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ANN APPROACH BASED STUDY TO PREDICT THE MECHANICAL PROPERTIES OF COPPER POWDER FILLED LLDPE COMPOSITES

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ABSTRACT

The effective mechanical properties of copper powder filled with linear low-density polyethylene (LLDPE) are studied by using artificial neural network (ANN) approach. It is a form of artificial intelligence, which deal with the function of human brain and nervous system. ANN technique is more important in many fields of engineering and research applications. This report presents the use of ANN technique for the accurate prediction of mechanical properties of copper powder filled LLDPE composites. ANN is based on Feed Forward Back Propagation (FFBP) using three different training functions (TRAINGDA, TRAINGDM, and TRAINGDX). The input parameters manipulated for prediction are Elongation at break, Stress at break, Young's modulus, volume fraction of the filler and many types of K constants. Copper filled with LLDPE have complex structure which is difficult to predict mechanical properties accurately. This prediction is done using ANN approach. Theoretical model is being compared with experimental data and found that comparison is in good agreement.

Keywords: Artificial Neural Network, Feed Forward Back Propagation, Training functions, Volume Fraction, Composite Materials.

1. INTRODUCTION:

Computer based modeling technique is extensively useful in science and engineering research during in these days. Polymer composites have been widely used due to their interesting properties, including cost effectiveness, low density, high specific strength, high correction resistance and ease of fabrication as well as their availability as renewable resources and potential. Anand R.

Sanadi et. al. [1] studied the mechanical properties of kenaf– PP composites have been evaluated. The effect of the fiber content on the tensile, flexural, and impact properties of the composites was determined. The use of a maleated PP to improve the fiber-matrix znteraction and adhesion has been discussed in regards to why and how they function to improve properties. By J. F. Chen et.al. [4] Presented a review of anchorage behavior under single/double shear tests and available shear anchorage strength models in the literature. These models are then assessed with experimental data collected from the literature, revealing the deficiencies of all existing models. Finally, a new simple, rational, and accurate design model is proposed based on an existing fracture mechanics analysis and experimental observations. K. Van de Velde et.al. [6] Investigated to assess the most suitable matrix polymer, one must know the properties of the available polymers. Since data tend to be widely scattered over many sources and are very scarce compared to the conventional polymers. M.E.Gomes et.al. [10] investigated to develop several methods based on conventional processing techniques and combined techniques, such as solvent casting and compression with salt leaching, were developed in order to obtain porous structures from starch based polymers that are suitable for bone tissue engineering applications. Ye.P. Mamunya et.al. [11] Studied about the filling of a polymer with metallic particles results in an increase of both electrical and thermal conductivity of the composites obtained. Nevertheless, only in a few papers the electrical and thermal properties of such two-phase systems are ompared with each other. D. Metın, et.al. [12] Investigated to improve the mechanical properties of the PP–zeolite composites by enhancement of the interphase and to analyse the interfacial properties of the composites quantitatively from the mechanical results. B. Alcock et.al. [19] Introduced all-polypropylene composites and reports the tensile and compressive properties of unidirectional composites. These composites show good retention of tape properties despite the relatively high temperatures used in composite manufacture.. The creation of highly oriented, co-extruded polypropylene (PP) tapes allows the production of recyclable „all-polypropylene‟ composites, with a large temperature processing window (O30 8C) and a high volume fraction of highly oriented PP (O90%). These composites show little deviation of mechanical properties with compaction temperature. A.S. Luyt et.al. [20] Investigated the thermal, mechanical and electrical properties of copper powder filled polyethylene composites. The influence on these properties of the amount of copper powder in the polymer matrix is discussed. Metal filled polymer composites are widely used for electromagnetic interference shielding. They have a lighter weight than metals and are less costly. The physical properties and the percentage of the filler materials must be known in order to determine the usefulness of the materials. It is therefore important, from a scientific and practical point of view, to understand the effects of metallic filler on the properties of a polymer matrix. G. Bogoeva-Gaceva et.al. [25] Observed to present a brief review of the most suitable and commonly used biodegradable polymer matrices and NF reinforcements in eco composites, as well as some of the already produced and commercialized NF eco composites. Xue Li et.al. [26] studied about the different chemical modifications on natural fibers for use in natural fiber-reinforced composites is reviewed. Alireza Ashori et.al. [27] Investigated the easibility of using recycled high density polyethylene (rHDPE), polypropylene (rPP) and old newspaper (rONP) fiber to manufacture experimental composite panels. Martin Claude Ngueho Yemele et.al. [28] investigated the potential of bark from two species for the production of wood–plastic composites. The specific objectives were to study the effects of wood species, bark content, and size on the flexural and tensile properties of extruded bark-high density polyethylene (HDPE) composites; and to compare the composite properties to a control made with wood floor. A.P. Martinez-Camacho et.al. [29] observed to assess the thermal, spectroscopic and mechanical properties, as well as the antifungal activity of chitosan films, plasticized and non-plasticized, prepared by casting, Most of the mechanical properties of chitosan films are comparable to those of commercial polymers of medium strength such as cellulose. Singh et.al.[32] recently used an ANN and adaptive neuro fuzzy interface system in the study of the thermal conductivity of rocks through physico mechanical properties.

2. Theoretical Model:

From previous two decades, various theoretical models have been described to calculate the mechanical properties (elongation at break, stress at break, and young's modulus) of two phase and multiphase composites. Two mathematical models have been considered for prediction of elongation at break of polymer composites by using the equations for powder-filled composites:

$$\delta_c/\delta_p=(1-K_3\phi^{1/3}) \tag{1}$$

$$\delta_c/\delta_p=(1-K_4\phi^{2/3}) \tag{2}$$

Where δc is the elongation of the composite, δp is the elongation of the polymer, ϕ is the volume fraction of the filler, and K3 and K4 are constant depending on the dimension of dispersed particles and on the treatment applied to them (K3=0.9, K4=1.5) [1,18]. The commonly two mathematical expressions of tensile stress at break that define the dependences on the configuration of two phase composites and which are based on the first power law and two-third power law are

$$\rho_c/\rho_p=(1-\phi) \tag{3}$$

$$\rho_c/\rho_p=(1-\phi^{2/3}) \tag{4}$$

Where ρc is the tensile stress at break of the composite, ρp is the tensile stress at break of the polymer, and ϕ is the volume fraction of the filler. The power laws are derive from the current relation between the area fraction and volume fraction of the enclosure [19], [20].the first law relationship for the case of spherical enclosures and the two-third power law with suitable weighting factor can be used for simple mathematical consideration of a completely random distribution of the dispersed phase. The following four mathematical models were used:

$$\rho_c/\rho_p=(1-\phi)K_c \tag{5}$$

$$\rho_c/\rho_p=(1-\phi^{2/3})K_d \tag{6}$$

$$\rho_c/\rho_p=(1-K_e\phi^{2/3}) \tag{7}$$

$$\rho_c/\rho_p=\exp(K_f\,\phi) \tag{8}$$

This mathematical model equation describes the structure of no adhesion type. In the first power law equation (5) the parameter Kc accounts for the weakness in the structure presented through discontinuity in stress transfer or formation of stress concentration indicates the filler-polymer interface, similarly with the parameter Kd in the eq. (6) [19], [20]. The weighting factor Ke shows the quality of the connection between the polymer matrix and fillers and also represents the stress concentration. If the value of stress concentration is higher than the value of K_e will be higher [8]. Various empirical and theoretical models have been suggested to predict young's modulus for polymer composites with dispersed fillers. Reviews of many of these models are given by eq. (9) [3], eq. (10) [10], eq. (11) [19], eq. (12) [19] and others eq. (13), and eq. (14). Einstein model may only be appropriate for the polymer composite filled with low amounts of no interactive spherical particles in the existence of a perfect bonding between the phases. This model indicates the reinforcing action of filler will not dependent on the filler particle size [19], [3], [4].

