Prediction of Electrochemical Machining Process Parameters using Artificial Neural Networks

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Abstract— **Electrochemical machining (ECM) is a non-traditional machining process used mainly to cut hard or difficult to cut metals, where the application of a more traditional process is not convenient. It offers several special advantages including higher machining rate, better precision and control, and a wider range of materials that can be machined.**

A suitable selection of machining parameters for the ECM process relies heavily on the operator's technologies and experience because of their numerous and diverse range. Machining parameters provided by the machine tool builder cannot meet the operator's requirements. So, artificial neural networks were introduced as an efficient approach to predict the values of resulting surface roughness and material removal rate. Many researchers used artificial neural networks (ANN) in improvement of ECM process and also in other nontraditional machining processes as well be seen in later sections.

The present study is, initiated to predict values of some of resulting process parameters such as metal removal rate (MRR), and surface roughness (Ra) using artificial neural networks based on variation of certain predominant parameters of an electrochemical broaching process such as applied voltage, feed rate and electrolyte flow rate. ANN was found to be an efficient approach as it reduced time & effort required to predict material removal rate & surface roughness if they were found experimentally using trial & error method. To validate the proposed approach the predicted values of surface roughness and material removal rate were compared with a previously obtained ones from the experimental work.

Keywords- Electrochemical Machining, Artificial neural networks, Matlab neural networks toolbox.

I.Introduction

Electrochemical machining (ECM) has seen a resurgence of industrial interest within the last couple of decades due to its many advantages such as no tool wear, stress free, no thermal damage to the workpiece, smooth surfaces of machined product and ability to machine complex shapes in electrically conductive materials, regardless of their hardness [1].In addition to high metal removal rates for high-strength and difficult to machine alloys. Fragile parts that are not easily machinable can be shaped by the ECM process [2].

Owing to the complexity of electrochemical machining (ECM), it is very difficult to determine the values of resulting material removal rate and surface roughness based on usage of different cutting conditions hence, increases the difficulty of selection of optimum machining parameters as well.

To decrease the difficulty of prediction process, intelligent techniques using artificial neural networks were developed as an efficient approach to predict the values of resulting material removal rate and surface roughness from an electrochemical broaching process.

Many researchers have so far concentrated on the process improvement in ECM as well be shown in sectionII. And to the best of the knowledge of the authors no effort has been put on the development of multi input- multi output models to correlate the effect of various machining parameters on the predominant electrochemical machining criteria. Keeping this is in consideration, the present study has attempted to develop a multi input-multi output neural network model that maps the relationship between different process parameters to predict the values of process performance measuring parameters.

II. Review on Previous Research Work

Asokan P. et la, presented a practical method of optimizing cutting parameters for ECM based on multiple regression models and multiple input single output ANN model [3]. Shanget .Q.P et la, Studied the effect of different process parameters on anode accuracy and developed an ANN model with back propagation as the learning algorithm to predict the machining accuracy of anode in electrochemical machining with an uneven interelectrode gap [4]. Kozak, j.et la, presented the concept and prototype of a computer aided engineering (CAE) system that can be used to solve different tasks of ECM, such as: tool-electrode design, selection of optimal input machining parameters [5].

Many authors showed the applicability of ANN in different nontraditional machining processes such as, Kuo Tsai et la., showed the ability of different neural networks models to predict the surface finish based on the effect of changing the electrode polarity in the EDM process. [6]. Mohan Sen et la.,presented a hybrid neural network and genetic algorithm (NNGA) approach for the multi-response optimization of the electro jet drilling (EJD) process, where ANN model was used to predict the response parameters of the process and then, a genetic algorithm was applied to the trained neural network model to obtain the optimal process parameters [7].whereas, Soleimanimehr h. et la, Developed an artificial neural network (ANN) for prediction of aluminum workpieces' surface roughness in ultrasonicvibration assisted turning (UAT) and also, investigated the effect of tool wear as the main cause of surface roughness [8].

