American Journal of Engineering and Applied Sciences, 2012, 5 (2), 157-162
ISSN: 1941-7020

doi:10.3844/ajeassp.2012.157.162 Published Online 5 (2) 2012 (http://www.thescipub.com/ajeas.toc)

Epoxy Insulators' Lifetime Prediction Implementing Neural Network Technique

[1]Nasrat, L.S. and [2]A.M. Ibrahim

[1]Department of Electrical Power and Machines,
Faculty of Engineering, South Valley University, Aswan, Egypt
[2]Department of Electrical Power and Machines,
Faculty of Engineering, Ain Shams University, 1 El-Sarayat St, Abbassia, Cairo, Egypt

Received 2012-05-26, Revised 2012-08-07; Accepted 2012-08-07

ABSTRACT

Due to wide implementation of Epoxy insulators in industrial applications and its economic implications; development of various Epoxy insulator materials has to be evaluated along with a reliable prediction methodology of their lifetimes. In this study, a new methodology based on Artificial-Neural-Networks (ANN) is developed to predict Epoxy insulators lifetime using laboratory measurements of their surface leakage current under accelerated aging. The effect of adding fillers with various concentration rates to the Epoxy insulators such as; Calcium Silicate ($CaSiO_2$), Mica and Magnesium Oxide ($Mg(OH)_2$) on their lifetimes is compared with the base case (no filler and dry condition). Furthermore, the lifetime of each specimen under study is examined under various weather conditions such as dry, wet, salt wet (NaCl) and hydro carbon solvent Naphtha. The obtained results are weighing against the experimental measured data based on two ANN techniques; i.e., Feed-Forward-Neural-Network (FNN) and Recurrent-Neural-Network (RNN). The results obtained from the FNN and RNN are compared to validate the proposed methodology to predict the lifetime of epoxy insulators in terms of the type and percentage concentration of filler. The obtained Epoxy insulators predicted lifetime under various filler concentrations and weather conditions are compared and conclusions are reported.

Keywords: Recurrent-Neural-Network (RNN), Feed-Forward-Neural-Network (FNN), Artificial-Neural-Networks (ANN), Processing Elements (PE)

1. INTRODUCTION

Electrical aging of polymer insulated materials is still poorly known phenomena and the physical sense of the various parameters involved in the aging models is far from being obvious (Crine, 2007; 2005). Polymeric insulators have been worldwide applied, due to their lightweight, excellence in mechanical strength and possess superior contamination performances compared with the conventional porcelain or glass (Izumi *et al*., 2000). However, the long-term characteristics of the mechanical, electrical and contamination characteristics of the material have not been sufficiently clarified and the establishment of its assessment and diagnostic methods is desired (Hackam, 1998). Both the mechanical and electrical properties of polymers can be further improved or modified by the addition of inorganic fillers. These fillers increase the mechanical strength and change the electrical properties of the composites (Brosseu *et at*., 2001; Ng *et al*., 2001).

Polymers are considered to be good insulating materials due to their stable physical and chemical properties (Ieda *et al*., 1994). The most commonly used thermoset plastic in polymer matrix composites are epoxy resins due to their good properties on curing and commonly used as coatings and composite matrices (Ellis, 1993). However, the current problems in engineering applications of epoxy thermosets include low stiffness, strength and the exothermic heat generated by the curing of epoxy resins that causes serious processing difficulties (Dean *et al*., 2003). These characteristics can be further improved by adding inorganic fillers that increase the mechanical strength and change the electrical properties of the composites (Ng *et al*., 2001). Therefore, additives are often used to modify the properties and characteristics of materials that include diluents, fillers, modifiers, flame retardants, antioxidants, or plasticizers. Recently, many investigators reported that the incorporation of inorganic fillers into the epoxy resins exhibits good electrical and thermal stability.

