fault tolerance. This paper describes the application of ANN for fault location recognition in transmission power system.

II. POWER SYSTEM MODEL

The data used to train the ANN learning algorithms consisted of calculated currents and voltages at both line ends. A small part of Croatian transmission system which consists of a single-circuit 110 kV transmission line connecting two substations was analyzed in this paper. A model shown in Fig. 1 used for load flow and short circuit calculation was developed using EMTP-RV software [6] in order to obtain the mentioned voltage and current values.

The 110 kV transmission line is 60 km long, equipped with single ground wire and it transmits power from substation 1 to substation 2. The position of conductors at towers is shown in Table I and characteristics of conductors are shown in Table II.

Constant distributed parameter transmission line model was used in EMTP-RV. Skin effect was taken into account in calculations. Ground return resistivity was assumed 250 Ωm.

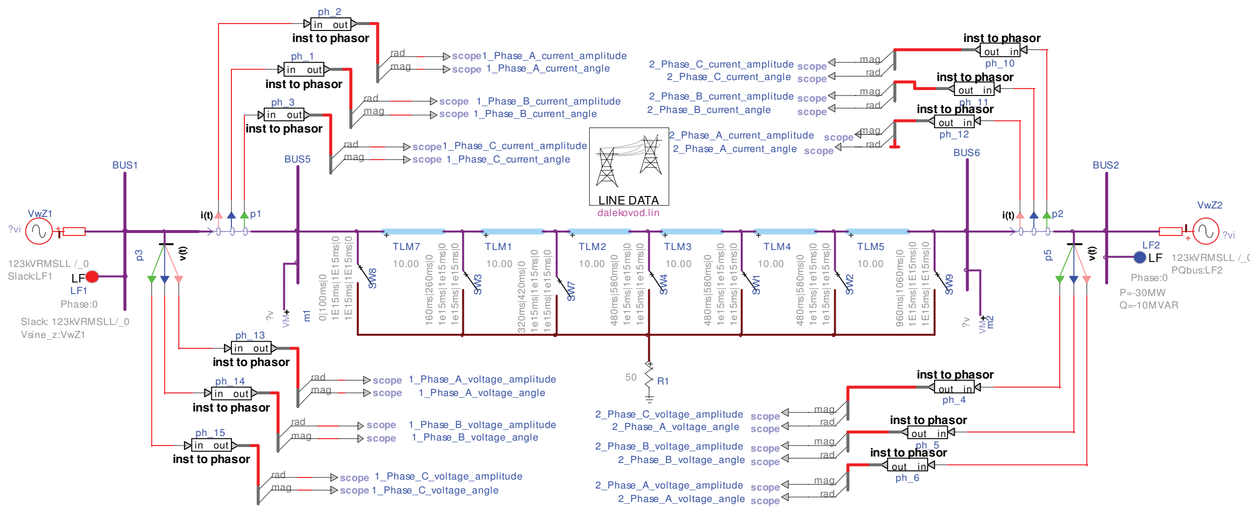

Fig. 1. Model for load flow and short circuit calculation in EMTP-RV software

TABLE I

Position of conductors at towers and midspan

Conductors	Horizontal position (m)	Vertical height at tower (m)	Vertical heigth at midspan (m)
Phase A	3.8	28.8	10
Phase B	-3.3	32.6	12.2
Phase C	2.8	28.8	14.4
Ground wire	0	37.7	20.778

TABLE II

Characteristics of conductors

Conductors	Phase conductors	Ground wires
Cross section (mm^2)	240	120
External diameter (mm)	31	22
DC resistance (Ω/km)	0.119	2.85

Parameters of equivalent network were calculated from short circuit currents by using the following expressions [7]:

$$Z_d = \frac{c \cdot U_n}{\sqrt{3} \cdot I_{sc3}} \tag{1}$$

$$Z_0 = \frac{c \cdot U_n}{\sqrt{3}} \cdot \left(\frac{3}{I_{sc1}} - \frac{2}{I_{sc3}} \right) \tag{2}$$

where:

I_{sc1}, I_{sc3} – single-phase and three-phase short circuit currents;
U_n – rated voltage;
c – factor =1.1.

Substations were modelled with voltage sources behind Thevenin equivalent [8].

