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Simulating EDM Model Of Nano Copper Hybrid Composites Using Generalized Neural Network Tools

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ABSTRACT

The generalized neural network models are developed to model Electrochemical Discharge Machining (EDM) in preparing Nano copper hybrid composites . The sintered copper composite preforms were machined using EDM at room temperature. The Cu–2%CNT reinforced composite exhibited lower TWR (Tool Wear Rate) with superior MRR(Material Removal Rate), whereas Cu-2% CNT–2% B_4C composite exhibits higher TWR with inferior MRR. This result highlights the experiential effect of the pulse off time and exoneration (discharge) current on the responses of the copper composites during electrical discharge machining. For enhancing the EDM process , the softcomputing tool like Neural network was designed to study the properties of composites with different combination of input parameters like like pulse off time, discharge current and constant pulse on time.Due to over-fitting for the available samples, the conventional training method was not suitable to identify the required output parameters for unseen test data. Hence the standard generalization tools like early stopping, regularization and Bayesian network were employed to enhance the neural network to recognize any independent test data.

Highlights

- EDM is used for optimal machining of Nano hybrid composite preforms.
- Generalized tools of Neural network will support in analyzing the various properties of composites
- The intelligent based models will save the enery of human resources.

Keywords:- copper; boron-carbide; nanotubes; EDM; Neural networks ; machining; Early stopping ,regression ,Bayseian.

I. INTRODUCTION

A micromachining process , called Electochemicl Discharge Machining is comprising of Electro Chemical Maching (ECM) and Electro Discharge Machining . It can support a variety of materials including metals,ceramics, composites, alumina, glass, etc. It is applied in various potential areas [1]. This kind of hybrid machining is followd in preparing copper hybrid composites. In this study, Carbon Nanotubes (CNT's) and nano boron carbide (B_4C) are used as reinforcements whereas copper is taken as a matrix in fabrication of nano composites. While preparing this kind of composite , the output parameters like MRR(Material Removal Rate) and TWR (Tool Wear Rate) with respect to the input parameters like pulse off time, discharge current and constant pulse on time. It is tough process to analyze with different combination of input parameters in hardcomputing. To overcome this critical process , the softcomputing based model like Neural Network is preferred to study the properties with less effort. The neural network has two majors stages like training and testing. The trained network with sufficient samples and architecture , should be generalinzed to adapt independent test data, since the generality is closely related with the capacilyt of network[2] . For enhancing the generality of the Neural network , the generalization tools like early stopping, regularization and Bayesian network are adaopted to improve the predictability of nework. The purpose of the present investigation is simulatinng the Neural Network based models while preparing copper hybrid nano composites using EDM approach in Nano Lab with good generalization .

II. LITERATURE SURVEY

It has been demonstrated [3] that, conventional machining of these composites leads to high tool wear rate. A non-traditional machining technique like Electro discharge machining (EDM) is an alternative method to effectively machine these composite preforms [4], which is commonly used to produce complex profiles on any conducting metal and alloy having higher hardness. A fuzzy logic approach has been adopted in EDM to predict the responses so that imprecision and uncertainly in experimentation can be handled conveniently[5]. Habibollah Haron et al. applied Fuzzy logic in modeling of machining processes such as to predict the surface roughness and to control the cutting force in various machining processes[6] Experiments wereconducted byvarying the peakcurrent and voltageand the correspondingvalues metal removal rate (MRR) were measured.[7]. In the previous research, the softcomputing tools like Neurla Networks , Fuzzy logic and Genetic Algorithms were applied in simplifying the manufacturing process of of powder metallurgy[8]. While EDM machining, the softcomputing tools were used to optimize the output parameters.But the generalizations tools were not used in studying the mechanical properties during EDM Machining to imprve the generalizty of the models[5,6,7,9]

III.EXPERIMENTAL DETAILS & METHODOLOGIES ADOPTED

The schematic representation of the EDM machine is shown in Fig. 1. Scanning electron microscope was used to characterize the surface modification layer of the copper hybrid composite specimens. The composite preforms were weighed by a precision electronic balance (Make: Sartorius, Model: BS 224S) with 0.1 *mg* accuracy before and after each test to calculate the material removal rate. MRR is expressed as the ratio between the work piece removal weight (WRW) and period of machining time in minute (T).

