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Prediction of process parameters effect on MRR and surface roughness in Abrasive water jet cutting using Artificial Neural Network

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Abstract A machining operation is basically a material removal process, where material is removed in the form of chips. In a machining operation, the output parameter is achieved by controlling various input parameters. This paper discusses the effects of various input parameters in abrasive water jet cutting on the material removal rate and surface finish (as the output parameters). The results presented in the paper are obtained from an experimental study carried out on an abrasive water jet cutting machine. ANN based on back propagation (BP) is used to predict the effect of various input parameters on the outputs. Experiments are carried out on the mild steel and stainless steel. The five input parameters of the model consist of thickness, pressure, flow rate of abrasive, feed rate and SOD whereas the output are surface finish and material removal rate. In present work an attempt has been made to use Neuro solution for the ANN applying to abrasive water jet cutting process. The ANN is subsequently trained with experimental data. Testing of the ANN is carried out using experimental data not used during training. The result shows that the outcomes of the calculation are in good agreement with the experimental results; this indicates that the developed neural network can be used as an alternative way for knowing the process parameters effect on cutting performance.

Keywords Abrasive Water Jet cutting, Artificial Neural Network, Back propogation, Material removal rate.

AWJC	Abrasive water jet cutting
MRR	Material Removal rate (gm/min)
SOD	Stand of Distance (mm)
Sf	Surface roughness (µm)
ANN	Artificial Neural Network
BP	Back propagation
MSE	Mean square error

1. INTRODUCTION

Abrasive water jet cutting has various distinct advantages over the other non-traditional cutting technologies, such as no thermal distortion, high machining versatility, minimum stresses on the work piece, high flexibility and small cutting forces. Also has been proven to be an effective technology for cutting various engineering materials [1]. It is superior to many other cutting techniques in processing variety of materials and has found extensive applications in industry [2]. In this method, a stream of small abrasive particles is introduced in the water jet in such a manner that water jet's momentum is partly transferred to the abrasive particles. The main role of water is primarily to accelerate large quantities of abrasive particles to a high velocity and to produce a high coherent jet. This jet is then directed towards working area to perform cutting [3]. It is also a cost effective and environmentally friendly technique that can be adopted for processing number of engineering materials particularly difficult-to-cut materials[4,5]. However, AWJC has some limitations and drawbacks. It may generate loud noise and a messy working environment. It may also create tapered edges on the kerf, especially when cutting at high traverse rates [6,7]. As in the case of every machining process, the quality of AWJC process is significantly affected by the process tuning parameters [8,9]. There are numerous associated parameters in this technique, among which water pressure, abrasive flow rate, feed rate , standoff distance and diameter of focusing nozzle are of great importance and require to control properly[10,11].

Artificial neural networks (ANNs) are biologically inspired by intelligent techniques. Artificial neural networks have been very popular in many engineering fields because of their fascinating features such as learning, generalization, faster computation and ease of implementation. The learning process automatically adjusts the weights and thresholds of the processing elements. Once adjusted with minimum difference between ANN output and targeted output, the neural network is said to be trained. Artificial neural networks have found extensive applications in diverse fields like manufacturing, signal processing, bio-electric signal classification, pattern recognition, speech recognition, image processing, communications, autonomous vehicle, navigation control of gantry crane to name a few. Even in manufacturing, ANN applications to cold forging, for predicting the flow stress in hot deformation, for tool wear monitoring, for prediction of machining behavior, and for optimization of manufacturing processes among many others, are well documented and only a few illustrative references are cited here[2,3,4,5]. In this paper MRR and surface finish are considered as the performance measurement. In order to effectively control and optimize the Abrasive water jet cutting process, predictive models for MRR and surface finish are developed using ANN for mild steel, and stainless steel.

2. EXPERIMENTATION

2.1. Experimental set up of Abrasive water jet cutting process

The experimental set-up of abrasive water jet cutting consists of a main tank, a storage tank, an air compressor, abrasive water jet cutting head and work holding arrangements as shown in fig 1. The cutting head with a nozzle is mounted on a stationary work table. The SOD is adjusted by the vertical movement of the cutting head and is measured by the graduated scale fitted to the cutting head. The cutting head has a provision to accommodate nozzles of different orifice diameters.