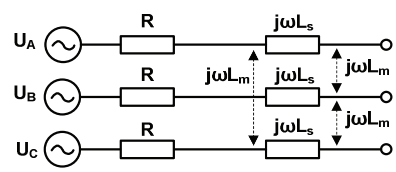

Fig. 2. Thevenin equivalent

Thevenin impedance was calculated by using the following expression:

$$[Z]_{TH} = [R]_{TH} + j\omega[L]_{TH} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} + j\omega \begin{bmatrix} L_S & L_m & L_m \\ L_m & L_S & L_m \\ L_m & L_m & L_S \end{bmatrix} \tag{3}$$

Thevenin impedance is coupled *RL*-branch with an impedance matrix given by the series connection of *R* and *L*. The matrices $[R]_{TH}$ and $[L]_{TH}$ can be entered directly or using sequence data. The power variant Fortescue transformation matrix $[A]$ is used in EMTP-RV to calculate the full matrices from sequence components.

$$[Z]_{TH} = [A] \cdot [Z_{012}] \cdot [A]^{-1} \qquad [A] = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \tag{4}$$

Sequence data (zero and positive resistance and reactance) are shown in Table III. Large numbers of training data have been generated using EMTP-RV, considering fault at 0 km, 10 km, 20 km, 30 km, 40 km, 50 km and 60 km of the line. Each short circuit was calculated for fault resistances of 0 Ω, 10 Ω, 25 Ω and 50 Ω. Also different power flow conditions were taken into account.

TABLE III

Calculated sequence data for susbstation 1 and 2

Substation no.	Positive sequence data (Ω)		Zero sequence data (Ω)	
	R_d	X_d	R_0	X_0
1	5.12	14.96	7.30	27.09
2	7.74	29.72	6.24	31.75

In the first step the load flow calculations were performed by varying active (0 - 100 MW) and reactive power (10 - 30 MVAr). The results of three-phase load flow calculations (voltages at the beginning and at the end of line before the fault occurrence) are used as input parameters for the calculation of short circuit.

For each fault resistance and power flow condition 7 short circuits on different locations were simulated according to Table IV.

TABLE IV

Simulation fault location and timings data

Fault location (km)	0	10	20	30	40	50	60
Beginning of the fault (ms)	0	160	320	480	640	800	960
End of the fault (ms)	100	260	420	580	740	900	1060

The first harmonic of the instantaneous value of the current and voltage were converted to polar coordinates representing amplitude and angle of the phasor in a rotating reference frame. Polar coordinates in stationary state of the fault were used as input data for ANN.

Figures 3 - 6 show calculation results in case of single phase short circuit in phase A with a fault resistance 10 Ω. Power flow of 100 MW and 30 MVAr was analyzed. Occurrence of short circuit on each location is shown.

