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PREDICTION AND INFLUENCE OF PROCESS PARAMETERS IN WIRE CUT ELECTRIC DISCHARGE MACHINING FOR HSS BY USING ARTIFICIAL NEURAL NETWORKS

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***Abstract:** performance characteristics like cutting speed, surface roughness, wire vibration and spark gap for different thickness ranging from 5mm to 80mm for machining 18-4-1 grade high speed steel (HSS) in wire electric discharge machining (WEDM). Experiments were performed at different levels of discharge current on different levels of plate's thickness and experimental results of spark gap, cutting speed, surface roughness, and wire vibration were taken. In WEDM, there is a risk of breakage of wire that affects the overall efficiency of the process. To decrease the breakage of wire and to save the time with the lengthy calculation , Artificial neural network (ANN) are very useful for predicting the required targets. The selected inputs are thickness, current and the selected outputs are spark gap, cutting speed, wire vibration and surface roughness. By comparing the three algorithms Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugated Gradient, the results obtained from Levenberg-Marquardt are more accurate than other two algorithms when correlated with experimental results from the base paper using statistical tool such as MAPE and R^2. By using L-M Algorithm the MSE value of best validation performance is 0.013364 at epoch 10 which is in acceptable limits.*

***Keywords:-** WEDM, High Speed Steel, Artificial Neural Networks, MAPE and R^2*

1. INTRODUCTION:

Presently a-days, the non-conventional machining forms turn out to be successfully utilized for high machining execution. Due to its Machining of hard materials like super alloys and tool steels turned out to be exceptionally troublesome and expensive in regular machining. Recently the WEDM has turned into a standard system in the industry to machine such sort of hard metals. The WEDM is equipped for making complicated shapes .High speed steel is a high carbon tool steel, containing a large dose of tungsten. Because of high hardness, its mach inability is exceptionally poor and traditionally hard to machine. Unconventional machining processes were introduced and developed during the Second World War to machine such kind of materials. Wire cut electric discharge machining (WEDM) process is one of the techniques used to machine such hard materials it is a non-contact and rough thermal process which produces arrangement of electric sparkles to expel undesirable material from the parental through melting and evaporation. The cathode and the work piece must have electrical conductivity keeping in mind the end goal to create the start [1].The geometry of kerf is a critical characteristic that defines the performance of the process execution of the procedure [2]. Studies were completed to quantify the impact of the procedure parameters on kerf width for different materials. Gupta et al. examined kerf geometry and effect of peak current, spark voltage, pulse on time and pulse off time on kerf width in WEDM of a hard alloy like high strength low alloy steel [3]. The thickness of the plate is one of the basic parameters that impact the setting of process parameters to get required MRR and kerf width. Hoang and Yang [4] investigated kerf geometry and impact of process parameters on kerf size and MRR in dry smaller scale WEDM of titanium compound. Capacitance, feed rate, air injection pressure and open voltage were considered using taguchi L27 outline of experiments. Air injection pressure, wire feed rate, and capacitance were observed to be critical parameters on kerf size. The thickness of the plate is likewise observed to be a critical factor on the kerf size. This is on account of machining of thick plates needs a high measure of current that vibrates the wire and thusly kerf size increments. Prasad and Gopalakrishna [5] created scientific models for kerf size and assessed wire wear proportion in WEDM of AISI-D3 metal.

Based on the above literature, it is seen that the wire vibration has a huge impact on the execution attributes, kerf size, surface roughness etc. In the present think about, the impact of the amplitude of wire vibration on the cutting speed and spark gap is examined in WEDM of HSS steel. Trials have been led on various plates of thickness. The vibration of the wire is estimated with an accelerometer toward the path opposite to work feed. Expectation models have been produced for the execution attributes utilizing the Artificial neural system to predict them for given sets of process parameters.