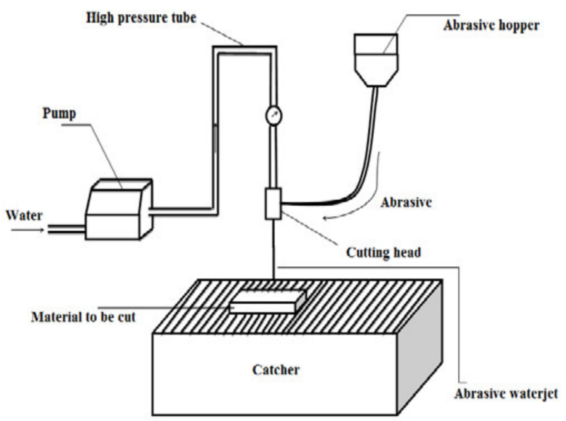


Fig 1. Schematic of an abrasive water jet cutting process

The equipment used for machining the sample is equipped with ultrahigh pressure pump with designed pressure of 2758 bar. The machine is equipped with a grain feed type of hopper an abrasive feeder system pneumatically controlled rate and work piece table. Sapphire orifice is used to convert high pressure jet in to a collimated jet to form an abrasive water jet. The abrasives are supplied by compressed air from hoppers to mixing chamber and regulated using metering device. The debris of material and slurry are collected in to a catcher tank. The impact of high-pressure abrasive particles on the work surface lead to erosion of the work material, such that material removal takes place. Experiments are carried out by making a cut on mild steel and stainless steel plates of 50x50cm with constant pressure of 2758 bar (40,000 psi). Total 58 experiments are carried out with varying flow of abrasive, feed rate, SOD and thickness of plates. Different parameter level and sample experimental data are shown in table 1, 2 & 3.

Table 1 Levels of parameters used in experiment

Parameter	Unit	Level 1	Level 2	Level 3
Flow of Abrasive	gm/ min	250	300	-
Feed rate	mm/ min	100	200	300
SOD	mm	1	2	3
Plate thickness (mild steel)	mm	3	5	8
Plate thickness (stainless steel)	mm	2	4.5	6

Table 2. Sample Experiments data Material : Stainless steel, Pressure: 2758 bar constant for all experiments

Plate thick ness (mm)	Flow rate of Abrasive (gm/min)	Feed rate. (mm/ min)	SOD (mm)	MRR (gm/ min)	Sf (Ra) (µm)
2	250	100	1	15.8	4.52
4.5	250	200	2	13.5	4.91
6	250	300	3	10.4	5.21
2	300	100	1	18.3	4.41
4.5	300	200	2	14.3	4.83
6	300	300	3	10.7	5.11

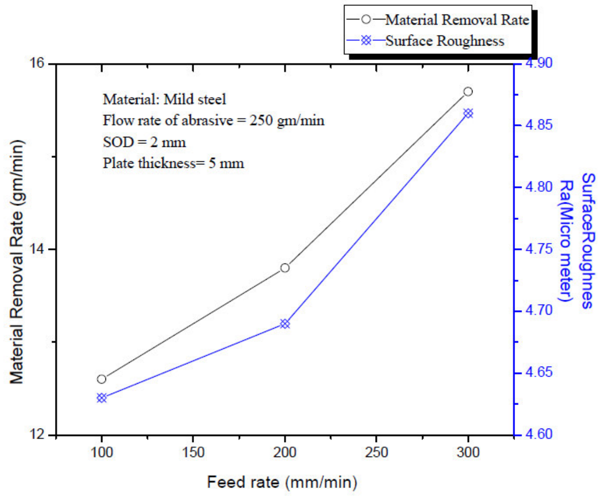
Table 3. Sample Experiments data Material : Mild steel, Pressure: 2758 bar constant for all experiments