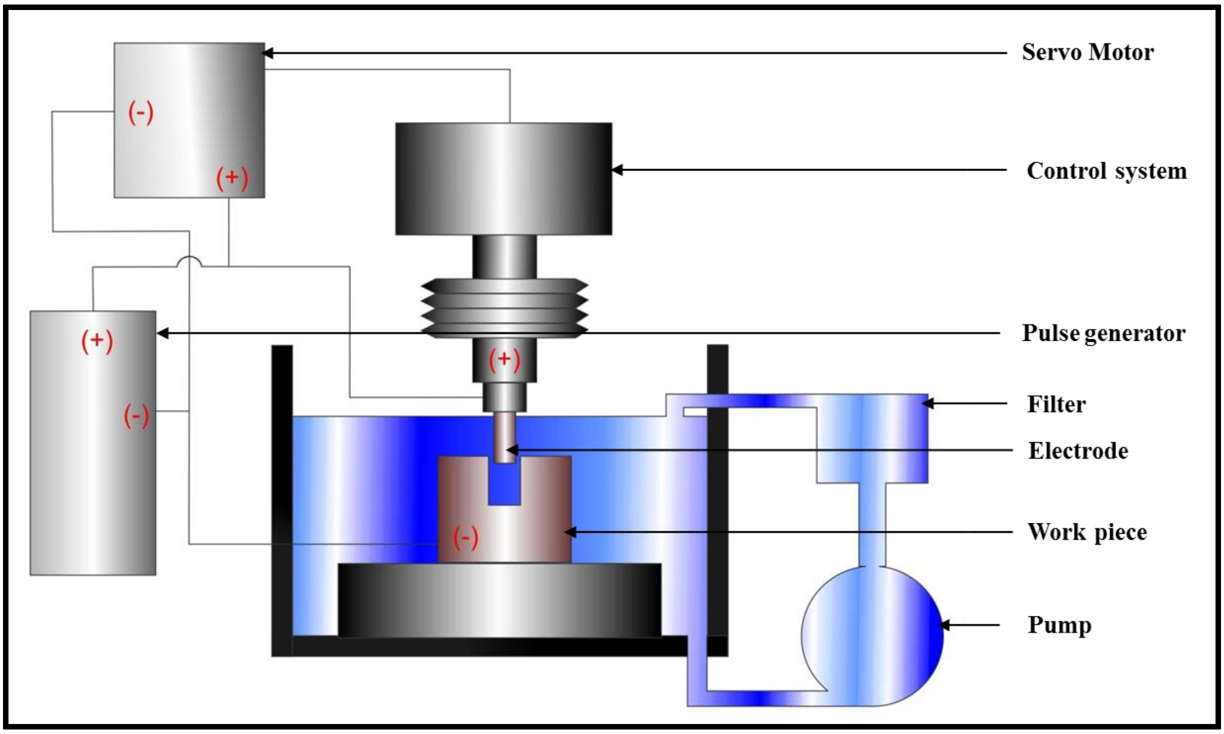
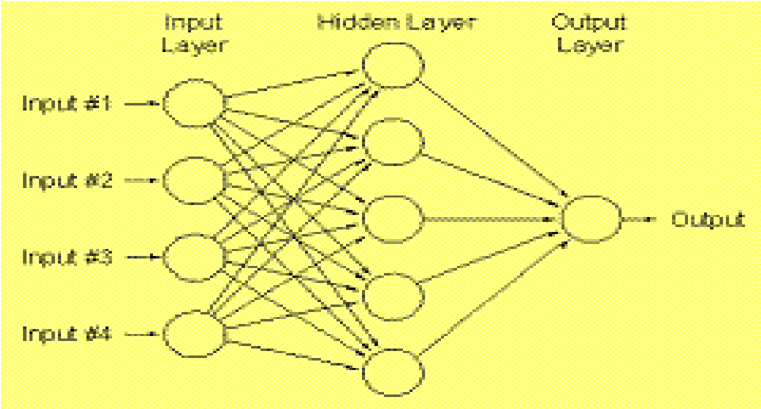