2. INTRODUCTION OF ANN

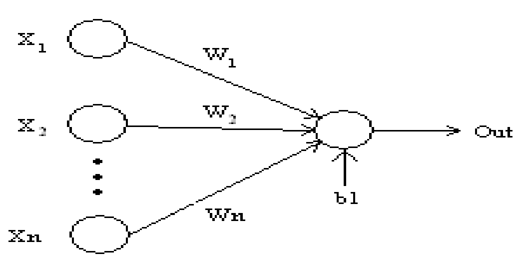
Artificial neural networks can be most adequately characterized as computational
Models with particular properties such as the ability to adapt or learn to generalize or to cluster or organize data and which operation is based on parallel processing. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function, which is usually the sigmoid, Gaussian, trigonometric function, and so on.
Predict: - to predict the output vectors using input values.
Classification:-to process the classification stage using input values.
Function approximation:-to learn the functional relationships between the inputs and desire outputs values.
Data Association:-it is classification, plus recognizing data that has error.
A typical multi-layered neural network and an artificial neuron are illustrated in Figure 1. Each neuron is characterized by an activity level (representing the state of polarization of a neuron), an output value (representing the firing rate of the neuron), a set of input connections (representing synapses on the cell and its dendrite), a bias value (representing an internal resting level of the neuron), and finally a set of output connections (representing a neuron's axonal projections). Those components of the unit are described mathematically by real values. Thus, each connection owns a synaptic weight (strength) that defines the effect of the incoming input on the unit activation limit. The negative and positive weights can be used. Referring to Figure 1, the signal flow from inputs $x_1...x_n$ is considered to
be unidirectional, shown via arrows, like a neuron's output signal flow (y). The neuron output signal y is determined by the following expression:
$Y = f(net) = f(\sum_{j=0}^{n} Wj\, Xj)$ (1)
Where is the weight vector and the function f (net) is referred to as an sigmoid (transfer) function. The variable net is defined as a scalar product of the weight and input vectors.

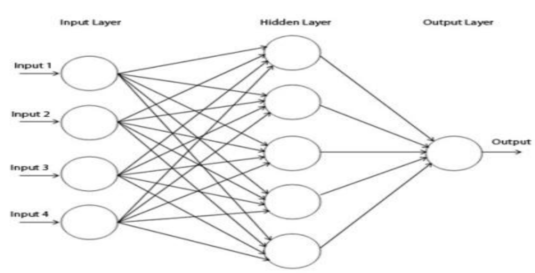
net = $w^T x = w_1x_{1+}w_2x_{2+}\ldots\ldots\ldots\ldots\ldots+w_nx_x$ (2)

T is transpose of a matrix and in simple from of output Y is Computed as

Y= f (net) = 1= 0 if $w^Tx=\theta$;

When θ is called the threshold level and that kind of node is named as linear threshold unit. The feature of the neural network is significantly a function of the interaction between the different neurons. The main structure contains three types of neuron layers: (1). Input, (2). Hidden, and (3). Output.





a). single-Layered Artificial Neural Network b). **Multi- Layered Artificial Neural Networks**

Figure 1 Structural diagram of an Artificial neuron and a Multi-Layered Artificial Neural Network

In feed-forward networks, the signal flow is directed from the input to output layers, by constraint of the feed-forward direction. The data processing can be distributed over the multiple layers, but no feedback connections are present, that is, connections extending from the outputs of units to inputs of units in the same layer or previous layers.

Recurrent networks contain feedback connections. Contrary to feed-forward networks, the dynamical properties of the network are important. In some cases, the activation values of the units undergo a relaxation process such that the network will evolve into a stable state in which these activations do not change anymore. In other applications, the changes of the activation values of the output neurons are significant, such that the dynamical behavior constitutes the output of the network. The learning process of neural networks can be classified into three distinct sorts of learning:

1. Supervised
2. Unsupervised
3. Reinforcement

Supervised :-The learning algorithm would fall under this category if the desired output for the network is also provided with the input while training the network. By providing the neural network with both an input and output pair it is possible to calculate an error based on it's target output and actual output. It can then use that error to make corrections to the network by updating it's weights.

Unsupervised :-In this paradigm the neural network is only given a set of inputs and it's the neural network's responsibility to find some kind of pattern within the inputs provided without any external aid. This type of learning paradigm is often used in data mining and is also used by many recommendation algorithms due to their ability to predict a user's preferences based on the preferences of other similar users it has grouped together.

Reinforcement :-Reinforcement learning is similar to supervised learning in that some feedback is given, however instead of providing a target output a reward is given based on how well the system performed. The aim of reinforcement learning is to maximize the reward the system receives through trial-and-error. This paradigm relates strongly with how learning works in nature, for example an animal might remember the actions it's previously taken which helped it to find food (the reward).

2. Collection of data

Experimental data were divided into two parts, 64 samples were used with 2 inputs and 4 targets . The input and targets are shown in the table 1. Out of 64 samples, 70% of data samples are given to the training purpose, 15% of data samples are given to the validation purpose and remaining 15% of data samples are given to the testing purpose. The data is used for training, validation and testing of these three algorithms in the neural networks.