Some other authors [9- 13] have used ANN models either to study the effect of different nontraditional machining process parameters on resulting process performance measures or predict the optimal values of process parameters or predict the values of process measures.

From the above it's clear that no multi input multi output ANN model has been presented to predict different measuring parameters of an electrochemical machining processes so, the present study is initiated to develop a multi input multi output ANN model to predict the values of surface roughness & material removal rate resulting from an electrochemical broaching process.

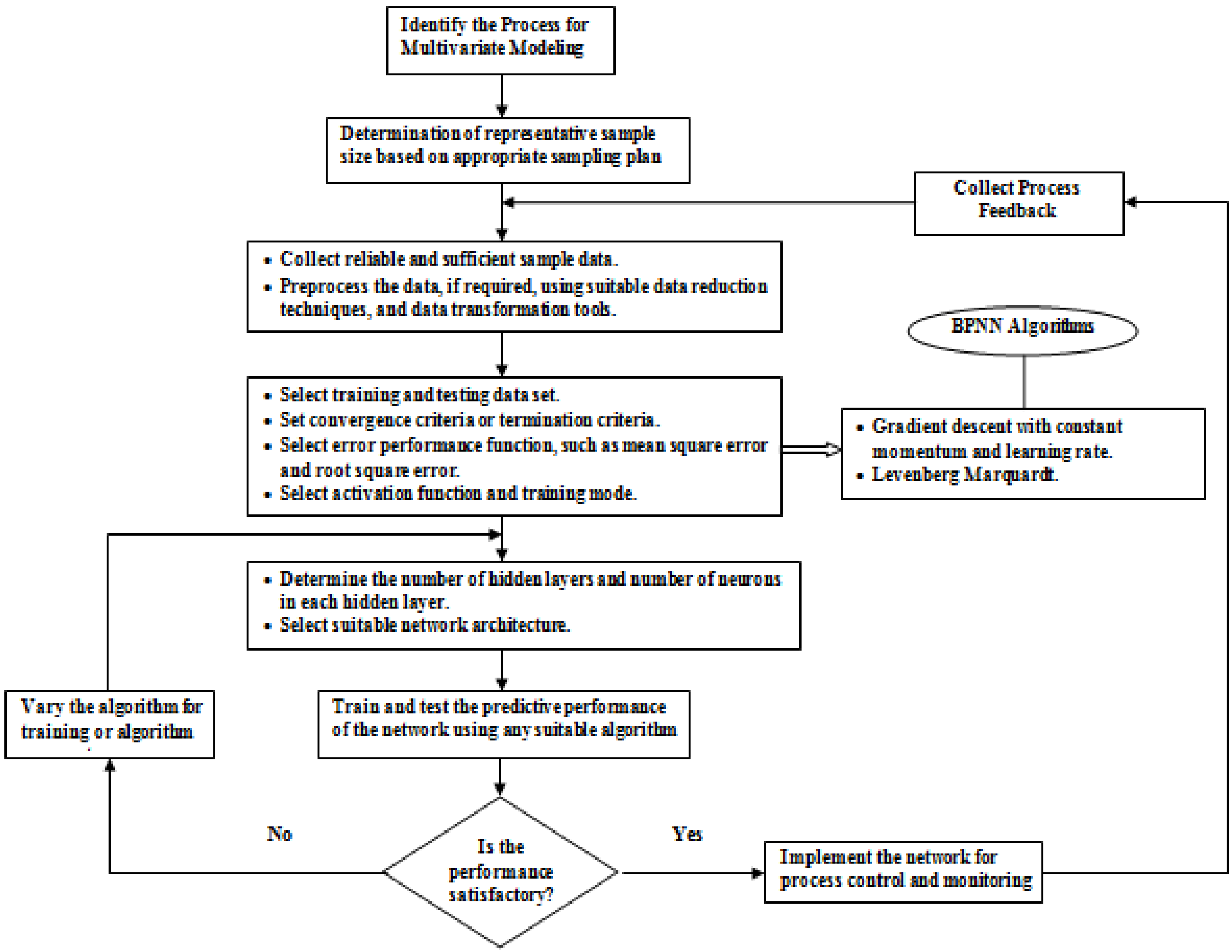

Figure 1.A typical flow diagram for nonlinear multivariable process modeling using feedforward backpropagation algorithm