Figure 1: electrical discharge machining

Mainly , in this work the neural network based models are developed to predict the properties of copper Hybrid composites during FDM. As given in Fig:2 , the Backpropagation Neural network is modelled as a collection of nodes , which are organized as input layer , hidden layer and output to find the association between input and output parameters. The network has three majors stages namely : Training ,validation and Tesing. During Trianing ,the intelligent model was trained with sufficient data samples ,architecture and network convergence parameters The depedent samples are used for validating the developed model. For improving the accuracy of netowork predictability , it is tested using independent data samples. In this scenario , if the data samples and network architecture are not selected sufficiently, then the model will follow poor generalization ,since the generality is closely related to the capacity of machine [10,11]. If the number of samples are more than the capacity of the architecture , then the network will be "underfitting" to recognize the independent test sampels. If the number of samples are not suffient , the the network will be "overfitting " to yield poor generalization. In improving the predictability of network , the following techniques are used while analysing the output paramters for the given input parameter under EDM process.



FigL2 BPN Neural Network Structure

a. Early stopping

In order to support generalization, the available data were divided into three subsets: training or estimation set (one half of total samples) for computing the gradient for updating the network weights and biases in a usual way, validation set (one fourth of total samples) for monitoring error periodically during training and independent testing set (one fourth of total samples). neural network against the validation dataset. The validation dataset is wholly independent from the training set and it allows us to determine an early stopping point[12] At every epoch , the validation is done to monitor while training. The error will .be reduced in every epoch , Stop training as soon as the error on the validation set is higher than it was the last time it was checked.The current weights of network is considered for testing the independent samples.

b. Regularization

Early stopping gives poor results if validation set is not a representative of all data points.. The general technique of regularization encourages smoother network mappings by adding a penalty term Ω to the standard (e.g. sum squared error) cost function .The changes in the error function is given below

$$\bar{\varepsilon} = \varepsilon + \alpha\Omega \quad \dots \quad (1)$$

$$\bar{\varepsilon} = \varepsilon + \alpha\left(\frac{1}{2}\varepsilon\omega_i^2\right) \quad \dots \quad (2)$$

$$\bar{\varepsilon} = \varepsilon + \frac{\alpha}{2}\omega^T\omega \quad \dots \quad (3)$$

Where α is a learning rate and Ω is a performance ratio. This error performance function will cause the network to have smaller weights and biases and will force the network response to be smoother and less likely to overfit.

c. Bayseian Training

Bayesian neural networks generally means "Bayesian approach to feed-forward networks."[13]. There is of course a whole class of models known as Bayesian networks, also known as belief networks.This kind of network is based on Bayesian Infererenc rule as given in Eq:4 , to predict the posterior propability of θ for the given data $\mathcal{D}$,

$$p(\theta|\mathcal{D}) = \frac{p(D|\theta)p(\theta)}{p(\mathcal{D})}$$

(4)

Where $p(\theta)$ is the prior probability of a parameter θ before having seen and $p(\mathcal{D}|\theta)$ (likelihood) is the propabilty of the data data $\mathcal{D}$, given θ

III. RESULTS AND DISCUSSIONS

The network is designed three inputs to represent like pulse off time, discharge current and constant pulse on time and two output parameters like MRR and TWR of Nano cpper composites. The sample data is givem in Table –I

S.No	Input Paramer1	Input Paramer2	Input Paramer3	MRR	TWR
6	7	0	0.0698	0.01745	6
7	5	0	0.2248	0.0487	7
7	6	0	0.1726	0.03315	7
6	7	0.5	0.0521	0.013025	6
7	5	0.5	0.1882	0.04705	7
7	6	0.5	0.1464	0.0316	7
7	5	1	0.1761	0.044025	7
7	6	1	0.1109	0.027725	7
7	7	1	0.0907	0.020175	7
5	7	1.5	0.0074	0.00185	5
6	5	1.5	0.1066	0.02665	6
6	6	1.5	0.0528	0.0132	6
7	7	1.5	0.0742	0.01855	7
5	5	2	0.031	0.00775	5
6	7	2	0.0273	0.006825	5
7	5	2	0.1521	0.038025	6

Table –I Smaple Data Set

a. Using conventional training

The network is designed with 3 input nodes representing , 3 hidden nodes and 2 hidden nodes representing MRR and TWR . Among 45 samples collected in the Lab , 35 samples are used for training and remaining samples are used for testing. The network training tooks 14 epoches for convergence as given in Fig:3