INPUT	***OUTPUT***
1. THICKNESS 2. CURRENT	1. SURFACE ROUGHNESS 2. WIRE VIBRATION 3. SPRAK GAP 4. CUTTING SPEED

Table -1 Input and Output represent for ANN

3. NEURAL NETWORK MODELLING

In the supervised learning, out of the Normalized data patterns, 70% of the inputs and targets are simultaneously given to the Neural Network tool such that it is trained well. The training of the data patterns were done with the help of 3 algorithms which are Levenberg-Marquardt (L-M), Bayesian Regularization and Scaled Conjugate method (SCM) algorithms. After training, the testing of the algorithm is done with the help of 15% of the data patterns. The layout of the Neural Net Fitting is as shown in the figure 2.

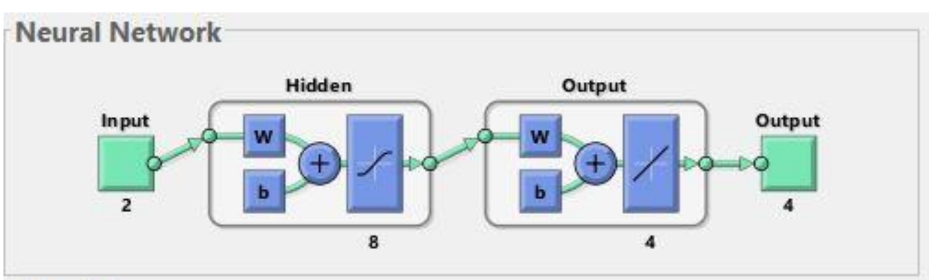


FIGURE: 2 Layout of the Neural Net Fitting

The saved inputs and targets were uploaded in the Neural Net Fitting tool. Then the uploaded data patterns were divided into 70% as training data, 15% as validation data and 15% as checking data. The number of hidden neurons was selected accordingly in order to get more accuracy. Then the L-M algorithm is selected and trained with more number of iterations. The Mean Square Error for the best validation performance is obtained as shown the figure 3.[6].