$$Y_c/Y_p=1+2.5\phi \tag{9}$$

The improved form of Einstein model [19];[3];[22] for the increasing modulus due to rigid pherical filler, also higher filler concentrations are being applicable for the collaboration between particles, is due to [10] and [23]:

$$Y_c/Y_p=1+2.5\phi+14.1\phi^2 \tag{10}$$

Thomas‟s model [19] represents an observed relation based on the data created by a system with monodisperse spherical particles:

$$Y_c/Y_p=1+2.5\phi+0.00273\{\exp(16.6\phi)\} \tag{11}$$

Quemada‟s model [19] uses a variable coefficient Kg = 2.5 that prove the difference between the interaction of particles and their geometrical shapes:

$$Y_c/Y_p=1/9(1-0.5K_g\phi)^2 \tag{12}$$

The above models [19] are used to calculate young's modulus of two phase systems, which are dependent on the volume fraction of filler particles. Eq. (14) is the improved form of eq. (13):

$$Y_c/Y_p=1-\phi^{2/3} \tag{13}$$

$$Y_c/Y_p=1-\phi^{2/3}/1-\phi^{2/3}+\phi \tag{14}$$

Here Yc is young's modulus of the composite material, Yp is young's modulus of the polymer, and ϕ is the volume fraction of the filler contents [19].

3. Artificial Neuron Network:

An artificial neuron network is a mathematical model which is designed to mimic the functioning of human brain. Base for structuring of artificial neuron network is biological neuron network structure. Basic unit for structuring of ANN is neurons which equally pretend the structure and functioning of biological neuron network. These neurons are interconnected and exchange messages between each other.

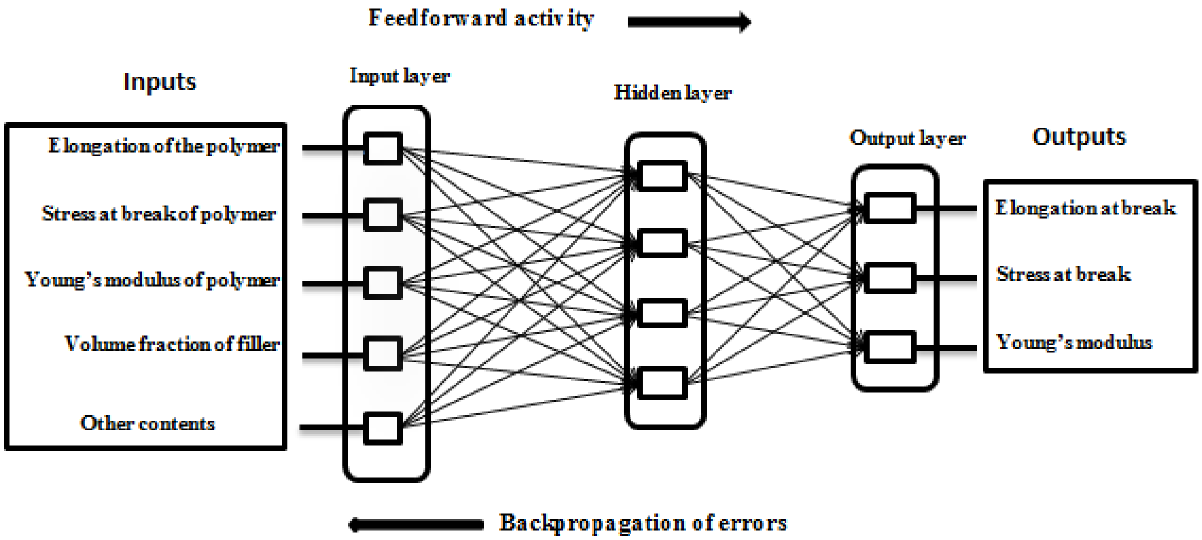

Figure 3.1 Artificial Neural Network (ANN)

Artificial neuron network consist of three layers named as input layer, output layer and hidden layer. Input layer is for receiving the messages and transmit them to hidden layer. Then hidden layer will function on the information and then process it to output layer. Several hidden layers can be put in between the output and input layers. Output layer will give a meaningful output for input to the external world.

3.1 Types of Artificial Neuron Network:

Artificial neuron network is classified into two types:

3.1.1 Feed forward Neural Network

3.1.2 Recurrent Neural Network

3.1.1 Feed forward Neural Network:

Feed forward neuron network is simplest artificial neuron network. Feed forward network contains three layers: input layer, output layer, and hidden layer. The signal given to the feed forward neural network will possess in only one direction. Data given to the input layer, this input data will process to the hidden layer and calculation is being processed. Each processing element makes its calculation established upon a weighted sum of its inputs. This output of one given to the next loop. There are further two types for feed forward neural network:

3.1.1.1 Single layer feed forward neural network

3.1.1.2 Multi-layer feed forward neural network

3.1.1.1 Single Layer Feed forward Neural Network:

Single layer feed forward neural network have direct connection between input and output layer. In single layer, the input source is projected into the output source but not vice-versa. The output is calculated in each neuron mode. There is no feedback in single layer feed forward neural network.

3.1.1.2 Multi-layer Feed forward Neural Network:

As the name indicates, multi-layer feed forward neural network is the network having multi-layer of hidden layer in between the input layer and output layer. There can be one or more hidden layer between the input and output layer. The source node in the network gives input to the input layer which further transmits the input to the hidden layer. Hidden layer will process given input and give suitable output for the network. This output from first hidden layer will be the input for the second hidden layer and the output from second will be the input for third layer and so on. The set of these output signals will be the output for the whole feed forward neural network. This multi-layer feed forward neural network have two types of connections first is partially connected and second one is fully connected.

Backpropagation:

Backpropagation is backward propagation of errors to the initial input until we get exact value with minimum error. Backpropagation is method commonly used to train a neural network. When input is applied to artificial neural network, then we do not have correct output. There will be some error in output given by ANN. This value further given to input again, it will make output near exact value. This process is being repeated again and again to find out the correct value. By using Backpropagation repeatedly, the connection in between the layers can be adjusted to give the better performance. Repeating the cycle in large number, the probability of error will be small and we get correct calculation with negligible error. PURLIN function is given as:

$$X_k = Y_k \tag{15}$$

A non-linear function TANSIG given as:

$$X_k = \frac{2}{[1+\exp(-2Yk)]-1} \tag{16}$$

The back propagation algorithm can be explained in following steps:

- All threshold values and weights are set within limit of small random values.
- Present input is represented as $Y_k = y_0, y_1, y_2 \dots y_{p-1}$, and required output is represented by $O_k = o_0, o_1, o_2 \dots o_{r-1}$, p represents the number of input nodes and r represent the number of output nodes.
- Actual output will be calculated with

$$X_{ki}=f[\sum_{j=0}^{p-1} WjXj] \tag{17}$$

Then transferred to the next input layer.