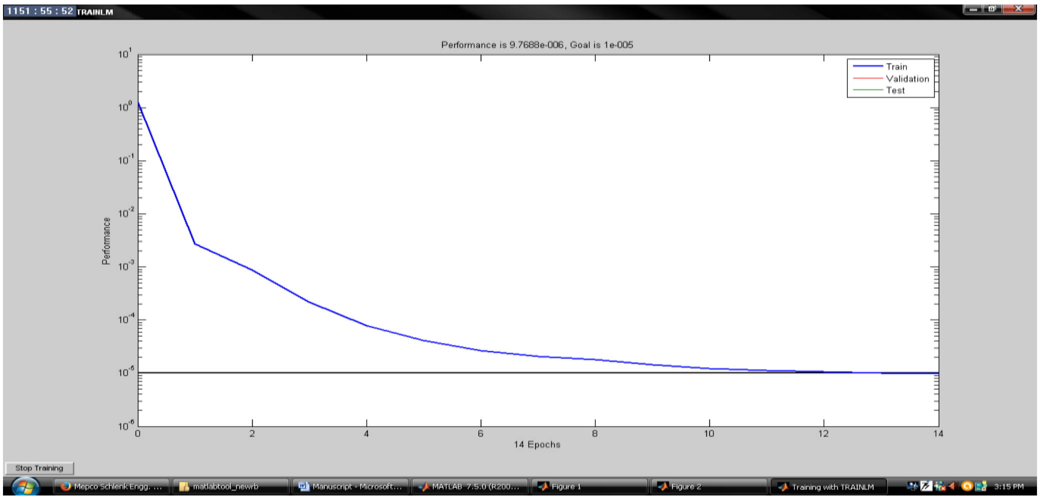
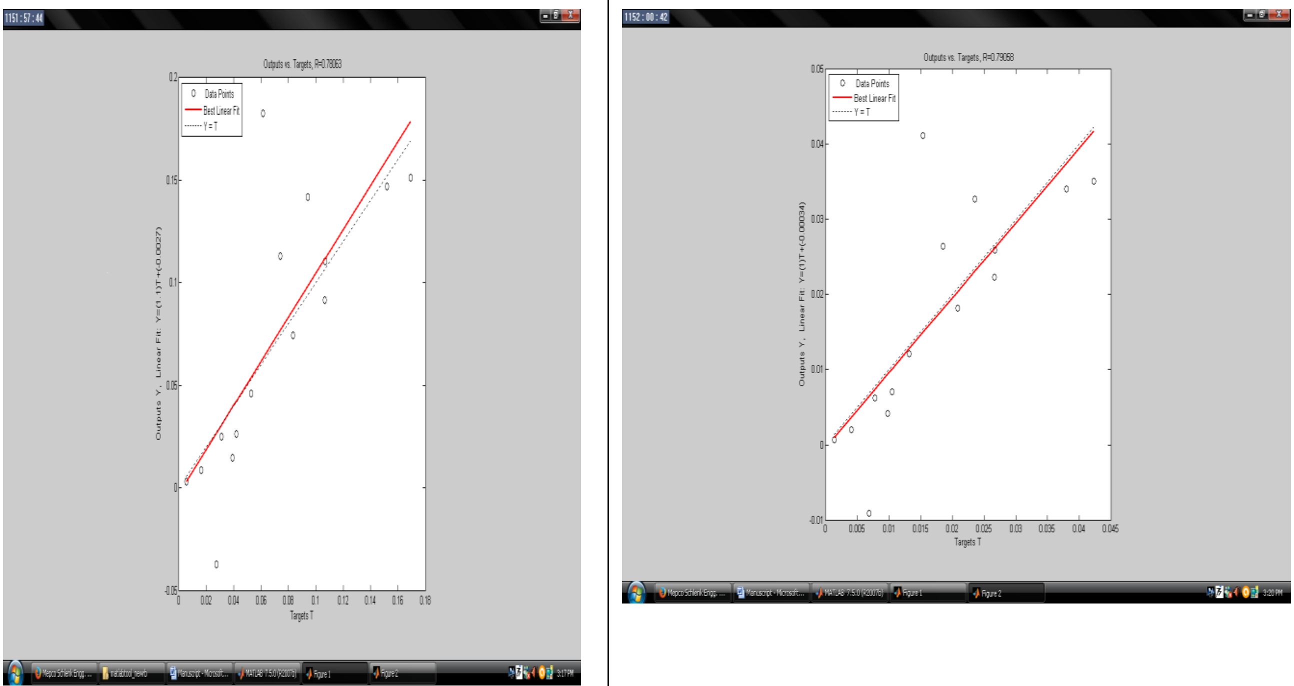