III. Review on Artificial Neural Networks

Artificial neural networks (ANNs), as one of the most attractive branches in artificial intelligence, has the potential to handle problems such as modeling, estimating, prediction, optimization, diagnosis, and adaptive control in complex nonlinear systems .The capabilities of ANNs in capturing the mathematical mapping between input variables and output features are of primary significance for modeling machining processes [11].

An ANN is essentially a mathematical model that mimics the human reasoning and neurobiology and is based on the following assumptions: information processing occurs in a number of simple elements called neurons; signals are transmitted between neurons over connection links; each connection link has an associated weight that multiplies the signal transmitted; each neuron applies an activation function to the incoming signal to determine its output signal. Multi layer feedforward network have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back propagation algorithm. This algorithm is based on error correction learning rule. Figure 1 illustrates a schematic structure of proposed multilayer feedforward backpropagation neural network. The backward linkages are used only for the learning phase, whereas the forward connections are used for both the learning and operational phases.

After adequate training of neural network based on the experimental data, it can not only make decisions based on incomplete and disorderly information, but can also generalize rules from those cases on which it was trained and apply these rules to new cases. The generalization of the network makes it possible to train a network on a representative set of input/output pairs and get good results without training the network on all possible input/output pairs[16].

The neural networks are commonly categorized in terms of their corresponding training algorithms as shown in Figure 2.There is no learning required for the fixed- weight networks, so a learning model is either supervised or unsupervised[6]. Figure 3 shows a typical flow diagram for nonlinear multivariable process modeling using feedforward backpropagation neural network algorithm.