 Output is given by summing of weights:

$$W_{jk}(n+1)=W_{jk}(n)=\mu\xi_{ki}\rho_{ki} \tag{18}$$

Weights are signified by Wjk (n) with limit j to k, gain term is represented by μ, and error term is indicated as ξki.

(1) Output unit will be:

$$\xi_{ki}=k\rho_{ki}(1-\rho_{ki})(o_{ki} -\rho_{ki}) \tag{19}$$

(2) Hidden unit will be:

$$\xi_{ki}=k\rho_{ki}(1-\rho_{ki})(o_{ki} -\rho_{ki})\sum_{n} \xi kn\, W_{in} \tag{20}$$

3.1.2 Recurrent Neural Network:

Recurrent neuron network is the network having one or more hidden layer with minimum one feedback loop. Input is given to the input layer and being processed by the hidden layer and an output is given for the network. This output of neuron will than given to its own input through feedback loop. This process is being repeated again and again until we get minimum error. Recurrent neural network depends upon the feedback used. In lattice recurrent neural network, the feed forward network is arranged in row and column.

4. Result and Discussion

Three training functions named as TRAINGDA, TRAINGDM, TRAINGDX are used to study the mechanical properties of copper powder filled with linear low density polyethylene (LLDPE). To predict the mechanical properties of copper filled with LLDPE, a three layered feed forward network is used. Mapping of input and output are done with FFBP network. Parameters of inputs are elongation of polymer (δ_p), stress in the polymer is (ρ_p), Young's Modulus for polymer (Y_p) and volume fraction of copper (ϕ). Elongation at break, Stress at break and Young's Modulus are the three output parameters used to observe the copper powder filled with linear low density polyethylene. This type of input parameters is directly associated to adequate results through ANN approach. Input is given to the network then output from every neuron is summed up and then matched with desired data. The error can be minimized by modifying the data from output to input layer.

4.1 Elongation at break:

Range for inputs of network is set between one to twelve hundred [1, 1200] to calculate the elongation at break. First layer contain 1200 TANSIG neuron and second layer have only one PURELIN neuron. 200 epochs are used to run the threshold TANSIG-PURELIN function. Third layer denote the output layer of the network. Copper filled with LLDPE shows elongation at break with in the range of 0 to 18%. Our calculated results are compared with two theoretical models [30]. We find that as we increase the volume fraction of copper, there will be decrease in elongation at break of composites. Two constants having value K_3=0.9 and K4=1.5 taken under observation will depend upon the size and treatment type of dispersed particles. The ANN approach clarifies the elongation at break of the copper powder filled with LLDPE composites is in well understanding with experimental outcomes. Experimental outcomes are equivalent with Eqn. (2) at value 16% higher volume fraction of copper powder.

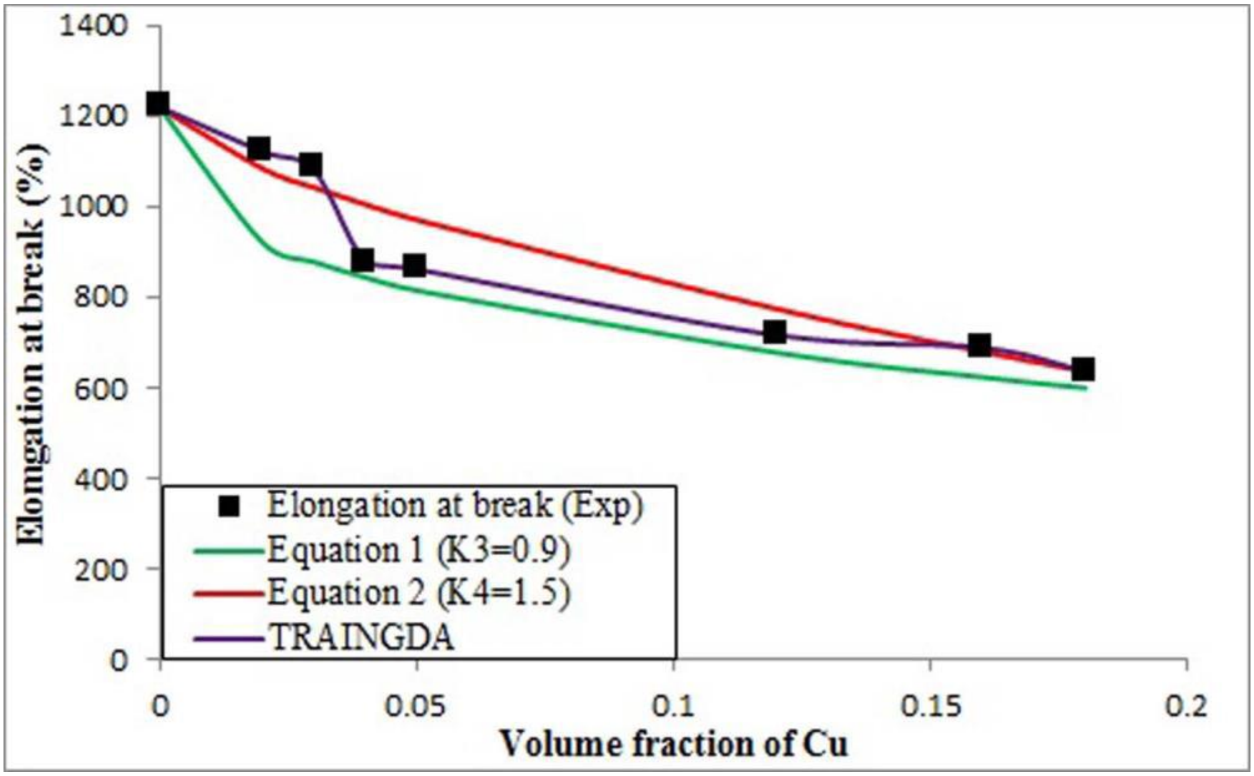

Fig.4.1 Elongation at break for LLDPE/Cu composites using training function TRAINGDA