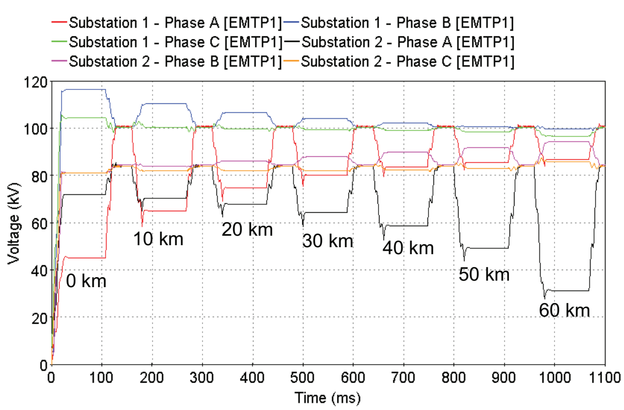

Fig. 3. Voltage phasor amplitudes

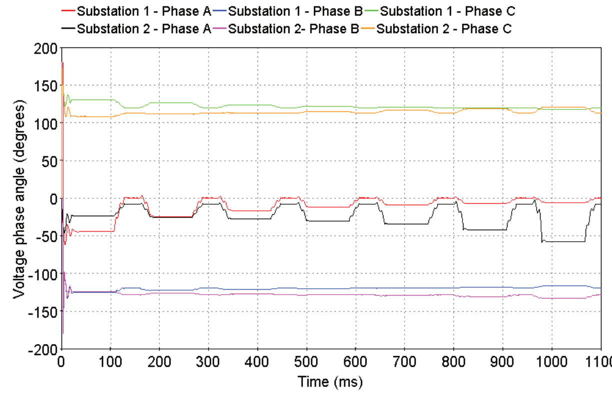

Fig. 4. Voltage phasor angles

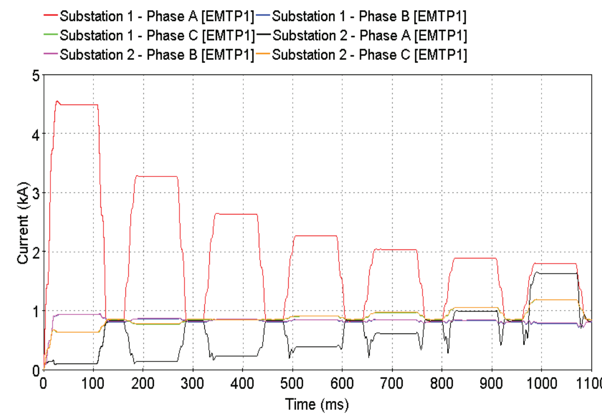

Fig. 5. Current phasor amplitudes

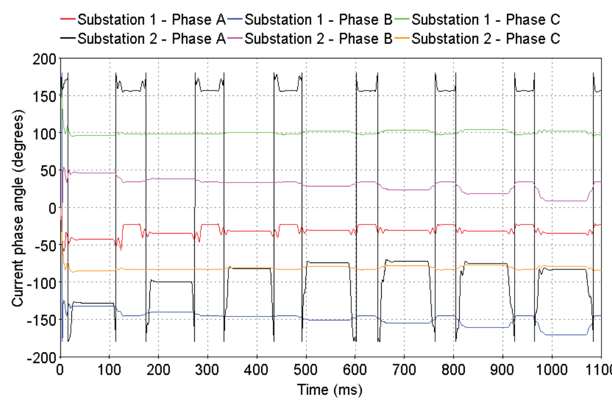

Fig. 6. Current phasor angles

III. ANN MODEL

Feedforward networks [1] often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems. In this paper the ANN uses back propagation learning algorithm (BP) and the gradient descending method to minimize the error. For optimization of the training method architecture based on the Levenberg–Marquardt (Trainlm) optimization technique was selected. Selection of number of hidden neurons in BP network is difficult to determine. Prediction accuracy of BP network increases with the number of hidden neurons. If the number of neurons in hidden layer is small, the network cannot learn very well and training accuracy gets affected as well. If the number of neurons is large, training time increases and the network leads to fitting ineffectively. The structure of BP ANN is shown in Fig. 7. The model of BP ANN is shown in Fig. 8.

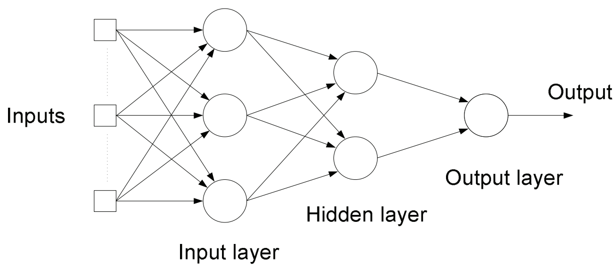

Fig. 7. The structure of BP ANN

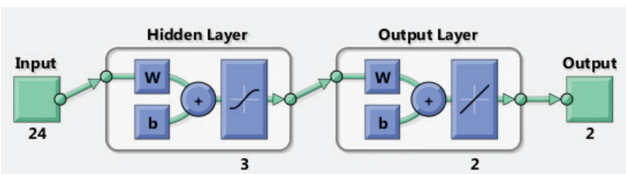

Fig. 8. The model of BP ANN

IV. TRAINING AND TESTING OF ANN FOR FAULT LOCATION

The Neural Network Toolbox, a part of Matlab software was used to set up the ANN topologies, train them and obtain the appropriate weights. Results gained from EMTP-RV simulations were used as an input vectors for ANN.

