

# Distance Transmission Line Protection Based on Radial Basis Function Neural Network

Anant Oonsivilai and Sanom Saichoomdee

**Abstract**—To determine the presence and location of faults in a transmission by the adaptation of protective distance relay based on the measurement of fixed settings as line impedance is achieved by several different techniques. Moreover, a fast, accurate and robust technique for real-time purposes is required for the modern power systems. The appliance of radial basis function neural network in transmission line protection is demonstrated in this paper. The method applies the power system via voltage and current signals to learn the hidden relationship presented in the input patterns. It is experiential that the proposed technique is competent to identify the particular fault direction more speedily. System simulations studied show that the proposed approach is able to distinguish the direction of a fault on a transmission line swiftly and correctly, therefore suitable for the real-time purposes.

**Keywords**—radial basis function neural network; transmission lines protection; relaying; power system.

## I. INTRODUCTION

TRANSMISSION line system is regarded with great importance in power system. Faults that occur frequently with transmission lines system, should affect electricity users. Faults, aforementioned may be caused by neither a single person, animal or natural occurrences. Thus to prevent and decrease damage that would happen, must systematically protect the transmission line system. Transmission line system using distance relay is very popular. Protective relaying is one of several features of power system design concerned with minimizing damage to equipment and interruptions to service when electrical failures occur. Distance relays are generally used for phase fault primary and back-up protection on sub-transmission lines, and on transmission lines where high-speed automatic reclosing is not necessary to maintain stability and where the short time delay for end-zone faults can be tolerated [1], [13].

Several distance relaying techniques have been expressed in several publications; where the presence and location of faults

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in a transmission. The fundamental principle is based on the measure of particular fixed settings, mainly the impedance at fundamental frequency between the relay location and the fault point [1], and [6]. By using modern digital signal processing methods, the distance relay techniques has been improved, particularly, the decision time which has been shortened [2], [13], [14], and [15].

In this context, using an intelligent system solves a problem in the remedy of power system widely. For example, dynamic load modeling [8], short term load forecasting [9], stability in power system [10] for transmission lines protection have been using neural network, could test by distance relay [5],[6],[21] and [22] neural network, electric base will not be used in calculation but, the path calculated will be used which is obtained by the format of learning or the ability to memorize of neural network; accompanied with flexibility in itself makes neural network very interesting. We can use neural network in learning and memorizing the format of fault and the format of condition changing of power system. Although this might force relay, it protects transmission lines, with increasing precision (zone1) and can be applied accompanied with distance prevention normally which, hypothetically will help testify the protection of transmission lines become much more accurate.

This paper proposed distance transmission lines protection based on radial basis function neural network.

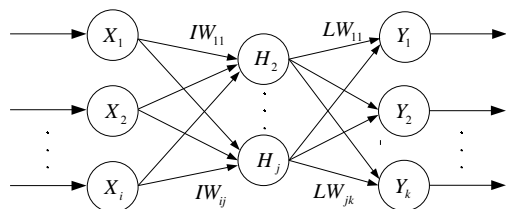
## II. NEURAL NETWORK

Artificial Neural Networks (ANN) or simply Neural Network (NN) are simplified to imitate central nervous system been motivated by the computing performed by human brain.

ANN is defined in [16] and [17] as a data processing system consisting of a large number of simple highly interconnected processing elements (artificial neuron) in architecture inspired by the structure of cerebral cortex of the brain. The duty and the work of neural, it could built large-sized and could teach the system for the lead gone are usable, especially, the principle works of neural, will find the weight value in work system of neural, then the comparison output beg for neural, that get with target value that fix. If the value output is not equal to target value, the system of neural will find the value of the weight until it reaches the value of output, the new substitute value is equal to target value. For the neural to be built give with the capability to learn. Must have input and output data to use in comparison, inspires the use ordered pairs in training network [11], and [12].

### A. Feed-forward Neural Networks

Feed-forward neural networks can be classified in a single layer or multilayer feed-forward neural networks. In this paper, only multilayer is considered. Multilayer FNN architecture comprises of input-layer(X); hidden-layer (H); and output-layer(Y); as shown in Fig. 1 [17].



Input - Layer Hidden - Layer Output - Layer  
 $X_i$  - input neurons;  $H_j$  - hidden neurons;  $Y_k$  - output neurons;  
 $IW_{ij}$  - input-hidden layer weights;  $LW_{jk}$  - hidden-output layer weights

Fig. 1 Multilayer Feed-forward neural network architecture

The FNN in Fig. 1 is based on connected neurons in a specified fashion which consists of  $n$  set input-layer (X);  $h$  set of hidden-layer (H) and  $o$  set of output-layer (Y). The hidden layer unit  $j$  receives input  $i$  through synaptic weights  $IW_{ij}$ ,  $i = 1, 2, \dots, n$ . Unit  $j$  computes a function of the input signal  $X_i$  and the weights  $IW_{ij}$ , and passes its output in the next successive layer and the equations are as shown in (1) and (2) [16] and [17].