Plate thick ness (mm)	Flow rate of Abrasive (gm/min)	Feed rate. (mm/ min)	SOD (mm)	MRR (gm/ min)	Sf (Ra) (µm)
3	250	100	1	16.3	4.45
5	250	200	2	13.8	4.69
8	250	300	3	10.8	5.09
3	300	100	1	18.6	4.4
5	300	200	2	15.1	4.69
8	300	300	3	12.8	4.96

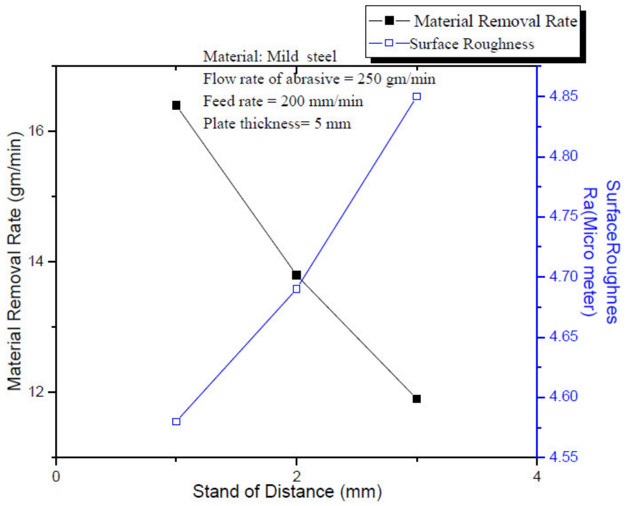
2.2 Results and Discussion

Surface roughness is one of the most important parameter in deciding quality of the cut. The effects of SOD and feed rate on the surface roughness are shown in fig2 and 3. The surface roughness is assessed based on the centre line average Ra. Surface roughness is increase with increase in SOD. Generally higher SOD, the more jet flaring which may increase extra drag from the surrounding environment. Therefore increase in the SOD result in increase jet diameter and which reduce kinetic energy of the jet at impingement. So surface roughness increase with increase in SOD. It is desirable to have a lower SOD which may produce a smooth surface due to increase kinetic energy.

Experimental results plotted in the fig 2and 3 shows that MRR is increase with increasing feed rate and decrease with SOD for both mild steel and stainless steel material. Increasing the feed rate more material is get exposed to the abrasive water jet which is responsible for higher MRR. Kinetic energy of the impinging jet reduced with increase in SOD because of that there is reduction in MRR.

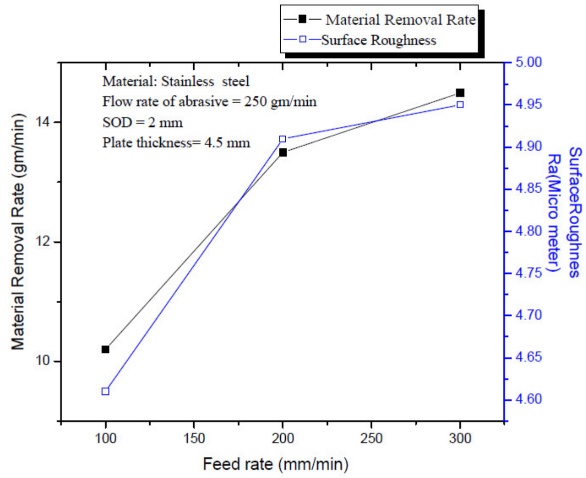


(a)

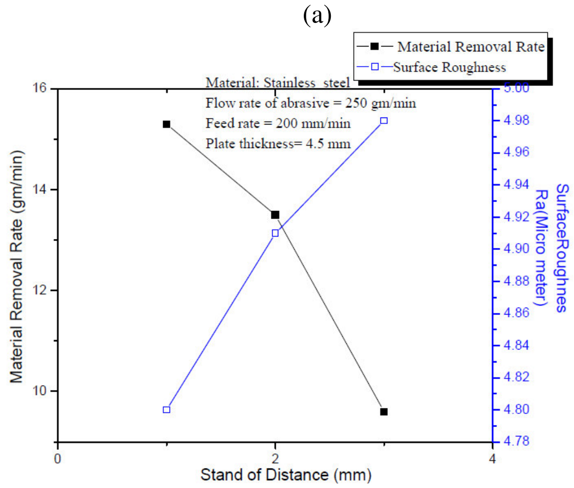


(b)