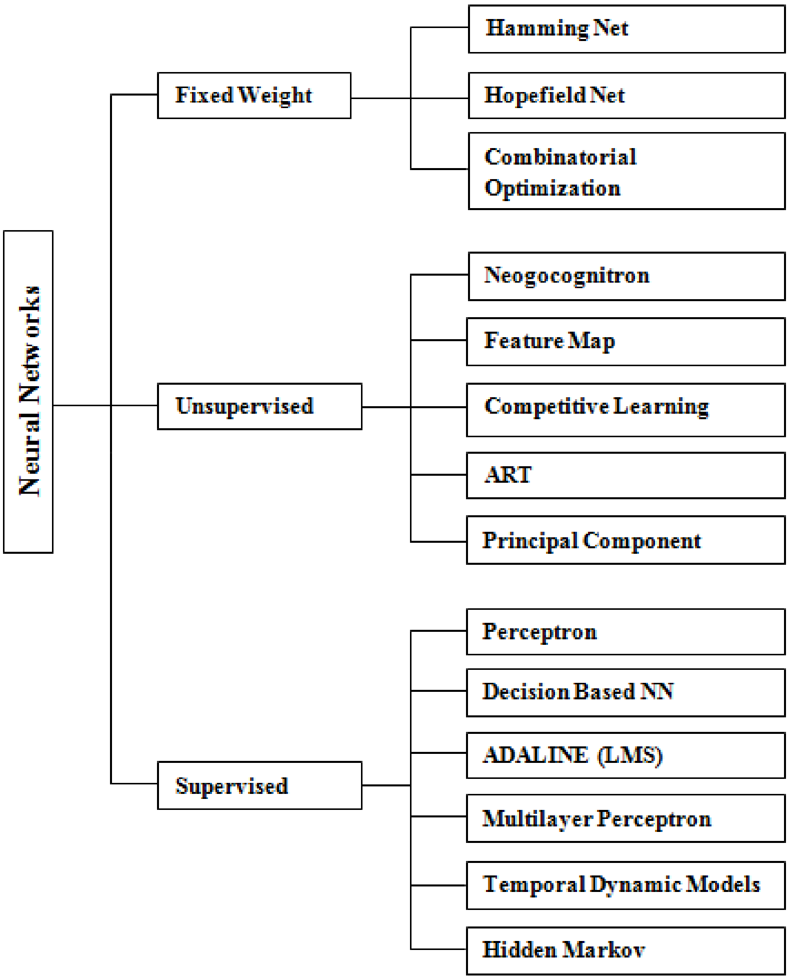

Figure 2.Taxonomy of Neural Networks

IV. Proposed Neural Network Approaches

In this study, a new approach has been presented to predict the resulting material removal rate and surface roughness based on variation of certain cutting parameters such as applied voltage, feed rate and electrolyte flow rate of an electrochemical broaching process. These parameters were varied within the following ranges: applied voltage from 15 to 35 volt, feed rate from 1.5 to 6 mm/min while electrolyte flow rates are 6 & 9 litres/min.

To establish a useful relationship between material removal rate, surface roughness, and different cutting parameters a feedforward backpropagation neural network was used.

In order to establish the process model, we first need to decide how many layers and how many neurons per layer of the network are utilized to describe the behavior of cutting process. It is easy to determine the number of neurons in the input and the output layers based on number of process parameters considered as input and output data respectively. As, applied voltage, feed rate & electrolyte flow rate are considered as process inputs while, material removal rate & surface roughness are considered as process outputs. Therefore, there are three neurons in the input layer and two neurons in the output layer. It should be noted that the number of hidden layers is critical for the convergence rate at the stage of training the network. Empirically speaking, one hidden layer should be sufficient in the feedforward networks because the number of neurons is typically assumed to be a governing parameter in the networks. However, it is not so easy to choose the appropriate number of neurons in the hidden layer for there is currently no definite rule to determining it except through experimentation. Using too few neurons impairs the neural network and prevents the correct mapping of input to output. Using too many neurons impedes generalization and increases training time.