Towards the hidden layer

$$net_j(t) = \sum_{i=1}^n x_i(t)IW_{ij} + \theta_j$$

$$y_j(t) = f(net_j(t)) \quad (1)$$

Away from the hidden layer

$$net_k(t) = \sum_{j=1}^k y_j(t)LW_{jk} + \theta_k$$

$$y_k(t) = f(net_k(t)) \quad (2)$$

where,

- $n$  is the number of inputs,
- $f$  is the layer output function (of any differentiable type)
- $\theta_j$  and  $\theta_k$  are the biases at the respective layers.

### B. Radial Basis Function Neural Network

Radial basis function neural network architecture consist of three layers: a input layer  $R^l$ , an hidden radial basis layer of  $S^1$  neurons, and an output linear layer of  $S^2$  neurons show in Fig 2.

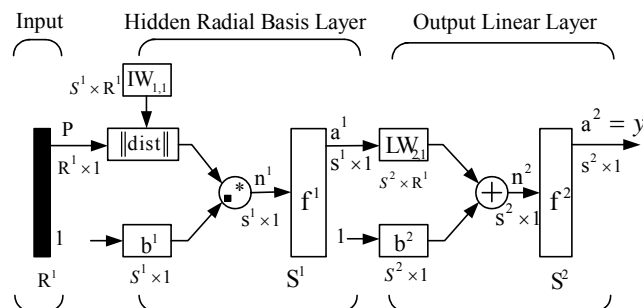


Fig. 2 Radial basis function neural network architecture

The input  $P$  and the input weight  $IW_{1,1}$ , and produces a vector having  $S^1$  elements. The elements are the distances between the input and  $IW_{1,1}$  formed from the rows of the input weight, will replace the  $dist$  and compute by euclidean norm,  $a^1$  to be output of radial basis hidden layer and to be input of output linear layer,  $a^2$  to be final output. Have  $f^1$  is radial basis transfer function, and  $f^2$  is linear transfer function.  $a^1, a^2$  can get from the algebraic equation as following could:

$$a^1 = f^1(\|IW_{1,1} - P\|b^1) \quad (3)$$

$$a^2 = f^2(LW_{2,1}a^1 + b^2) \quad (4)$$

Whereas:

- $IW_{1,1}$  ; weights value connections between input layer with radial basis hidden layer
- $LW_{2,1}$  ; weights value connections between radial basis hidden layer with output linear layer
- $b^1$  ; bias value in radial basis hidden layer
- $b^2$  ; bias value in output linear layer

Training neural network by radial basis transfer function ( $f^1$ ) with linear transfer function ( $f^2$ ) using neural network toolbox of MATLAB software [3]

Radial basis transfer function (radbas)

$$f^1[.] = radbas(n, b) = e^{-(n^2/b)} \quad (5)$$

Linear transfer function (purelin)

$$f^2[.] = a(n, b) = (n + b) \quad (6)$$

Whereas:

- $n$ ; summation output
- $b$ ; bias adjust.

### III. APPLICATION OF RADIAL BASIS FUNCTION NETWORK IN TRANSMISSION LINE PROTECTION

Fig.3 shows radial basis function neural network for transmission lines protection structure. Fig.4 the radial basis function neural network for classifying the input patterns into expected categories. There are three input signals required at the input layer in radial basis function neural network: V, I, and X. V is the voltage, I is the current, and X is the apparent impedance, the measurement of the faulted transmission line. The output consists of radial basis network which has a continuous value output in the region [0,1]. Output 1 indicates tripping, 0 indicates non-tripping.

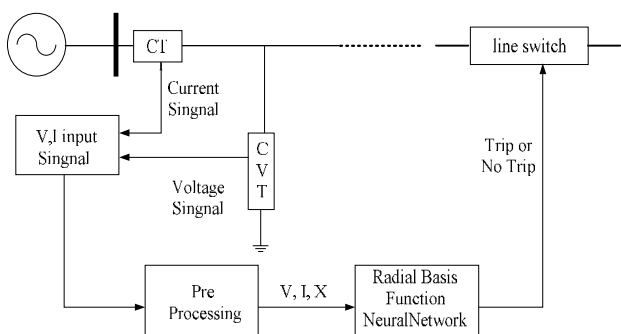


Fig. 3 Radial basis function neural network for transmission lines protection structure

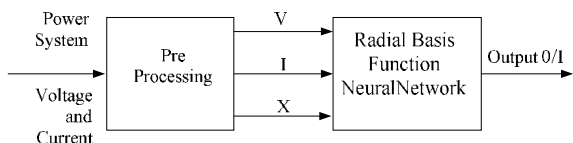


Fig. 4 Input patterns classify of radial basis function neural network

### IV. SIMULATION AND RESULT

Training patterns and test patterns got from fault simulation on transmission line of power system study using MATLAB and SIMULINK. Fig.5 depicts the 115 kV, 50 Hz simulated system one-line diagram. The other related parameters of the simulated system are shown in Table I.