Fig: 3 Network convergence for conventional Training

The network predictability is measured in terms of correlation coefficient(R) as givem in Eq:5

$$R = \frac{\sum_{i=1}^{N}\left(E_i - \bar{E}\right)\left(P_i - \bar{P}\right)}{\sqrt{\sum_{i=1}^{N}\left(E_i - \bar{E}\right)^2 \sum_{i=1}^{N}\left(P_i - \bar{P}\right)^2}} \qquad \text{--- (5)}$$

The developed network predicts MRR as 0.79058 and TWR as 0.78063 as given in the Fig:4(a-b). The network ia unable to predict the output accurately due to overfitting. This proves the poor generalization of neural Network. To overcome this problem , the network is trined using the generalizatrion tools**.**



Raw Data Vs Network output Fig.4(a)	Raw Data Vs Network output Fig.4(b)

Using early stopping

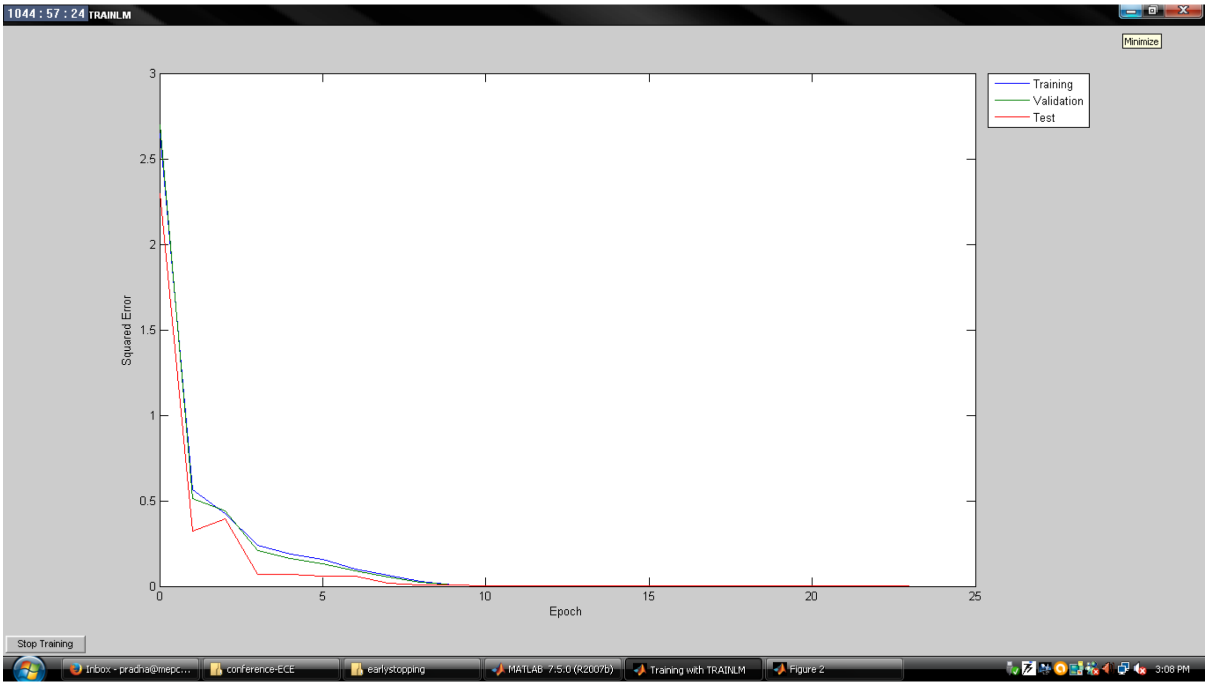


Fig:5 Early Stopping Model- Training

The network samples are divided in the ratio 2:2:1 as training set ,validation set and testing set respectively. The lnetwork is designed with 3 nodes in the input layer , 5 nodes in the hidden layer and 3 nodes in the output layer. earning parameter is linitialized as 0.3 A s given in Fig:5 , initially the validation error decreses and it tries to increase at nearly 3rd epoch , the network is tried to stop and these three sets are converged at 9th epoch. The values of output parameters are reported in Table 2.