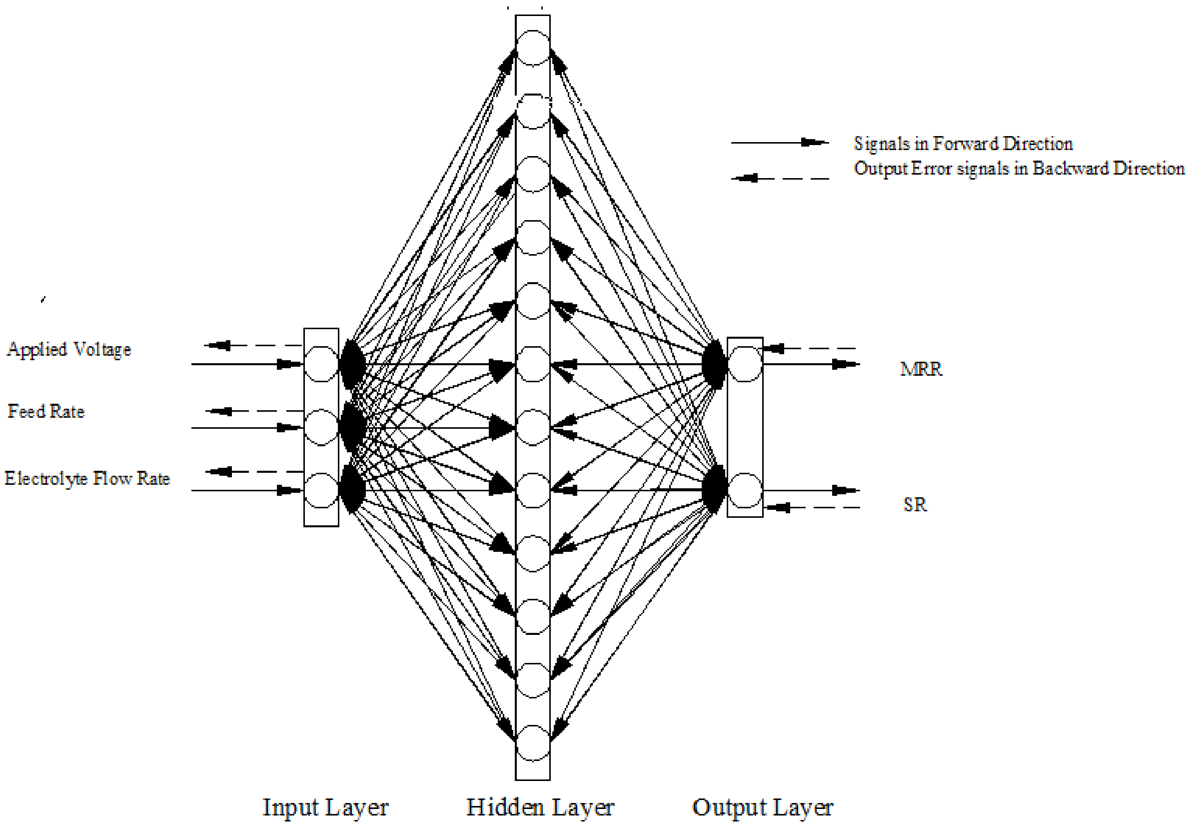

Figure3. Schematic Layout of the Proposed Neural Network Model

Since the selection of network architecture and parameters such as training algorithm, number of layers, number of nodes in hidden layer, value of learning parameters….etc. affects greatly the performance of used network; a great consideration was given to the selection of these parameters.

As there's no rule governing the selection of best network architecture and parameters; several networks have been tried using trial and error method until network with the best settings was reached. After, several trial and error iterations, one hidden layer with 12 hidden nodes was found to give minimum error between experimental and predicted output data using proposed neural network model. Fig. 3 shows the schematic layout of the proposed neural network model.

V. Variables Considered

This study presents the effect of variation of some predominant electrochemical broaching process parameters such as applied voltage, feed rate & electrolyte flow rate on resulting material removal rate and surface roughness. The data used in building network were obtained from experimental application of the electrochemical broaching process. However, these experimental data weren't enough for both training and testing of predicted data. Therefore, interpolation was used in order to increase number of data available for both training and testing of proposed network. A detailed description of used test rig in the process & effect of variation of input parameters on output parameters were discussed in [15].

VI. Training of Proposed Model

To carry out the training process, The input data were divided randomly so that 442 data of 552 available experimental data [15] were used for training of network while, remaining 110 data sets were presented to the trained network as new application data for verifying and testing the predictive accuracy of the proposed network model.

As for training the neural networks, it is critical to select an appropriate algorithm because the efficiency and the convergence of the training process are the primary issues at this stage. This means that the training algorithm is used for determining the appropriate network weights in order to accomplish the desired mapping between the inputs and the outputs [6].

In this study two different algorithms were tried for adjusting network weights in order to reduce the output error. At first training was conducted using gradient decent with momentum and then, levenberg marquardt was used. Training with levenberg marquardt algorithm was found to give outputs with errors much less than that produced by gradient decent algorithm. The calculated error percent using momentum were 0.75 % & 5.75 % for material removal rate and surface roughness respectively. While , those calculated by training using levenberg marquardt algorithm were 0.23% & 1.33 % for material removal rate & surface roughness respectively. Also, network trained using levenberg marquardt algorithm reached stabililty much faster than that trained with gradient descent with momentum algorithsm with smaller network size. Figure 4 shows value of calculated error percent vs different number of nodes for network trained using gradient descent with momentum algorithm. The training of network was conducted using **MATLAB Neural Networks Toolbox**.