Fig. 2. Effects of feed rate (a) and stand of distance (b) on surface roughness and MRR for Mild steel



(a)



(b)

Fig. 3. Effects of feed rate (a) and stand of distance (b) on surface roughness and MRR for stainless steel

3. ANN MODELLING FOR ABRASIVE WATER JET CUTTING USING NEURO SOLUTION SOFTWARE

3.1 Introduction

A Multi layer perception is developed using neuro solution and used for the prediction of the surface roughness and MRR. The back propagation is initially trained with experimental data and testing is performed with experimental data that is not used during training. For the water jet cutting the data is generated experimentally. The 28% data are taken for cross validation and 15% data are taken for the testing remaining data are taken for training. The scaling has the advantages of mapping the desired range of a variable to the full working range of the network input. All the input output data are normalized between 0.1 and 0.9 using the following equation. [6]. Sample data has been shown in the table 4 and table 5.

$$Y(nor)=(0.8/\Delta)Z+(0.9-(0.8Z_{max})/\Delta) \quad (1)$$

$\Delta = Z_{max} - Z_{min}$

Table 4 Sample Normalized Data for Stainless steel Normalized Pressure :0.9

Nor Thickness	Nor Flow rate of Abrasive	Nor Feed rate.	Nor SOD	Nor SF	Nor MRR
0.1	0.1	0.1	0.1	0.172	0.34
0.1	0.9	0.1	0.5	0.216	0.284
0.42	0.1	0.1	0.1	0.134	0.423
0.42	0.9	0.1	0.5	0.372	0.364
0.9	0.1	0.1	0.5	0.366	0.311

Table 5 Sample Normalized Data for Mild steel Normalized Pressure :0.9

Nor Thickness	Nor Flow rate of Abrasive	Nor Feed rate.	Nor SOD	Nor SF	Nor MRR
0.1	0.1	0.1	0.1	0.254	0.406
0.1	0.1	0.1	0.5	0.366	0.280
0.6	0.1	0.1	0.9	0.522	0.1
0.6	0.1	0.5	0.1	0.567	0.494
0.9	0.1	0.5	0.1	0.582	0.472

3.2 Back Propagation Neural Network

For many years there was no rule available for updating the weight of a multi layer network undergoing supervised learning. The weight adaptation rule is known as back propagation. Neural networks are mathematical models composed by several neurons arranged in different layers, linked through the variable weights. These weights are calculated by an iterative method during the training process when the network is fed with a large amount of training data, input and output pairs that represent the pattern attempting to be modelled [2].

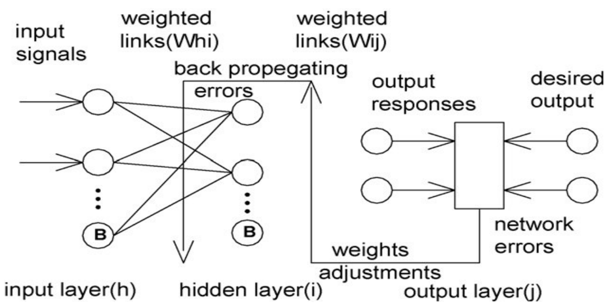


Fig. 4. A back propagation network [11]

The back propagation algorithm defined two aspects of the network: first a forward sweep from the input layer to the output layer, and then a backward sweep from

output layer to input layer. The forward sweep propagates input vector through the network to provide output at the out put layer. The backward sweep is similar to the forward sweep, except that error values are propagated back through the network to determine how the weights are to be changed during the training. During the back ward sweep value pass along the weighted connection in the reverse direction to that which is taken during the forward sweep. Fig.4 shows a back propagation network a unit in the hidden layer will send the activation to the every unit in the out put layer during the forward sweep and so during the back ward sweep a unit in the hidden layer will receive an error signals from the every unit in the out put layer [11].