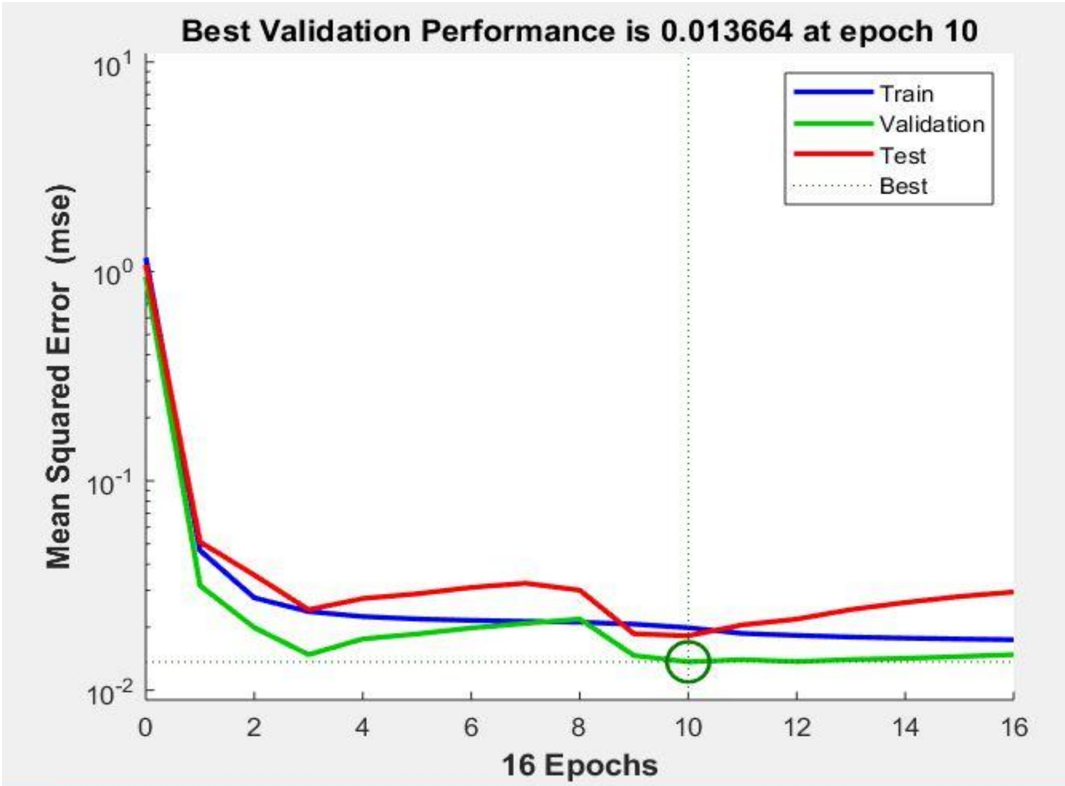


Figure 3: MSE for the best validation performance

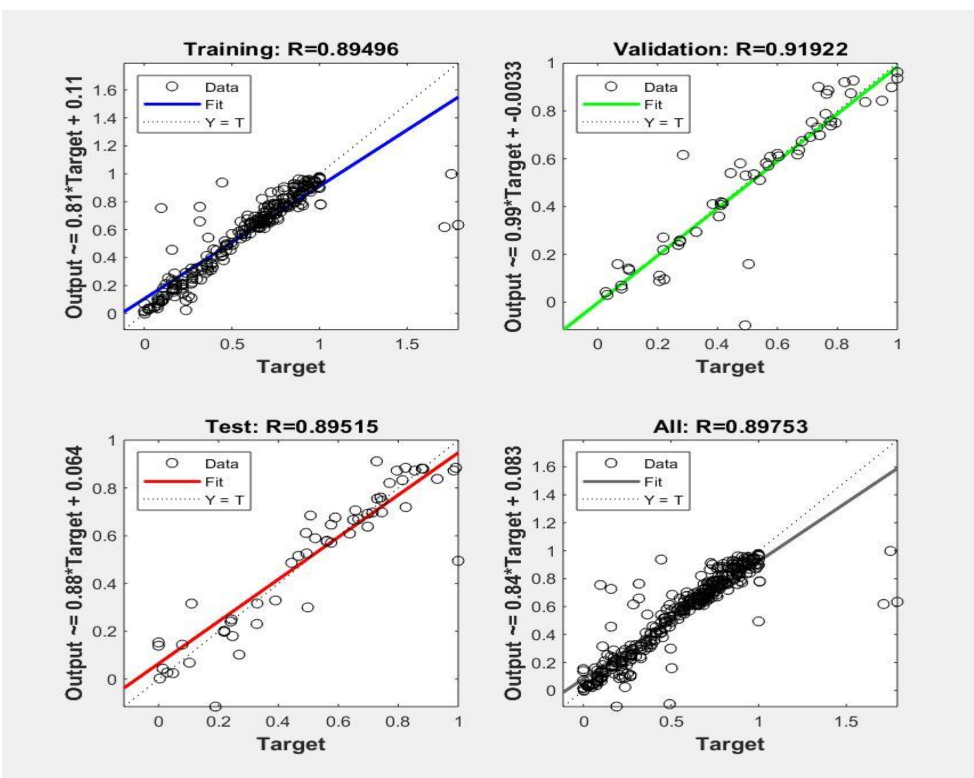


Figure 4: R value for the training, validation and testing data

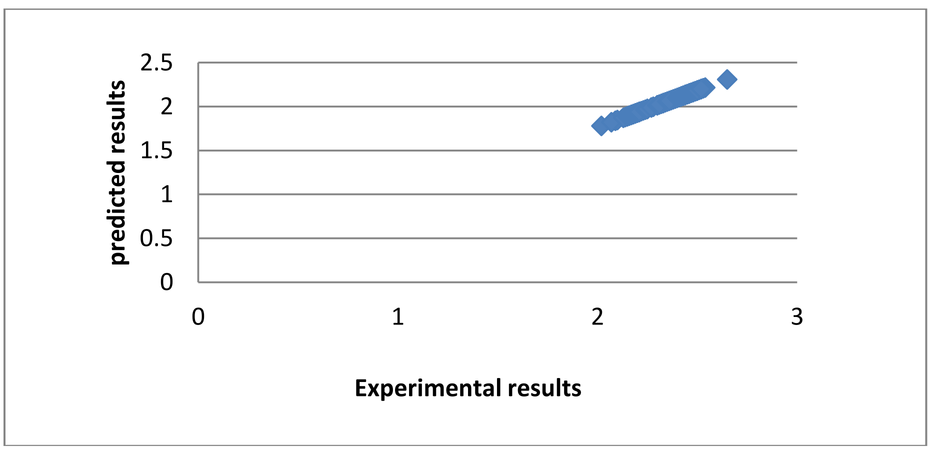
In the hidden neurons layer, the activation function is sigmoid function and in the output layer the function is linear function as shown in the figure 2. The mean square error for the best validation performance of the given data is 0.013664 at the epoch 10. The Value of R for the training, validation and testing data is shown separately as shown in the figure 4. The overall value of R for the given data is 89.783 % which is inacceptable limit