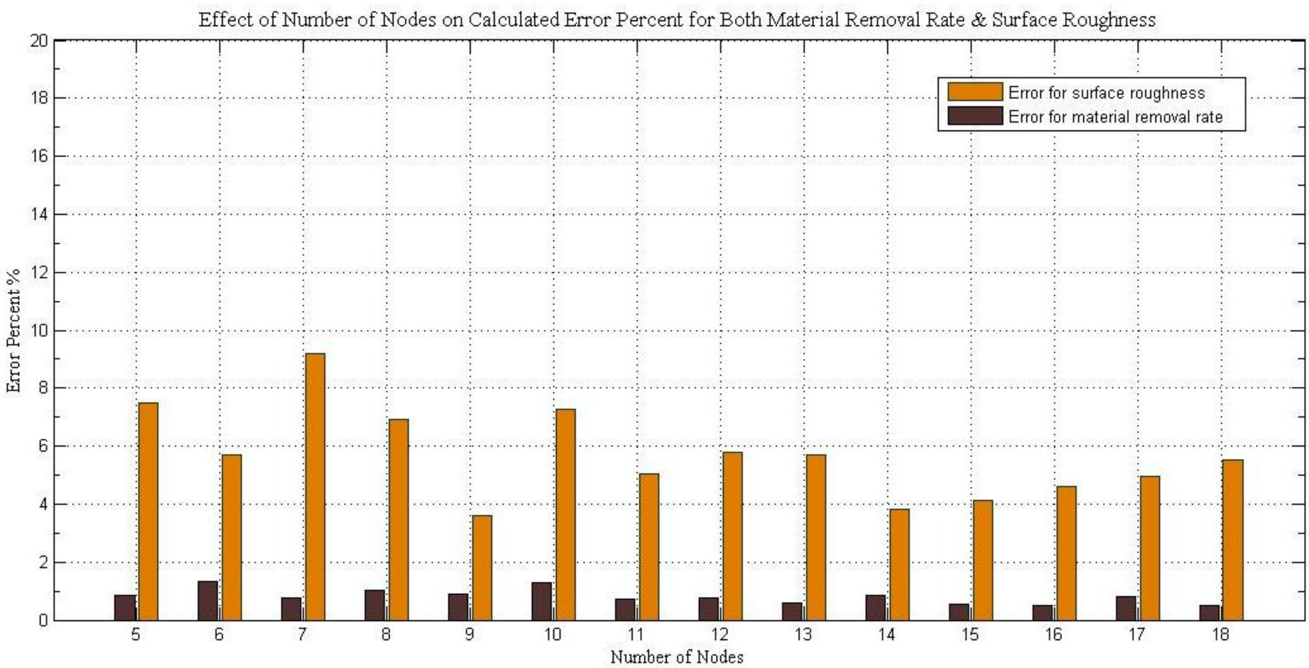

Figure 4.Calculated error percent vs number of nodes for gradient descent trained network

VII. Results & Discussion

Different neural network architecture & training algorithms were tried until the optimum model was reached. At first a feedforward backporpagation neural network with one hidden layer was tried, it was trained using gradient descent with momentum algorithm as stated in the previous section. However, by increasing number of nodes the value of calculated error kept varying within range of 0.3-1.6 % for material removal rate and 3.8-9.6 % for surface roughness as shown in Figure 4. So, levenberg marquardt training algorithm was tried instead of gradient descent algorithm. The network showed a great improvement in prediction efficiency. As, calculated error kept constant nearly in range of 0.23 & 1.33 % for material removal rate & surface roughness respectively after increasing number to hidden nodes to 12 in hidden layer unlike that trained with gradient descent algorithm whose calculated error kept changing even when increasing number of nodes in hidden layer to 18. So, network trained using levernberg marquardt algorithm managed to reach stability faster than that trained by using gradient descent with momentum. So, levenberg marquardt algorithsm was used for training proposed model. The training of the network was stopped after 23 epochs due to validation stop. The best network architecture was found to be as stated in table 1.