Using Regularization

The network is designed with 3 hidden nodes with 3 input nodes and 2 output nodes.In this model the performance ratio is randomly choosen as 0.5 in trial and error basis to smooth the network changes. The performance error function is selected as mean of squared errrs. At 27th epoch , the network is converged. The Fig:6 shows the training of regularization method. The network output will be varies depending the upon the choosen performanace ratio. Hence , it is a critical case to fix the optimal ratio value. To overcome this problem , the network is made to select the performance ratio value automatically. Table-2 lists the effects of the regularization and automated

Regularization.

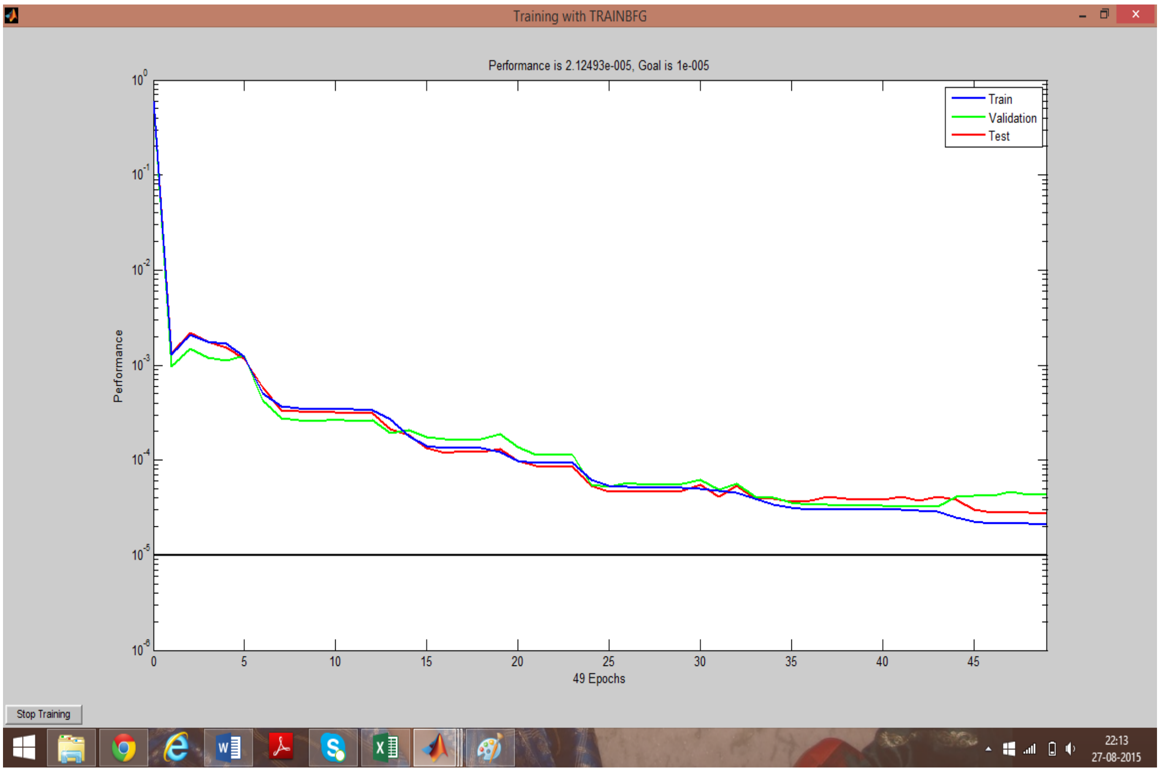


Fig:6 Regulrization Training Model

Using Bayseian

Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities. Bayesian regularization minimizes a linear combination of squared errors and weights. This kind of BPN uses the adaptive mu parameter to calculate error performance of the nwtowk at every epoch.By trial and error basis method , it is initialized as 0.1 , it is incremented by 2 and decremted by 0.2 at every epoch to have the maximm possibility of mu is 0.0002.The comparison of various generalization tools is reported in Table-2. The Bayesian Network model gives good results compared to other models. Fig:7(a) exhibits the results of Bayesian generalization to predict MRR value and Fig:7(b) shows the TWR value of Basyesian Regularization.