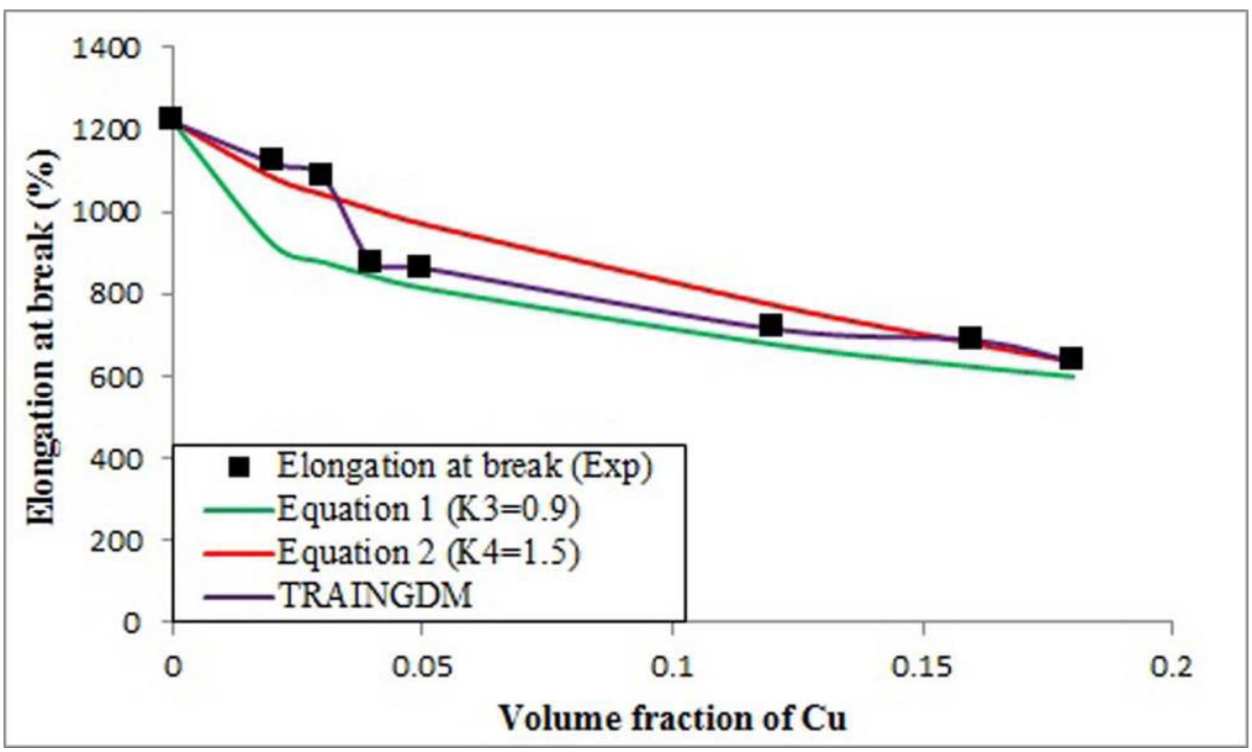

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Fig.4.2 Elongation at break for LLDPE/Cu composites using training function TRAINGDM.

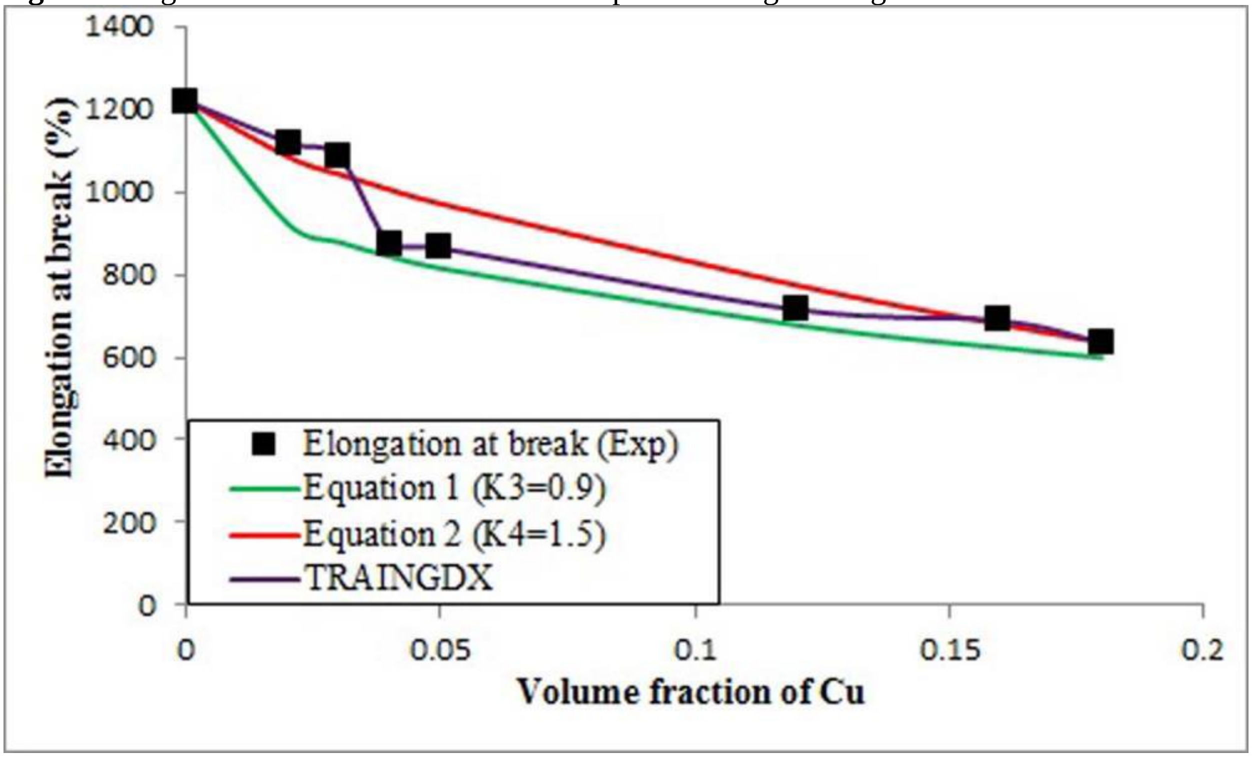

Fig.4.3 Elongation at break for LLDPE/Cu composites using training function TRAINGDX

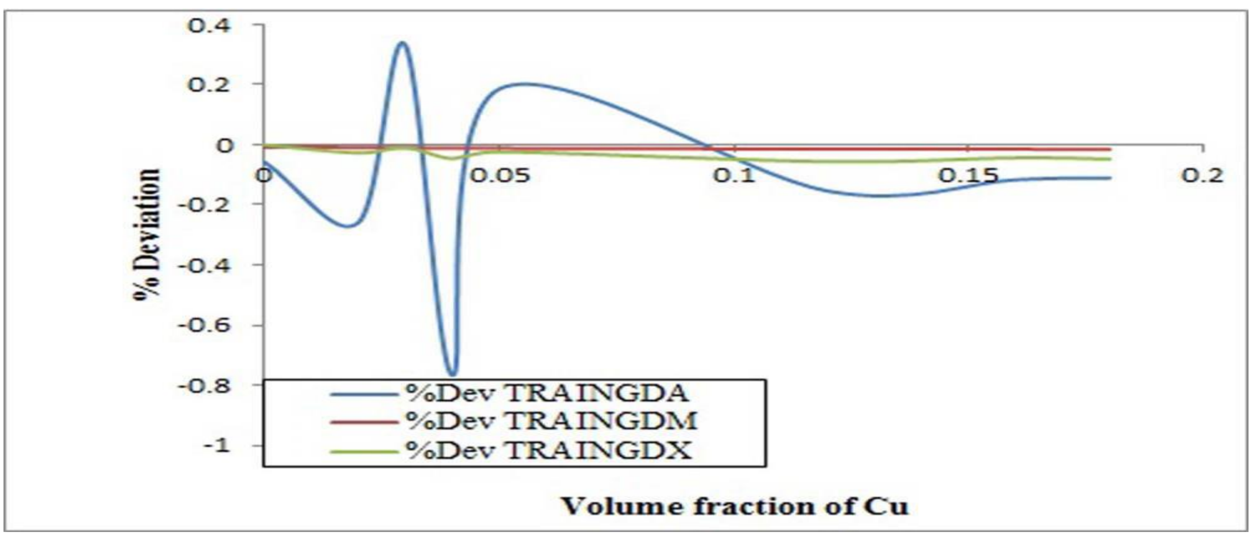

Fig.4.4 Deviation (%) for LLDPE/Cu composites using different training functions

Fig. 4.4 shows the Deviation (%) in elongation at break using different training functions for LLDPE/Cu composites. Training function TRAINGDA shows more deviation among all training functions.