A. *Training ANN*

Inputs were divided into three parts: one used for training (called training set consisting of 80% of data), one for validating (called validation set consisting of 10% of data), and one for testing (called testing set consisting of 10% of data). The training data and validation data set were randomly fed to the ANN.

In the first layer of the network, the net input is a product of the input times the weight plus the bias. If the input is very large, then the weight must be very small in order to prevent the transfer function from becoming saturated. It is standard practice to normalize the inputs before applying them to the network. Generally, the normalization step is applied to both the input vectors and the target vectors in the data set. In this way, the network output always falls into a normalized range. The network output can then be reverse transformed back into the units of the original target data when the network is put to use in the field. Most of the network creation functions in the toolbox, including the multilayer network creation functions, such as *feedforwardnet*, automatically assign processing functions to network inputs and outputs. These functions transform the input and target values which are provided into values that are better suited for network training. Preprocessing and postprocessing in this case was done automatically.

The ANN was formed as shown on Fig. 8 and fed with a set of 112 input vectors. Every vector consists of 24 elements containing amplitudes and angles of current and voltage phasors at both line ends. Target data set consists of 112 vectors containing fault location and fault impedance. The number of hidden neurons was determined experimentally and was set to 3. The training performance is shown on Fig. 9.

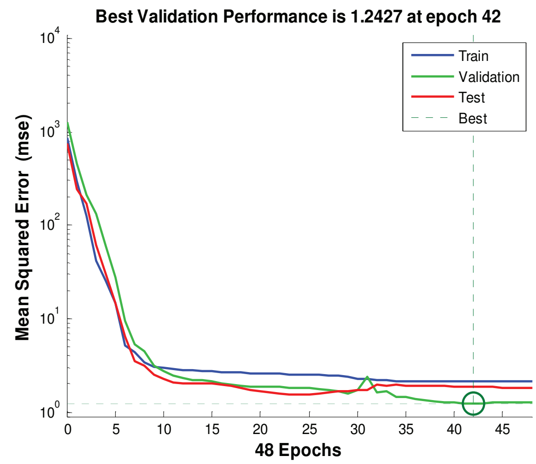

Fig. 9. The training performance

Fig. 9 shows the decreasing of Mean Squared Error (MSE) over time. After the best validation performance is reached the network is trained.

As a result of training an error histogram is generated showing the difference between target and output data (Fig. 10). The blue bars represent training data, the green bars represent validation data and the red bars represent testing data. The histogram can give an indication of outliers, which are data points where the fit is significantly worse than the majority of data.

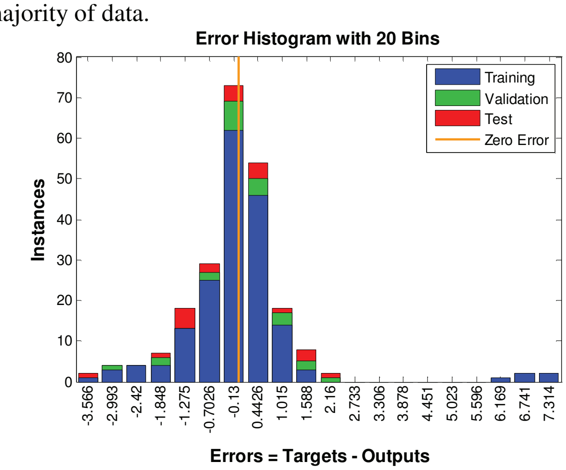

Fig. 10. Error Histogram Graph

B. *Testing the ANN*

Testing was conducted with 24 data sets (vectors) which were different than the data used for training. That included different fault locations, power flow conditions and fault resistance values. Results of ANN testing are shown in Tables V and VI where:

FL_{Test} - fault location used for testing of ANN;
FL_{ANN} - result of ANN fault locator;
FR_{Test} - fault resistance used for testing of ANN;
FR_{ANN} - result of fault resistance estimated by ANN.