Despite of the gained benefits by adding fillers, electrical aging of polymer insulated materials is still poorly known phenomena and the physical sense of the various parameters involved in the aging models is far from being obvious (Crine, 2007). Polymeric insulators possess superficial chemical changes caused by weathering and dry band arcing, erosion and tracking, which may ultimately lead to failure of the insulators (Gorur *et al*., 1988), difficult to evaluate service life, unknown reliability and difficult to detect faulty insulators. During normal dry conditions, the electrostatic field determines the voltage distribution of dry insulator and very small capacitive leakage current flows across the entire insulator. On the other hand, during wet conditions, the insulator's resistive surface leakage current is much higher than that of the dry insulator condition. Furthermore, the leakage current increases with increasing contaminant flow rate, with other conditions, due to the increased loss of hydrophobicity as well as reduced the surface resistivity of the insulator (Kindersberg *et al*., 1996). Therefore, the long-term characteristics of the mechanical, electrical and contamination characteristics of the material have not been sufficiently clarified and the establishment of its assessment and diagnostic methods is desired (Kim and Hackam, 1995). In the last two decades, a vareity of prediction models have been proposed in the literatures that include time-series models, regression models, artifitial neural network models, adaptive neuro-fuzzy interface system and support vector machine models (Gensoglu and Uyar, 2009).

In order to determin the flashover behaviour of polluted high voltage insulators, the researchers have been brought to establish a modeling using artifitial neural networks (Gencoglu and Cebeci, 2009). This research work aims to predict the lifetime of Epoxy insulators with different compositions of various fillers. It focuses on estimating an appropriate percentage concentration of filler such as; $CaSiO_2$, Mica and $Mg(OH)_2$ which produces enhancements of the epoxy lifetime under dry condition. The effect of contamination conditions such as; wet, NaCl and Naphtha on the lifetime prediction of epoxy insulators and composites is evaluated. A reliable FNN methodology has been proposed and developed to estimate the insulator lifetime using experimental data of insulator's leakage currents as a function of for various epoxy samples with different types and concentrations of filler under various reagent conditions. The obtained results are verified with various sets of experimental data. Conclusions and recommendations are reported for the test samples under study.

2. MATERIALS AND METHODS

2.1. Modeling Techniques using ANN

Artificial Neural Networks (ANN) are defined in (Tsoukalas and Uhrig, 1997; Rajasekaran and Pai, 2004) 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. They can be used to solve complex and nonlinear engineering problems by learning from previous experience, without looking for complex mathematical relationships between inputs and outputs. Once a neural network with an appropriate input and output signals is trained, it will contain the non-linearity of the desired mapping in the neural network, avoiding the knowledge of complex non-linear relationships (Oonsivilai *et al*., 2007; Oonsivilai and Oonsivilai, 2007).

2.2. Recurrent Neural Network (RNN)

2.3. Feed-Forward Neural Network (FNN)

FNN can be classified into a single layer or multilayer Neural Networks. In this study, only multilayer FNN architecture is used. It consists of n set input-layer (X); h set of hidden-layer (H) and o set of output-layer (Y) as shown in **Fig. 1**. The hidden layer unit j receives input i through synoptic weights IW_{ij}. Unit j computes a function of the input signal X_i and the weights IWij and passes its output in the next successive layer using (1) and (2) (Tsoukalas and Uhrig, 1997; Rajasekaran and Pai, 2004). 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:

$$net_k(t) = \sum_{j=1}^{k} y_i(t) LW_{jk} + \theta_k$$
$$y_k(t) = f(net_k(t)) \quad (2)$$

Where:

X_i, H_j, Y_k = Input, hidden and output neurons respectively

IW_{ij} and LW_{jk} = Input-hidden and hidden-output layer weights respectively

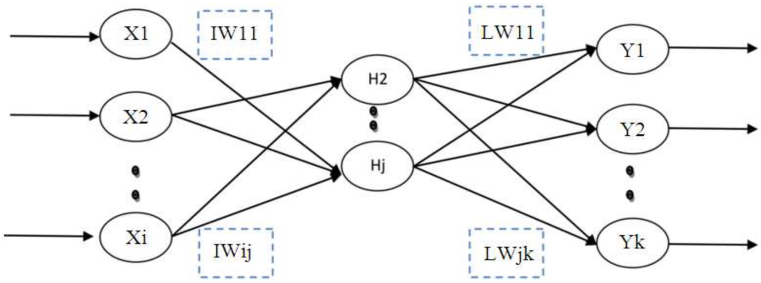

Fig. 1. Multilayer FNN architecture

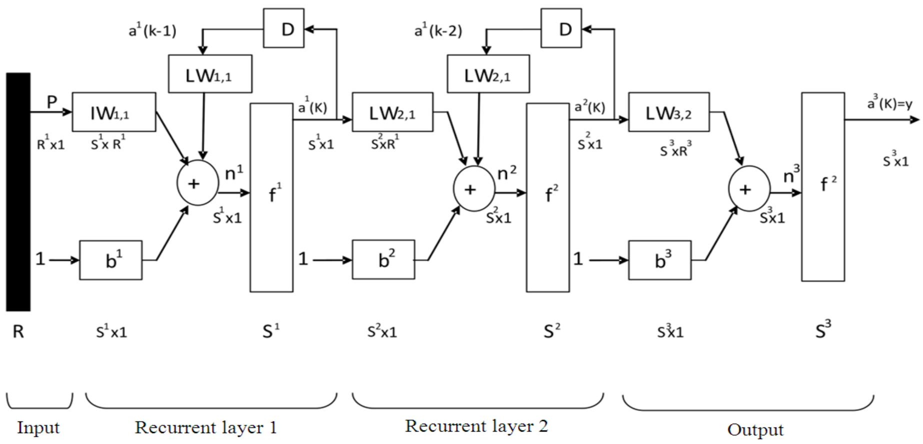

Fig. 2. Recurrent neural network structure

N	=	The number of inputs
F	=	The layer output function (of any differentiable type)
θ_j and θ_k	=	The biases at the respective layers

2.4. Recurrent Neural Network (RNN)

Recurrent network is the connections interval neural in feedback shown in **Fig. 1** by connecting the output of one or more Processing Elements (PE) in the same or preceding layers. **Figure 2** shows RNN's structure; Input patterns have P_1, P_2… P_R, (R= number of elements in input layer). $a^1(k)$ is output of hidden layer 1and input of hidden layer 2, $a^2(k)$ is output of hidden layer 2 and $a^3(k)$ is final output. Have f^1, f^2 and f^3 are transfer function, $a^1(k)$, $a^2(k)$ and $a^3(k)$ can be calculated from the algebraic equation as follow Eq. 3-5:

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

$$a^2(k) = f^2(LW_{2,1}a^1(k) + LW_{2,11}a^2(k-1) + b^2) \quad (4)$$

$$a^3(k) = f^3(LW_{3,2}a^2(k) + b^3) \quad (5)$$

Where:

$IW_{1,1}$	=	Weights value connections between input layer 1 with hidden layer 1
$LW_{2,1}$	=	Weights value connections between hidden layer 1 with hidden layer 2
$LW_{3,2}$	=	Weights value connections between hidden layers 2 with output layer 3
b^1, b^2 and b^3	=	bias values in hidden layers 1 and 2 and output layer 3 respectively.

Training neural network by gradient descent algorithm with tan-sigmoid transfer function using neural network toolbox of MATLAB software:

$$f[\times] = \text{logsig}(n, b) = \frac{1}{1 + e^{-(n+b)}}$$

Where as:
N = Summation output
B = Bias adjust.

2.5. Experimental Tests

2.6. Material Under Study

Epoxy material without/with three types of fillers ($CaSiO_2$, Mica and $Mg(OH)_2$) with various percentages are laboratory tested. The chosen Epoxy resin under study is the commercially available Araldite resin system which consists of an Epoxy resin Araldite CY231 and an anhydride hardener. A chemical preparation is laboratory carried out to add various filler percentage to the Epoxy specimen to obtain good homogeneity of filler in Epoxy samples by weight as shown in **Table 1**.

Ten material samples were laboratory prepared and tested under four different conditions such as; dry, wet, NaCl and Naphtha conditions. The samples are made of cylindrical rods having 12 mm diameter and 100 mm long. Two copper electrodes have been fixed into the samples, one at the top and the other at the bottom.

2.7. Set up Test

The applied voltage under this study is obtained from a single phase high voltage transformer (150kV-15 kVA). An autotransformer is used to adjust the primary voltage of the AC test system smoothly. The applied voltage under this study between two copper electrodes is adjusted to be 20 kV. The applied voltages are measured throughout a digital measuring instrument DMI551. The surface leakage current (mA) measurements are performed by means of a special system, which can register time variations of a voltage drop across a shunt resistor, supply voltage and phase shift between them.