4. Results and Discussions

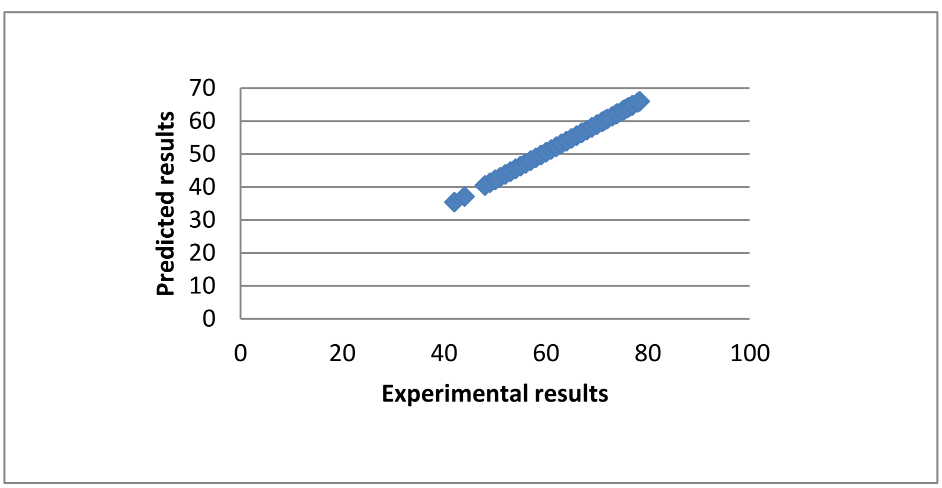
The relationship between the predicted and experimental results was defined using the statistical tool like MAPE and R^2. The MAPE and R^2 for the 4 outputs are shown in the below table 2. The value of the R^2 is above 0.85 for all the four outputs which reveals that there is a better interaction between the predicted and experimental values.

Parameters	Levenberg-Marquardt		Scalesd conjugated gradient		Bayesian regularization	
	R^2	MAPE	R^2	MAPE	R^2	MAPE
Surface roughness	0.864	12.2	0.821	13.2	0.833	14.1
Spark gap	0.992	7.2	0.9916	8.1	0.9918	7.7
Cutting speed	0.979	10.1	0.977	13.6	0.979	12.3
Wire vibration	0.991	11.3	0.984	20.5	0.991	21.5