TABLE 1 The Optimum Values of Network Parameters

Number of hidden layers	**1**
Number of hidden neurons	**12**
Initial learning parameter(mu)	**0.01**
Mu decrease factor	**0.1**
Mu increase factor	**10**
Maximum mu value	**$10x10^{10}$**
Activation Function	**Hyperbolic tangent**

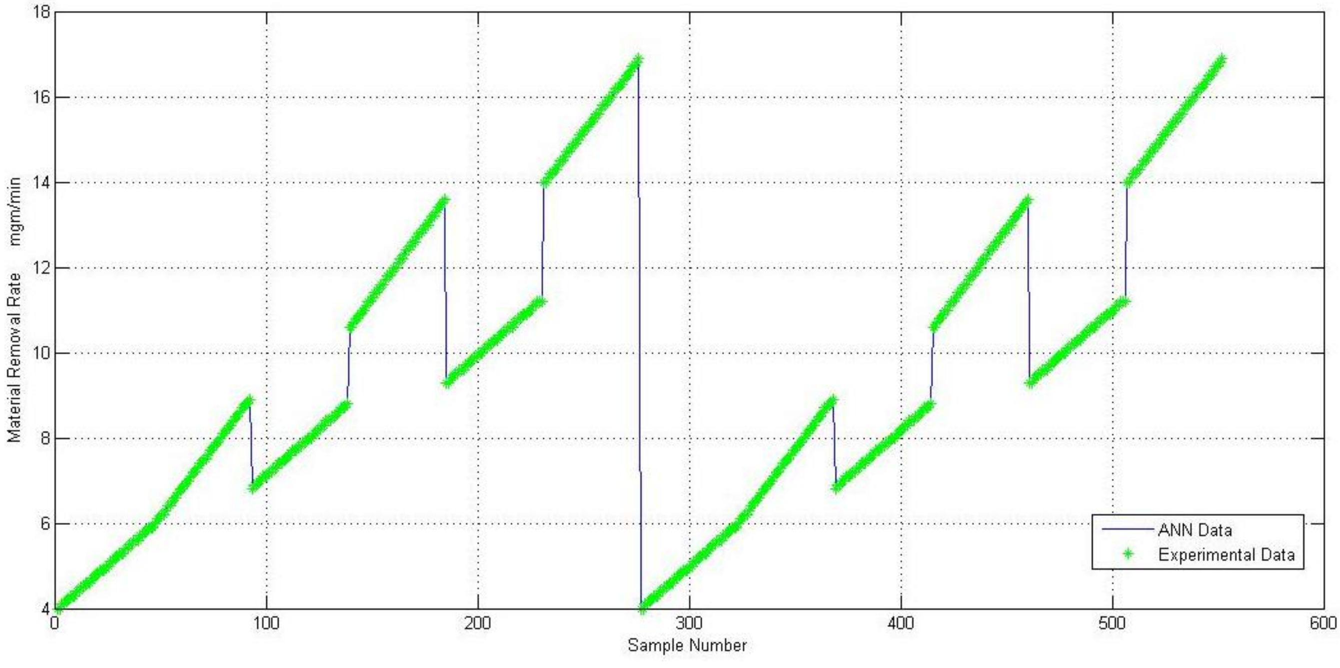

Figure5. Plot of comparison between the measured and predicted material removal rate

To enhance the efficiency of the proposed model for each input pattern, the predicted values of material removal rate and surface roughness were compared with the respective experimental ones respectively. Figures5&6 shows the graph of the predicted and the experimental values of the material removal rate and surface roughness respectively for both training & test patterns. Also, mean square error, mean absolute error, error percent and regression coefficient between predicted and expected output data were calculated and were found to be7.91x10^{-04}, 0.025, 0.23% for material removal rate &1.33 %, for surface roughness and 0.99998 respectively. The calculated regression coefficient is very close to 1 and this is acceptable from statistical point of view. On studying figures 5&6 and calculated error percent it is quite obvious that the predictive accuracy of the proposed model was good and the predicted results matched well with the experimental values.