3. RESULTS

3.1. Experimental Results

The lifetimes to reach complete breakdown for epoxy samples without/with the three types of fillers and various percentages under study were experimentally measured as given by **Table 2**. Results show that the lifetime of epoxy samples under dry test scenario condition are the highest among the samples' corresponding other test scenarios under study. Among the different samples of the dry test scenario, the no-filler sample has the highest lifetime up to 161 hrs.

3.2. Prediction of Lifetime by Neural Network for Epoxy Insulators

Experiments are performed on real time basis dataset that consists of ten samples with different filler percentages and types. Each of the ten materials is tested under four different conditions (dry, wet, NaCl and naphtha). In each case, an electric current is applied and recorded at different times. Our aim is to predict the lifetime epoxy insulators.

Table 1. Epoxy Insulators with various Filler Materials under study

Filler	No Filler	Ca SiO_2			Mica			$Mg(OH)_2$		
Sample code	W	C1	C2	C3	M1	M2	M3	G1	G2	G3
Filler Rate (%)	0	25	40	50	25	40	50	20	25	30

Table 2. Experimental Epoxy insulators Lifetime (hrs) with various filler concentrations and test scenarios under study

	No filler	$CaSiO_3$			Mica			$Mg(HO)_2$		
Scenario-I: Dry Test	W	C1	C2	C3	M1	M2	M3	G1	G2	G3
Epoxy insulators Lifetime (hrs)	161.00	149.00	130.00	109.00	84.00	106.00	140.00	70.00	62.00	59.00
Lifetime Portion of the Base Case (p.u.)	1.00	0.88	0.81	0.68	0.52	0.66	0.87	0.43	0.39	0.37
Scenario-II: Wet Test	103.00	110.00	88.00	65.00	51.00	62.00	91.00	48.00	39.00	37.00
Lifetime Portion of the Base Case (p.u.)	0.64	0.68	0.55	0.4	0.32	0.39	0.57	0.3	0.24	0.23
Scenario-III: Naph Test	60.00	78.00	69.00	62.00	33.00	43.00	50.00	30.00	24.00	20.00
Lifetime Portion of the Base Case (p.u.)	0.37	0.48	0.42	0.39	0.2	0.27	0.31	0.19	0.15	0.12
Scenario-VI: NaCl Test	49.00	68.00	60.00	53.00	25.00	31.00	37.00	23.00	15.00	12.00
Lifetime Portion of the Base Case (p.u.)	0.30	0.42	0.37	0.33	0.16	0.19	0.23	0.14	0.09	0.07

Table 3. FNN and RNN accuracy (%) for predicting Epoxy insulators Lifetime with various filler concentrations and test scenarios under

	No Filler	$CaSiO_3$			Mica			$Mg(HO)_2$		
ANN	W	C1	C2	C3	M1	M2	M3	G1	G2	G3
Scenario-I: Dry Test										
FNN	99.86	98.57	97.67	99.95	95.27	94.46	94.99	90.0	96.95	84.82
RNN	99.78	98.63	98.82	99.29	98.76	97.69	98.85	98.6	99.31	96.06
Scenario-II: Wet Test										
FNN	99.73	98.50	96.83	98.95	98.63	98.68	99.51	85.94	95.09	71.97
RNN	99.46	97.76	97.18	97.94	98.99	99.40	99.67	98.97	95.85	82.63
Scenario-III: Naph Test										
FNN	83.78	90.40	94.98	94.92	90.94	93.14	86.14	97.97	83.49	68.80
RNN	94.29	86.38	98.54	98.26	93.42	90.05	98.72	94.21	83.54	76.28
Scenario-VI: NaCl Test										
FNN	91.95	99.03	87.56	91.83	78.10	90.86	96.34	87.12	80.18	41.67
RNN	70.09	88.02	87.24	89.48	78.44	90.29	99.33	97.92	81.17	41.67