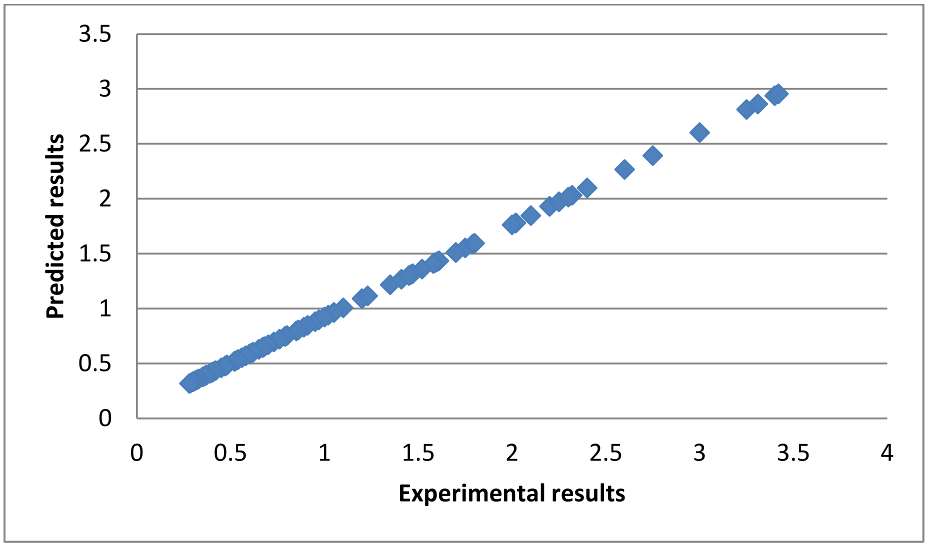
Table 2: MAPE AND R^2



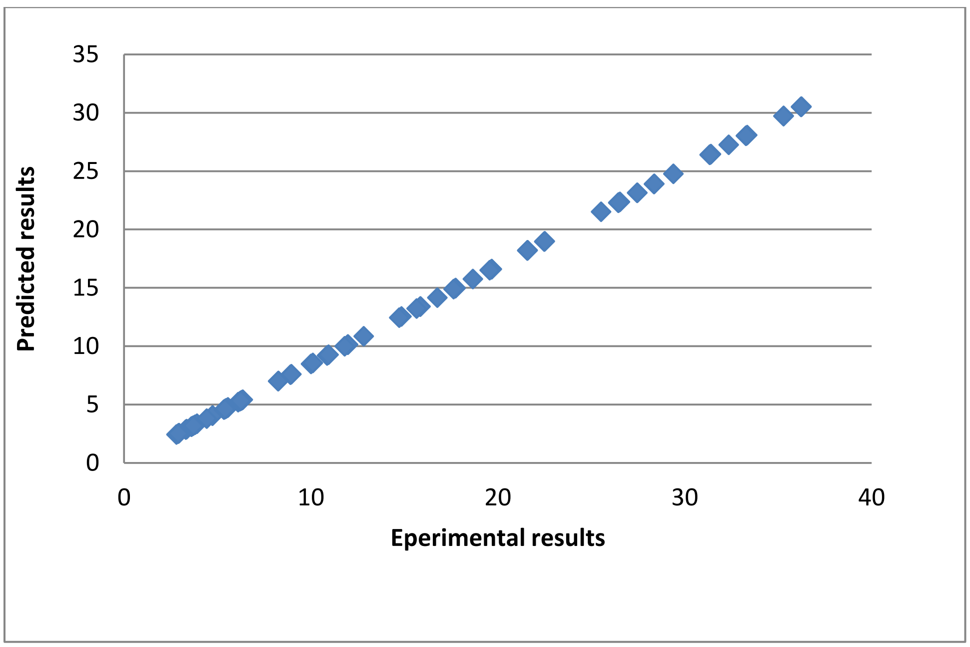
a) Relation between Experimental Vs Predicted Result of surface roughness



b) **Relation between Experimental Vs Predicted Result of spark gap**



c) **Relation between Experimental Vs Predicted Result of cutting speed**



d) Relation between Experimental Vs Predicted Result of wire vibration

Figure 5: Relation between Experimental and predicted results of 4 outputs

From figure 5, it is observed that the experimental and predicted values are nearly matched for all 4 outputs. Thus the ANN is successfully simulated. if any untrained inputs are given to the trained algorithms, the output are obtained as the linear behavior of the relation between the experimental and predicted results of all the 4 outputs. [7].

CONCLUSION

The experimental results taken from the thesis paper was successfully predicted with the help of ANN. The prediction of the selected targets was done with the help of these three algorithms. Out of these, L-M algorithms show better results. An Artificial neural system (ANN) was created and prepared with the gathered information of this examination work. The outcomes results that the two layer feed-forward neural system with one hidden layer was sufficient enough in predicting 2 different inputs for 4 different outputs. It can be concluded that the high values of the regression coefficient yielded when setting a regression line for predicted and measured datasets.

REFERENCES

[1] Wuyi Ming; Junjian Hou; Zhen Zhang; Hao Huang; Zhong Xu; Guojun Zhang;Yu Huang. Integrated ANN-LWPA for cutting parameter optimization in WEDM, Int J Adv Manuf Technol, 2016, 84, 1277–1294.

[2] Tosun, N.; Cogun, C.; Tosun, G. A study on kerf and material removal rate in wire electrical discharge machining based on Taguchi method, J Mater Process Technol, 2004, 152, 316–322.

[3] Mehmet Altug; Mehmet Erdem; Cetin Ozay. Experimental investigation of optimization of parameters using a genetic algorithm, Int J Adv Manuf Technol, 2015, 78, 1573–1583.

[4] Hoang, K.T.; Yang, S.H. Kerf analysis, and control in dry micro-wire electrical discharge Machining, Int J Adv Manuf Technol, 2015, 78, 1803–1812.

[5] Prasad, D.V.S.S.S.V.; Gopala Krishna, A. Empirical modeling, and optimization of kerf and wire wear ratio in wire electrical discharge machining, Int J Adv Manuf Technol, 2015, 77, 427–441.

[6]] Mehrotra.K, Mohan.C.K and Renga.S,,"Elements of Artificial Neural Network," Cambridge, MA, MIT Press, 1997.

[7] M.Jennes,R. Snoey,"Correlation between EDM data and machining settings", Ann. CIRP 24 (2) pp. 83–88. 1984.