4.2 Stress at break:

Stress at break of copper powder filled with LLDPE composites can be well predicted by network inputs ranges from one to fifty [1, 50]. First layer consist of 50 TANSIG neurons, whereas second layer consist of one PURELIN neuron. 200 epochs are used to run the threshold TANSIG-PURELIN functions, and the third layer will represent the output layer. ANN and theoretical models [30] are being drawn in range 0 to 18% with experimental data of stress at break of copper powder filled with LLDPE composites. As we increase the fraction of volume of copper then the stress at break will decrease. The experiment results are equivalent with the ANN function and theoretical models having approximately same concentration from starting point then there is much difference in experimental outcomes, theoretical model and ANN
Function.

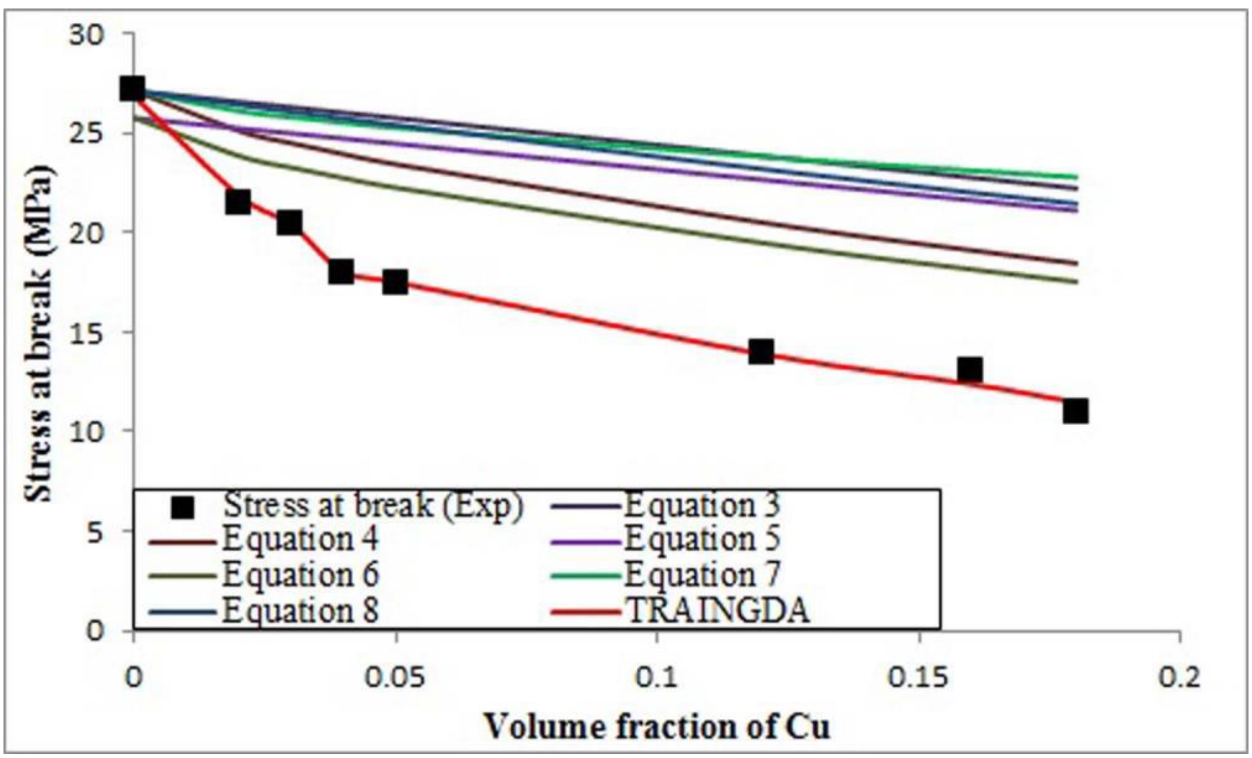

Fig.4.5 Stress at break for LLDPE/Cu composites using training function TRAINGDA.

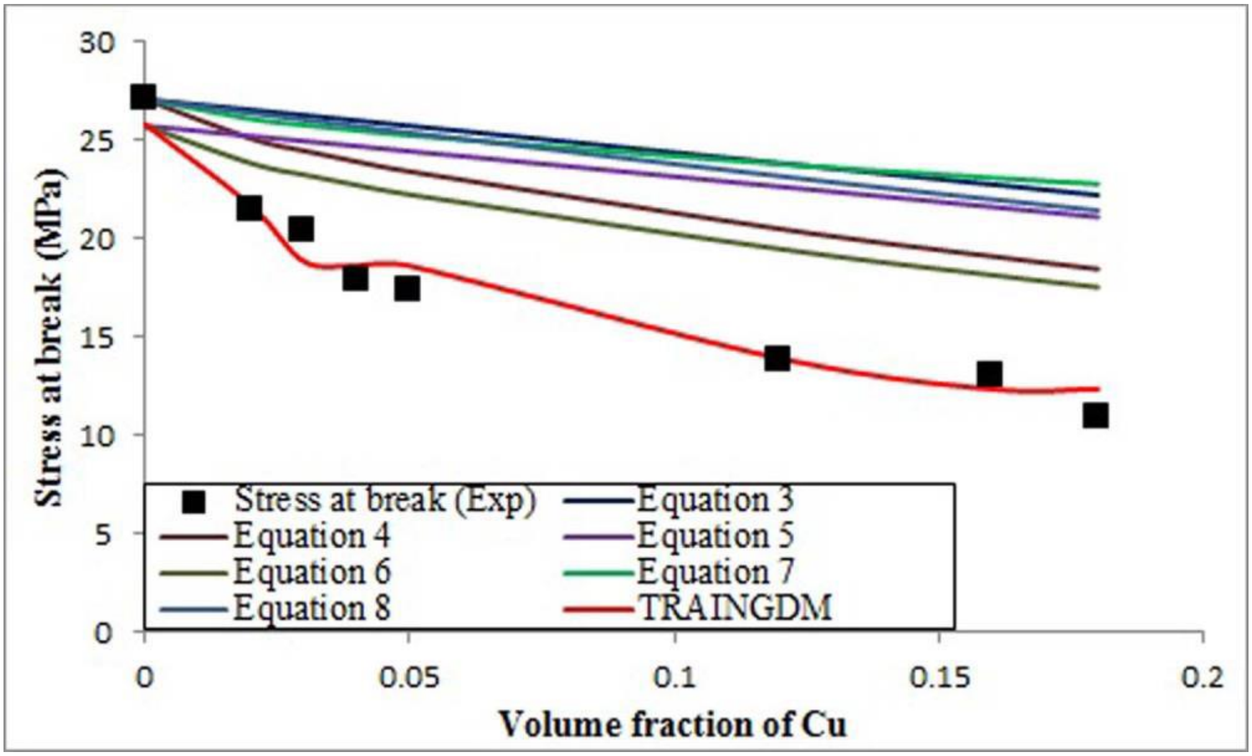

Fig.4.6 Stress at break for LLDPE/Cu composites using training function TRAINGDM.