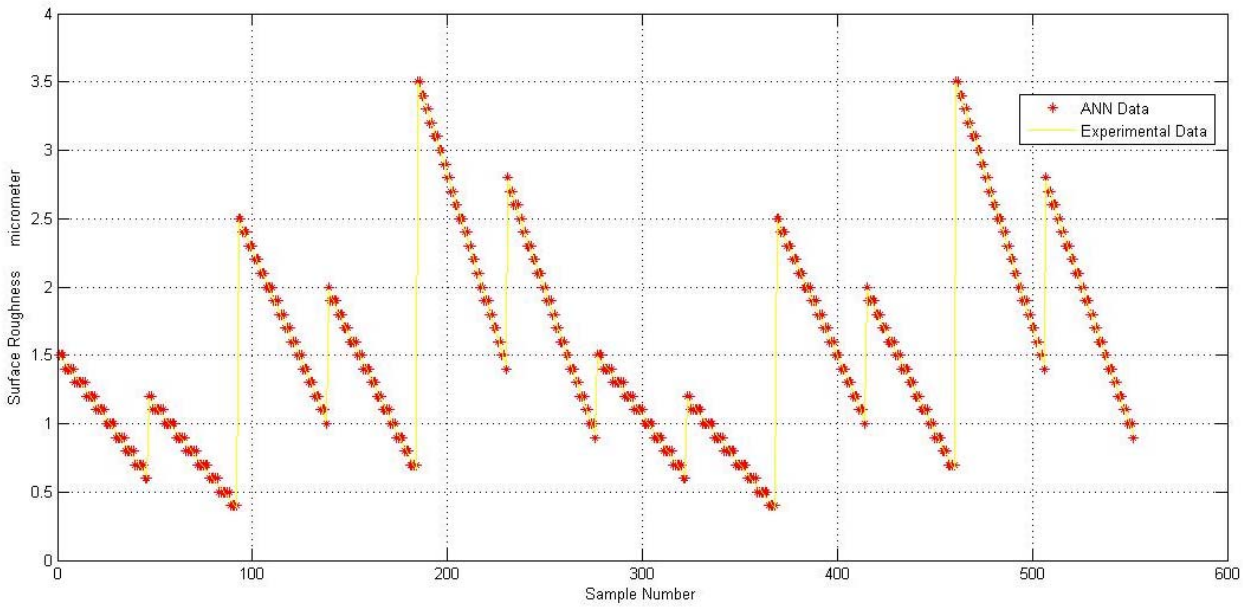

Figure 6.Plot of comparison between the measured and predicted surface roughness

VIII. Conclusion

The present study introduced a multi input multi output ANN based predictive model for prediction of resulting surface roughness and material removal rate of an electrochemical broaching process. The model served as a tool to calculate the resulting surface roughness and material removal rate based on variation of different input parameters without any need to conduct any experimental work. The proposed model was a feedforward backpropagation network consisted of 3 nodes in input layer, 12 nodes in hidden layer & 2 nodes in output layer with 0.01 as a learning parameter. The network was trained using levenburg marquardent algorithm as it gives the least error between predicted & experimental data with a small network size. Based on the comparison of calculated errors for both material removal rates and surface roughness and verification of results & studying figures 5&6; The predicted values using proposed ANN model were found to be in close agreement with the experimental data Hence, proves the accuracy of the proposed neural network model in prediction of resulting surface roughness and material removal rate.

IX. Future Work

Development of the proposed model or integrating it with any other optimization technique so that, optimum cutting conditions could be selected.

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