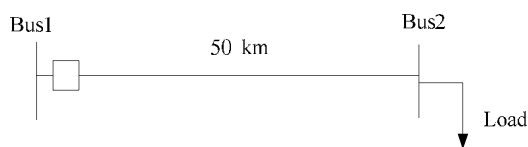


Fig. 5. One-line diagram of simulation system

The test will begin with fault occurrence simulation at the distance 0, 20, 40,60,80,84,88,92,96 and 100 % of the total line length. Every the distance fault occurrence has fault

resistance 0.000001,5,10, 15, 20, 25,30,35,40 and 50 ohms respectively. Already lead the data has that go to test with the radial basis neural network. Zone 1 protection is 80 % of the total line length. Fig. 6 shows the phase A-B-C current waveform, and the phase A-B-C voltage waveform for the three phase fault, the fault resistance is 5 ohms, at times 20ms - 60ms. Some part calculations of pattern data tests for the radial basis function neural network in case of fault resistance 5 ohms are shown in Table II. Accuracy transmissions line protections are show in Table III.

TABLE II  
 THE PARAMETERS OF THE SIMULATION TRANSMISSION SYSTEM

<b>Bus 1:</b>	Voltage 115 kV , 50 Hz
<b>Equivalent source impedance</b>	
	$Z1 = 0.00499 + j0.03384$ p.u. /km
	$Z0 = 0.00425 + j0.0369$ p.u. /km
<b>Length of transmission line: 50 km</b>	
<b>Line constant:</b>	
	$Z1 = 0.085811 + j0.36204$ p.u./km
	$Z0 = 0.25485 + j1.4223$ p.u./km
<b>Bus 2 :</b>	Load= 3.3+ j2.2 MVA

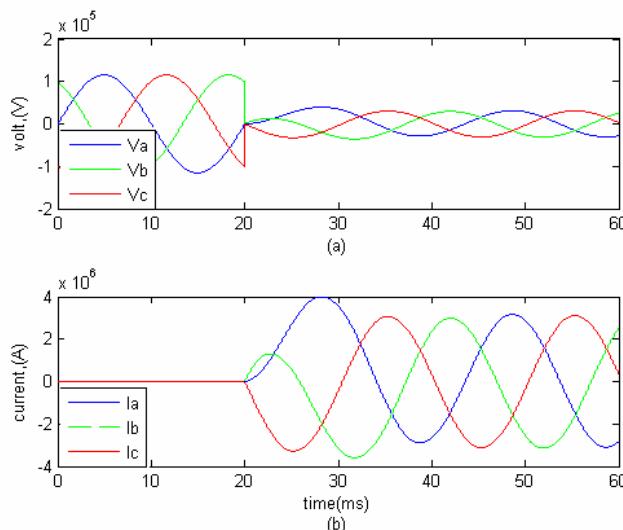


Fig. 6. Voltage and current waveform A-B-C fault

TABLE II  
 THE PATTERN DATA TESTS IN CASE OF A-B-C FAULT  
 FAULT RESISTANCE 5- OHMS

DISTANCE	MAGNITUDE VOLTAGE			MAGNITUDE CURRENT		
	VA	VB	VC	IA	IB	IC
%						
0	114760	114760	114760	30026	30026	30026
20	114680	114680	114680	19632	19632	19632
40	114750	114750	114750	13909	13909	13909
60	114810	114810	114810	10508	10508	10508
80	114850	114850	114850	8421	8421	8421
84	114860	114860	114860	8133	8133	8133
88	114860	114860	114860	7892	7892	7892
92	114870	114870	114870	7705	7705	7705
96	114870	114870	114870	7582	7582	7582
100	114870	114870	114870	7538	7538	7538

TABLE III  
ACCURACY TRANSMISSION LINE PROTECTION

DISTANCE(%)	ACCURACY(%)	ERROR(%)
0	100	0
20	100	0
40	100	0
60	100	0
80	100	0
84	85	15
88	100	0
92	100	0
96	100	0
100	100	0

### V. CONCLUSION

This paper analyzes and demonstrates the radial basis function neural network intelligent computational technique application associated with protective distance relay for transmission line protection. The method used is such that, the power system uses voltage and current signals to learn the hidden relationship existing in the input patterns. It is observed that the radial basis function neural network have ability to identify the precise fault direction and more rapidly. This makes it suitable for the real-time purposes. From testing it is correct in 85 transmission line percentage preventions, from the data tests 100 all the data set tests. Thus, radial basis function neural network with the ability to relay one type in transmission line prevention. Therefore radial basis function neural network could be used as an effective tool for real-time digital relaying purposes. This might allow distance relay work more accuracy and precision.