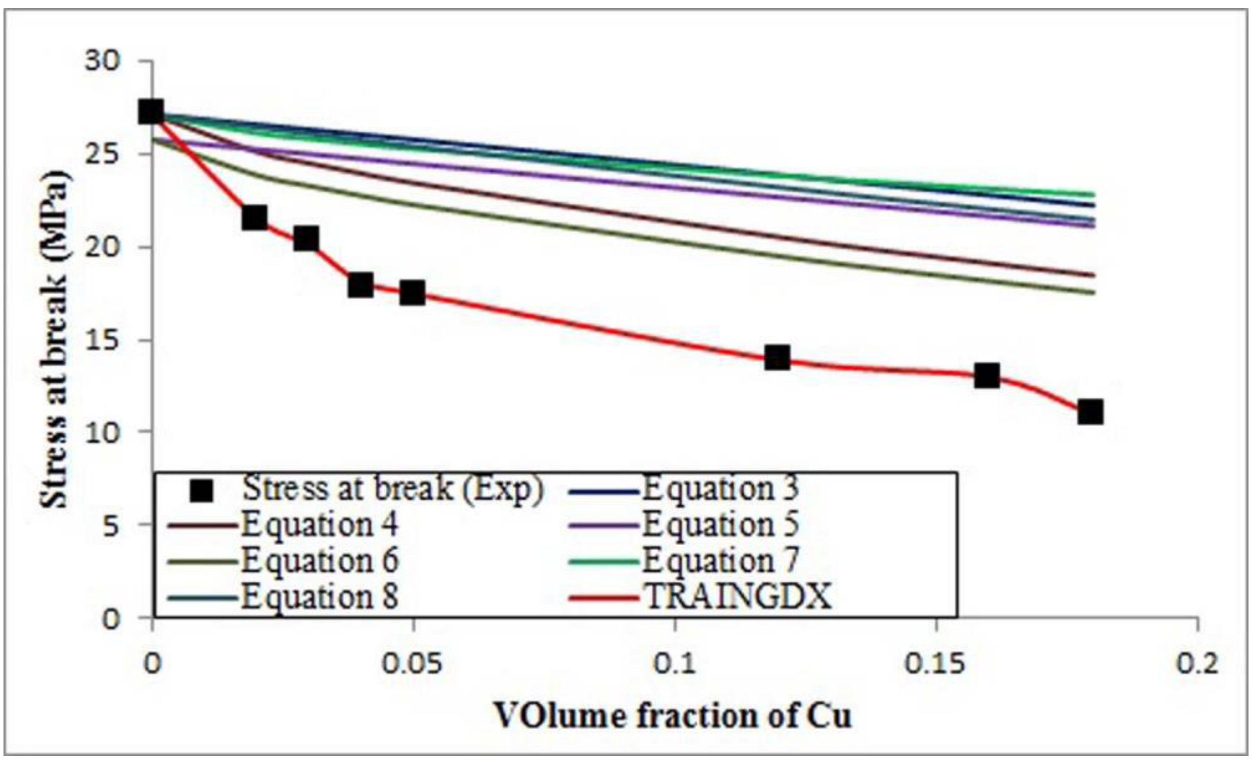

Fig.4.7 Stress at break for LLDPE/Cu composites using training function TRAINGDX.

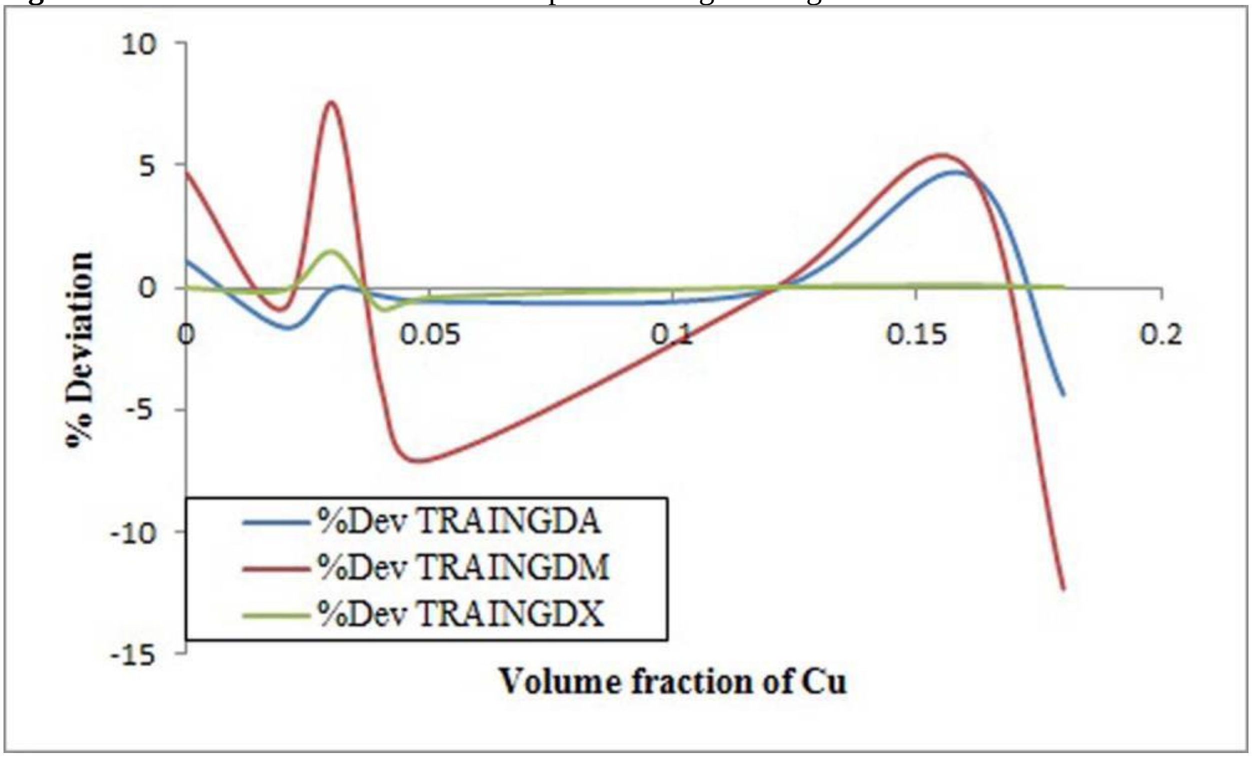

Fig.4.8 Deviation (%) for LLDPE/Cu composites using different training functions

Fig. 4.8 shows Deviation (%) in stress at break using different training functions for LLDPE/Cu composites. Training function TRAINGDM shows maximum deviation in comparison to other training functions.