Network model Type	**MRR**	**TWR**
Early Stopping	0.9957	0.99441
Regularization	0.99215	0.98692
Automated Regularization	0.98929	0.979556
Bayesian Network	0.99952	0.99692

Table -2 Comparison of various generalization Tools

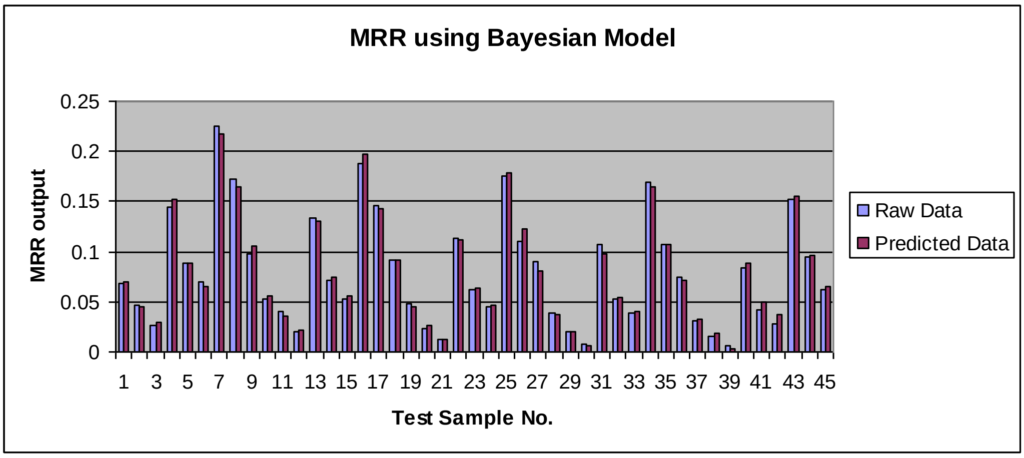


Fig:7 (a) Comparison of Raw and Expected output od MRR using Bayseian Model

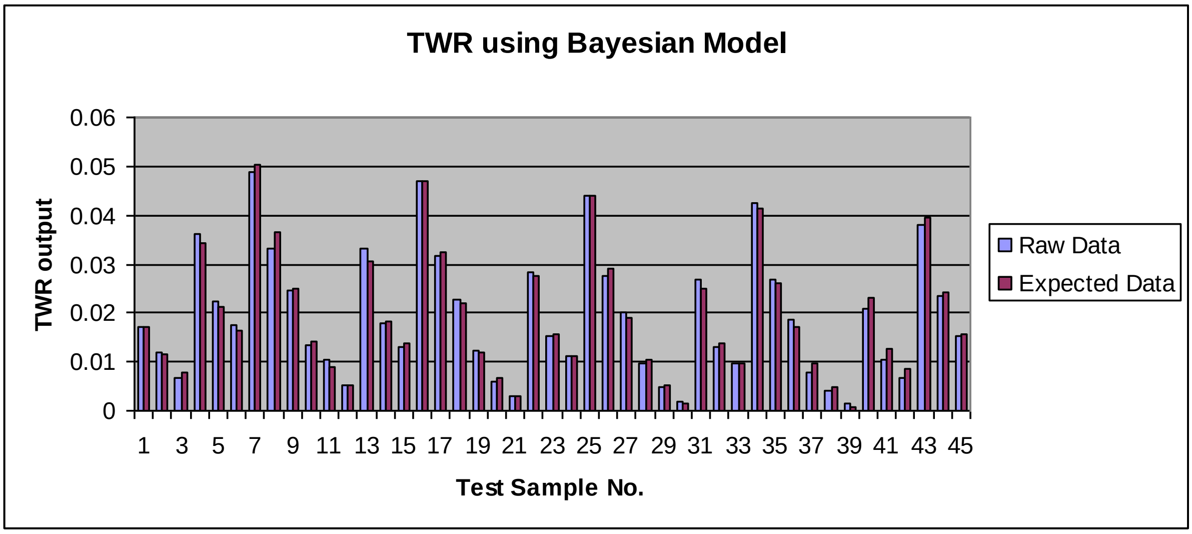


Fig:7 (b) Comparison of Raw and Expected output od TWR using Bayseian Model

IV. CONCLUSIONS

EDM is used for optimal machining of Nano hybrid composite preforms.While simulating this process by softcomputing approach , due to overfitting the models yield poor generalizstion, For improving the generalization , the neural network based generalization tools like early stopping , regularization and Bayesian networks are applied. Among these developed models , the Bayseian Model gives good results compared to other models .

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