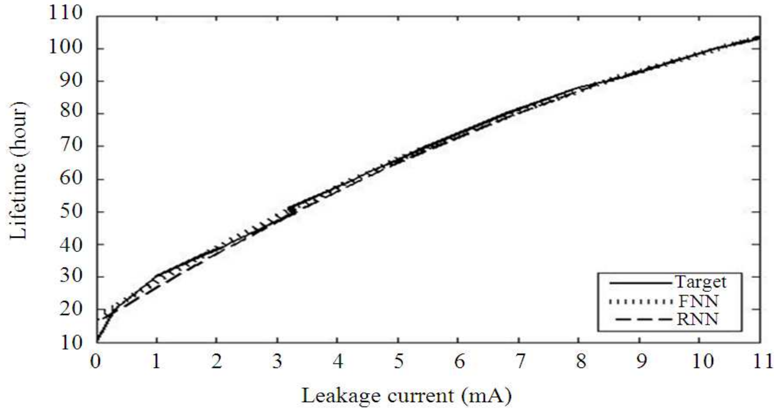

Fig. 3. Prediction of FNN outputs and RNN outputs for Epoxy Insulator without Filler under Wet Test Scenario

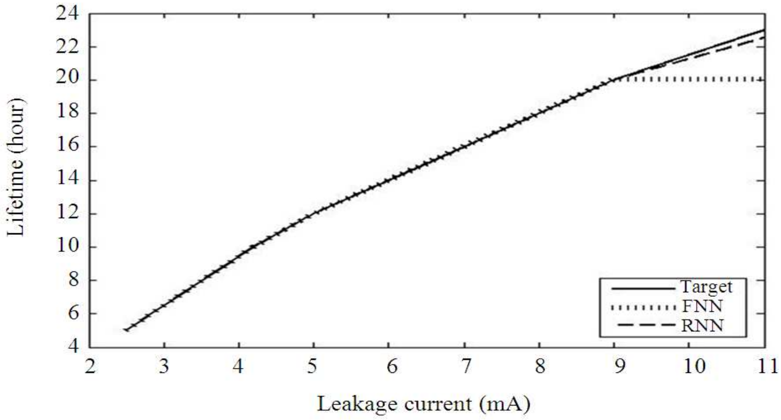

Fig. 4. Prediction of FNN outputs and RNN outputs for Epoxy Insulator with Mg(OH)2 Filler under NaCl Test Scenario

Both FNN and RNN are applied in order to predict the lifetime of epoxy insulators. Each has three layers (input, hidden and output). The inputs to the ANN are chosen so that they consist of the weather conditions, types of filler, concentration rates of fillers and the leakage currents at different times. ANN has only one output, which predicts the lifetime of epoxy insulators. A tan-sigmoid function producing outputs in the range of [-1, 1] is used as a transfer function for each neuron in the hidden layer while linear transfer function is used for the output layer.

The dataset is split into training and test sets; 90% of the training set is kept for training the neural network while 10% is used as validation set. Neural networks with one hidden layer are used with five hidden neurons. The neural network that produces the best accuracy on the validation set among the runs is chosen for prediction. The learning factor, which controls the rate of convergence and stability, is chosen to be 0.05. The training process is preceded until the average error between the actual output and the desired output reaches an acceptable value, which is taken to be 0.001. **Table 3** summarizes the percentage accuracies of different contamination conditions and fillers for FNN and RNN.

Figure 3 and 4 display how the outputs generated by FNN and RNN fit the target outputs. It is noticed that in most cases, FNN perform well as shown in **Fig. 3**. But for more complex curves as in **Fig. 4**, the resulted outputs don't fit the target outputs in some intervals.

4. DISCUSSION

Based on the experimental measurements, it is noticeable that, increasing the concentration % of both $CaSiO_3$ and $Mg(HO)_2$ fillers, decrease the sample's lifetime. On the contrary, increasing the concentration % of Mica filler increases its lifetime.

A comparison between RNN and FNN shows that, RNN has higher performance than FNN, in general. RNN gives an accuracy (number of correct decisions of testing cases/total number of testing cases *100) of 99% in the testing phase while using FNN gives 97%.

5. CONCLUSION

In this study, the leakage current of Epoxy material is estimated under accelerated aging. Surface aging of epoxy samples is investigated under different conditions. The effects of adding different fillers to the epoxy resin on the electrical performance of epoxy insulators are studied. From the experimental work it has been found that the suitable percentage of filler added to the epoxy specimens is 25% of calcium silicate under the different environmental conditions (NaCl and naphtha).

FNN is compared with RNN for similar samples to predict the lifetime of epoxy insulators in terms of the type and percentage concentration of filler. It is applied to real world datasets. The FNN showed a good performance on most of the datasets. The obtained results from RNN showed higher accuracy than those obtained using FNN.