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### REFERENCES

[1] P.M. Anderson, *Power system protection*, McGraw-Hill, 1999.  
 [2] K. Warwick, A. Ekwue and R. Aggarwal, *Artificial intelligence techniques in power System*, London, Institution of Electrical Engineers, 1997  
 [3] H. B. Demuth, M. Beale, *Neural Network Toolbox for Use with MATLAB*, 1998.  
 [4] M. T. Hagan, H. B. Demuth, M. Beale, *Neural Network Design*, Oklahoma State University, 1996.  
 [5] W. Qi, G.W. Swift, P. G. McLaren, A. V. Castro, "An artificial neural network application to distance protection". International Conference on Intelligent Systems Applications to Power Systems, pp. 226-230,1996.  
 [6] D. V. Coury, D. C. Jorge, "Artificial neural network approach to distance protection of transmission lines". IEEE Transactions on Power Delivery, pp. 102-108, 1998.

[7] L. Wu, C. Liu, C. Chen, "Modeling and testing of a digital distance relay using MATLAB/SIMULINK". IEEE Trans. on Power Delivery, pp.253-259, 2005.  
 [8] A. Oonsivilai, and M.E El-Hawary, "Power system dynamic load modeling using adaptive-network-based fuzzy inference system Proceedings of the IEEE Canadian Conference on Electrical and Computer Engineering, pp 1217-1222, 1999.  
 [9] A. Oonsivilai, and M.E. El-Hawary, "Wavelet neural network based short term load forecasting of electric power system commercial load". Proceedings of the IEEE Canadian Conference on Electrical and Computer Engineering, pp. 1223-1228, 1999.  
 [10] A. Oonsivilai, and M. E. El-Hawary. "A self-organizing fuzzy power system stabilizer". Proceedings of the IEEE Canadian Conference on Electrical and Computer Engineering, pp. 197-200, Canada, 1999.  
 [11] A. Oonsivilai, R. Boonwuitiwat, T. Kulworawanichpong, and P. Pao-La-Or, "Artificial neural network approach to electric field approximation around overhead power transmission lines". EuroPes 2007.  
 [12] R. Oonsivilai, and A. Oonsivilai, "Probabilistic neural network classification for Model  $\beta$ -Glucan Suspensions". Proceeding of the 7<sup>th</sup> WSEAS Int. Conf. on Simulation, Modeling and Optimization, pp. 159-164, 2007.  
 [13] C. L. Wadhwa, *Electrical Power Systems*, Fourth Edition, New Age International, 2006.  
 [14] A. G. Phadke and J. S. Thorp, *Computer Relaying for Power Systems*, John Wiley & Sons, Ltd. 1988.  
 [15] A. A. Girgis and R. G. Brown, "Adaptive Kalman Filtering Computer Relaying: Fault Classification Using Voltage Models", *IEEE Transaction on Power Apparatus and System*, Vol. PAS-104, No. 5, pp. 1167-1177, May 1985.  
 [16] S. Rajasekaran and G. A. Vijayalakshmi Pai, *Neural Networks, Fuzzy Logic, and Genetic Algorithms: Synthesis and Applications*, Prentice-Hal Ltd., 2003.  
 [17] L. H. Tsoukalas, and A. U. R. Uhrig, *Fuzzy and neural in Engineering*, John Wiley and Sons, Inc., 1997.  
 [18] A. Oonsivilai., and B. Marungsri, "Application of artificial intelligent technique for partial discharges localization in oil insulating transformer". *WSEAS Transaction on Systems.. Issue 10, Vol 8, October, ISSN : 1109 - 2777*, pp: 920 -929,2008  
 [19] R. Oonsivilai, and A. Oonsivilai. "Apply a genetic algorithm to natural cheese product". Proceeding of the 8<sup>th</sup> WSEAS International conference on applied computer science (ACS'08). ISSN 1790 - 5109, pp: 269 - 274. 2008.  
 [20] A. Oonsivilai., and R. Oonsivilai, "A genetic algorithm application in natural cheese products". *WSEAS Transaction on Systems. Issue 1, Vol 8, January, ISSN : 1109 - 2777*, pp:44-54.,2009  
 [21] S. Saichoomdee, A. Oonsivilai ,B. Marungsri, T. Kulworawanichpong and P. Pao-La-Or. "Distance transmission lines protection based on recurrent neural network". International Conference on Science, Technology and Innovation for Sustainable Well-Being.(STISWB)., pp. 266-269. ,2009  
 [22] A. Oonsivilai and S. Saichoomdee "Appliance of Recurrent Neural Network toward Distance Transmission Lines Protection". IEEE TENCON '2009/Singapore ,2009