4.3 Young's Modulus:

Estimation of Young's Modulus copper powder filled with LLDPE composition is done with network inputs ranges from one to one hundred fifty [1, 150]. First layer contain 150 TANSIG neurons, and second layer contain one PURELIN neuron. The 200 epochs efforts to run the threshold TANSIG-PURELIN functions. Output layer is being represented by third layer. ANN training function and theoretical models [30] are compared with variation in experimental Young's Modulus [30] of copper powder filled with LLDPE composites. When the value of copper fraction is increased then there is increase in Young's Modulus of composites. The range in between ANN and theoretical model drawn with Young's Modulus of copper powder of LLDPE composites is 0 to 18%. The outcomes estimated by the ANN approach for copper powder have better concentration until limit reaches to 5%. After this limit theoretical model is different in comparison with experimental data. ANN function with different approach will estimate the outcomes as they have been well agreed with experimental data.

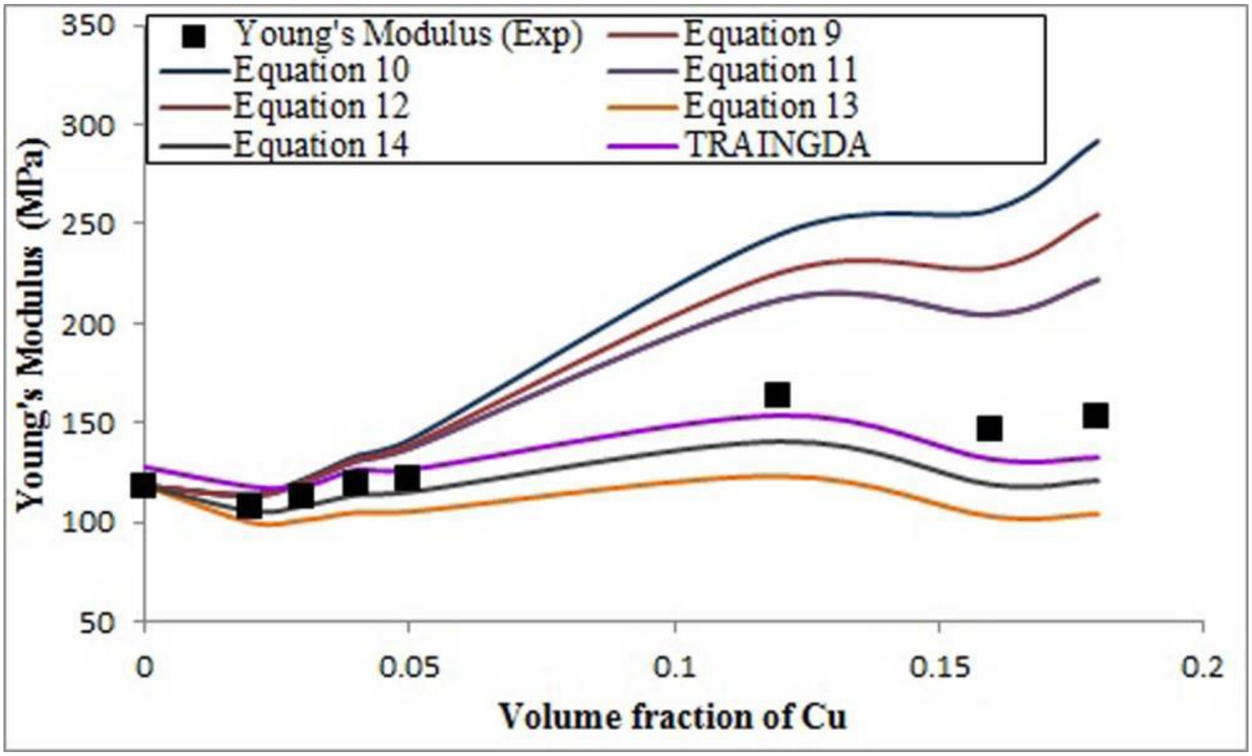

Fig.4.9 Young’s Modulus for LLDPE/Cu composites using training function TRAINGDA.

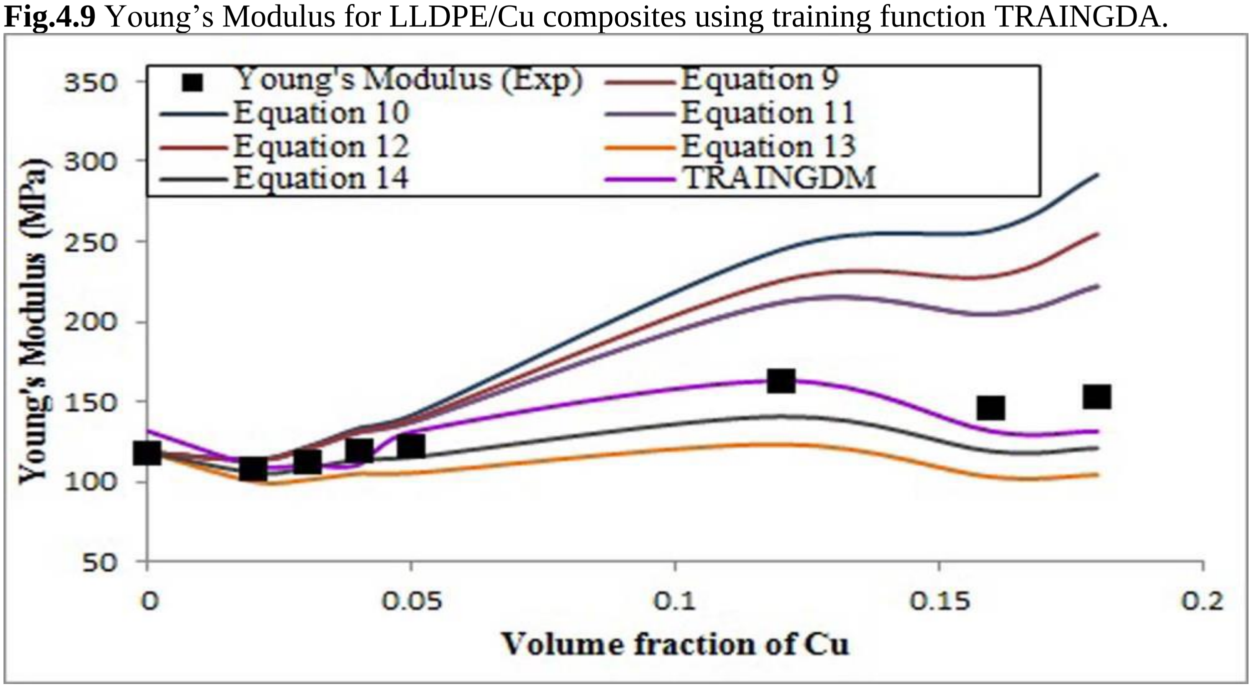

Fig.4.10 Young’s Modulus for LLDPE/Cu composites using training function TRAINGDM.