6. REFERENCES

Brosseu, C., P. Queffelec and P. Talbot, 2001. Microwave characterization of filled polymers. J. Applied Phys., 89: 4532-4540. DOI: 10.1063/1.1343521

Crine, J.P., 2005. On the interpretation of some electrical aging and relaxation phenomena in solid dielectrics. IEEE Trans. Dielec. Elect. Ins., 12: 1089-1107. DOI: 10.1109/TDEI.2005.1561789

Crine, J.P., 2007. A molecular model for the electrical aging of XLPE. Proceedings of the Annual Report-Conference on Electrical Insulation and Dielectric Phenomena, Oct. 14-17, IEEE Xplore Press, Vancouver, BC., pp: 608-610. DOI: 10.1109/CEIDP.2007.4451572

Dean, J.M., N.E. Verghese, H.Q. Pham and F.S. Bates, 2003. Nanostructure toughened epoxy resins. Macromolecules, 36: 9267-9270. DOI: 10.1021/ma034807y

Ellis, B., 1993. Chemistry and Technology of Epoxy Resins. 1st Edn., Blackie Academic and Professional, London, ISBN-10: 0751400955, pp: 332.

Gencoglu, M.T. and M. Cebeci, 2009. Investigation of pollution flashover on high voltage insulators using artifitial neural network. Exp. Syst. Appli., 36: 7338-7345. DOI: 10.1016/j.eswa.2008.11.008

Gensoglu, M.T. and M. Uyar, 2009. Prediction of Prediction of flashover voltage of insulators using least squares support vector machines. Exp. Syst. Appli., 36: 10789-10798. DOI: 10.1016/j.eswa.2009.02.021

Gorur, R.S., E.A. Cherny, R. Hackam and T. Orbeck, 1988. The electrical performance of polymeric insulating materials under accelerated aging in a fog chamber. IEEE Trans. Power Deli., 3: 1157-1164. DOI: 10.1109/61.193898

Hackam, R.H., 1998. Outdoor high voltage polymeric insulators. Proceedings of the International Symposium on Electrical Insulating Materials, Sep. 27-30, IEEE Xplore Press, Toyohashi, pp: 1-16. DOI: 10.1109/ISEIM.1998.741674

Ieda, M., M. Nagao and M. Hikita, 1994. High-field conduction and breakdown in insulating polymers. Present situation and future prospects. IEEE Trans. Dielect. Elect. Ins., 1: 934-945. DOI: 10.1109/94.326660

Izumi, K., T. Takahashi, H. Homma and T. Kuroyagi, 2000. Development of line post type polymer insulation arm for 154 kV. IEEE Trans. Power Deliv., 15: 1304-1310. DOI: 10.1109/61.891519

Kim, S.H. and R. Hackam, 1995. Effects of saline-water flow rate and air speed on leakage current in RTV coatings. IEEE Trans. Power Deliv., 10: 1956-1964. DOI: 10.1109/61.473357

Kindersberg, J., A. Scutz, H.C. Karner and R.V. Huir, 1996. Service performance, material design and applications of composite insulators with silicone rubber housings. CIGRE 33-303.

Ng, C.B., B.J. Ash, L.S. Schadler and R.W. Siegel, 2001. A study of the mechanical and permeability properties of nano- and micron- TiO_2 filled epoxy composites. Adv. Compos. Lett., 10: 101-111.

Oonsivilai, A., R. Boonwuitiwiwat, T. Kulworawanichpong and P. Pao-La-Or, 2007. Artificial neural network approach to electric field approximation around overhead power transmission lines. ACTA Press.

Oonsivilai, R. and A. Oonsivilai, 2007. Probabilistic neural network classification for model β-Glucan suspensions. Proceedings of the 7th WSEAS International Conference on Simulation, Modelling and Optimization, (SMO' 07), ACM Press, Wisconsin, USA., pp: 159-164.

Rajasekaran, S. and G.A.V. Pai, 2004. Neural Networks, Fuzzy Logic and Genetic Algorithms: Synthesis and Applications. 1st Edn., Prentice-Hall of India, New Delhi, ISBN-10: 8120321863, pp: 456.

Tsoukalas, L.H. and R.E. Uhrig, 1997. Fuzzy and Neural Approaches in Engineering. 1st Edn., John Wiley and Sons Inc., New York, ISBN-10: 0471160032, pp: 587.