TABLE V

ANN testing results - fault location

Load flow condition	FL_{Test} (km)	FL_{ANN} (km)	$Error_{FL}$ (%)	$Error_{FLT}$ (%)
0	5	6.065	21.30	1.77
	5	4.345	13.10	1.09
73 MW, 24 MVAr	5	4.004	19.92	1.66
90 MW, 27 MVAr	5	6.243	24.86	2.07
0	15	16.270	8.47	2.12
	15	14.323	4.51	1.13
73 MW, 24 MVAr	15	15.537	3.58	0.90
90 MW, 27 MVAr	15	18.014	20.09	5.02
0	25	24.705	1.18	0.49
	25	24.459	2.16	0.90
73 MW, 24 MVAr	25	25.799	3.20	1.33
90 MW, 27 MVAr	25	28.193	12.77	5.32
0	35	34.561	1.25	0.73
	35	34.280	2.06	1.20
73 MW, 24 MVAr	35	36.083	3.09	1.80
90 MW, 27 MVAr	35	37.065	5.90	3.44
0	45	45.046	0.10	0.08
	45	45.516	1.15	0.86
73 MW, 24 MVAr	45	45.903	2.01	1.50
90 MW, 27 MVAr	45	46.044	2.32	1.74
0	55	55.142	0.26	0.24
	55	56.080	1.96	1.80
73 MW, 24 MVAr	55	55.771	1.40	1.29
90 MW, 27 MVAr	55	53.877	2.04	1.87

The percentage error of fault locating was calculated by using the following expression:

$$Error_{FL}(\%) = \frac{|FL_{ANN} - FL_{Test}|}{FL_{Test}} \cdot 100 \tag{5}$$

The maximum percentage error of ANN fault locating was less than 25 %.

The percentage error of fault locating with regard to line length d was calculated by using the following expression:

$$Error_{FLT}(\%) = \frac{|FL_{ANN} - FL_{Test}|}{d} \cdot 100 \tag{6}$$

Maximum percentage error of fault locating with regard to line length was less than 6 %.

TABLE VI

ANN testing results - fault resistance

Load flow condition	FR_{Test} (Ω)	FR_{ANN} (Ω)	$Error_{FR}$ (%)
0	7	8.491	21.30
	33	33.060	0.18
73 MW, 24 MVAr	40	40.363	0.91
90 MW, 27 MVAr	60	57.078	4.87
0	7	6.861	1.98
	33	32.668	1.01
73 MW, 24 MVAr	40	40.685	1.71
90 MW, 27 MVAr	60	57.616	3.97
0	7	6.231	10.99
	33	33.986	2.99
73 MW, 24 MVAr	40	40.067	0.17
90 MW, 27 MVAr	60	58.326	2.79
0	7	6.074	13.23
	33	33.643	1.95
73 MW, 24 MVAr	40	41.234	3.09
90 MW, 27 MVAr	60	58.650	2.25
0	7	6.662	4.84
	33	33.336	1.02
73 MW, 24 MVAr	40	40.911	2.28
90 MW, 27 MVAr	60	57.996	3.34
0	7	7.550	7.86
	33	32.775	0.68
73 MW, 24 MVAr	40	41.070	2.67
90 MW, 27 MVAr	60	55.830	6.95

Maximum percentage error of the fault resistance estimation was calculated by using the following expression:

$$Error_{FR}(\%) = \frac{|FR_{ANN} - FR_{Test}|}{FR_{Test}} \cdot 100 \tag{7}$$

The maximum error of ANN fault resistance estimation was lower than 22 % occurring in case of low resistance faults. In majority of cases the percentage error of fault locating and fault resistance estimation was less than 10 %.

V. CONCLUSIONS

This paper describes the application of ANN for fault location and fault resistance estimation in transmission power system, in case when limited amount on input data is used for ANN training. A power system model for load flow and short circuit calculations was developed in EMTP-RV software. Voltage and current values at the both line ends obtained from different fault conditions were used as an input vectors for ANN training. Different fault locations, power flow conditions and fault resistance values were analyzed. The ANN with back propagation learning algorithm (BP) was applied.

In majority of cases the percentage error of fault locating and fault resistance estimation was less than 10 %. Mean value of percentage error of fault location estimation was equal to 6.6 %. Mean value of fault resistance percentage error was equal to 4.3 %. Test results show that this approach provides robust and accurate location of faults for different power system operating conditions and gives an accurate fault resistance assessment, even when using simple ANN architecture. Estimation of fault location calculated by ANN can be valuable information to maintenance and repair crews as an additional information.

VI. REFERENCES

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