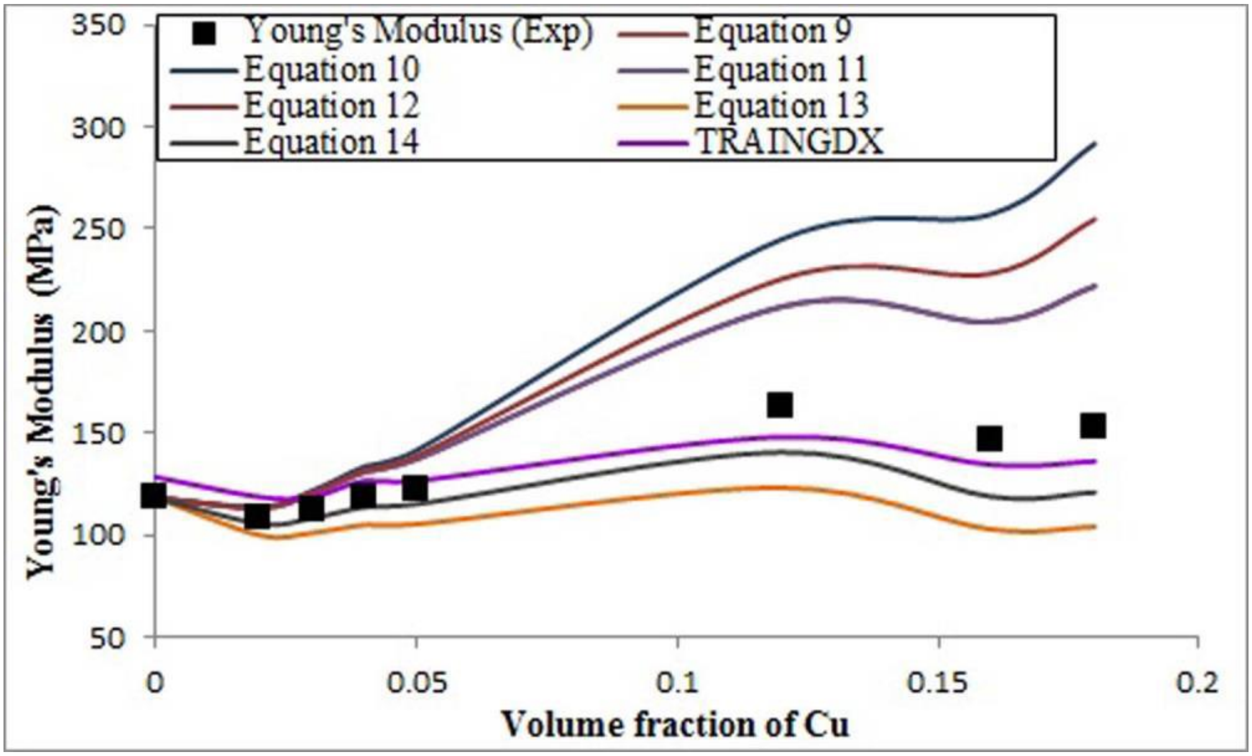

Fig.4.11 Young's Modulus for LLDPE/Cu composites using training function TRAINGDX

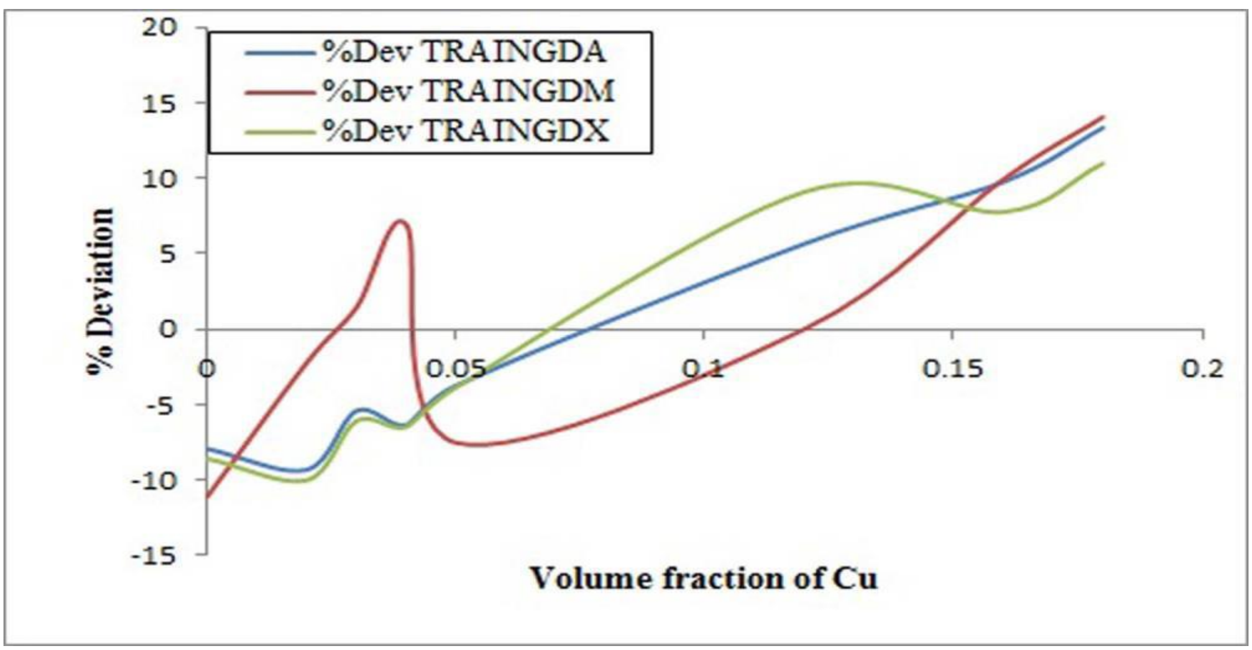

Fig.4.12 Deviation (%) for LLDPE/Cu composites using different training functions.

Fig. 4.12 shows the Deviation (%) in Young's Modulus using different training functions for LLDPE/Cu composites. Training function TRAINGDM have more deviation then other training functions.

5. CONCLUSIONS

An artificial neural network is used as a new method to predict non linear behavior of the mechanical properties of copper powder filled LLDPE and it has shown that ANN method has a good prediction capability. A three layer feed forward back propagation neural network that is fully connected to the succeeding layer through the connection weights is used for the prediction of the mechanical properties of copper filled with LLDPE composites. In comparison with other unfilled polymer mechanical properties increases in filler content of polymer. The input parameters are main parameters that change the mechanical properties of particulate polymer composites. In this paper we have used three training functions named (TRAINGDA, TRAINGDM and TRAINGDX) of FFBP networks. The reported result on the mechanical properties of copper powder filled LLDPE by using different training functions of ANN approach agreed well with experimental data. In comparison with other existing theoretical models, ANN method does not require any additional empirical factor. It is clarified that ANN approach has a good modeling efficiency for a new three or more phase complex materials.ANN approach can be comprehensive to examinations of other materials of mechanical properties of particle filled composites.

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