3.3 ANN Architecture

Five different inputs and two outputs (surface finish, MRR) are given to ANN. Consider the eight hidden nodes and single layer feed forward neural network, network architecture is become as follows (Refer fig.5).

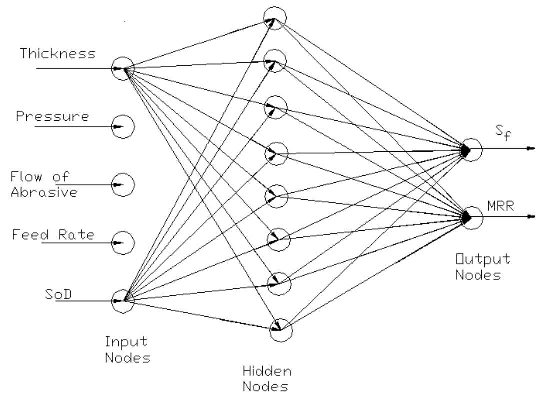


Fig. 5. ANN Architecture

3.4 Training of ANN

For this study will be broach under a supervised learning strategy, which means that for all the input parameters ,the objective out puts are known and batch pattern training style is chosen. The training set construction represents a key point of the network generalization property especially for avoiding the over fitting problem. For avoiding the over fitting problem, the early stopping technique is used considering the three data sets: training, cross validation and testing. The training set for training and weight adjustments. The validation set to refine the network by early stopping technique and finally the testing data set an unseeing set during the training that is used to determine the network performance by an error computation [21].Using this training technique the ANN is trained.

3.5 Network Experimentation

Neuro Solution version 4.3 is used for present application which was found by Curt Lefebvre and Jose Principle. Neuro Solution based on the back propagation learning algorithm with momentum term is used. Network parameter such a learning rate, momentum, no of hidden nodes in hidden layer, no of hidden layers and activation functions were chosen based on the parametric study reported in the literatures [20] .The parametric study was intended to obtain the optimal parameters for faster convergence of data and minimum MSE. For abrasive water jet cutting five parameters are selected as an input to ANN based on the experimentation. ANN was trained with the experimental data up to 40000 epochs. The parametric variation was selected based on the effect of it on MSE as reported in literature [14, 17, and 19]. Subsequently network was tested with that experimental data which are not used during training [14, 19]. After testing, ANN results are compared with experimental results for the % of error of MRR and surface roughness in abrasive water jet cutting. Optimal parameter value for ANN architecture is shown in table 6.

3.6 Testing Results of ANN

Testing results of ANN are shown in table 7. In the testing results R value is near to 1 which shows desired output and ANN outputs are very close. Graphical representation of desired output and ANN output are shown in fig 6 (a) and (b).

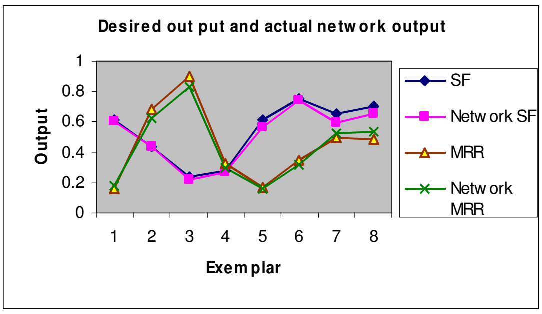
Table 6. Optimal parameter values for ANN architecture

Sr. No.	Parameter	Data Normalized as a whole set	
		Mild steel	Stainless steel
1	Number of Inputs	5	5
2	Number of out puts	2	2
3	Number of hidden nodes	8	8
4	Number of hidden layers	1	1
5	Momentum	0.7	0.7
6	Learning rate	0.6	0.8
7	Activation function	Sigmoidal	Sigmoidal
8	Normalized range	0.1 to 0.9	0.1 to 0.9

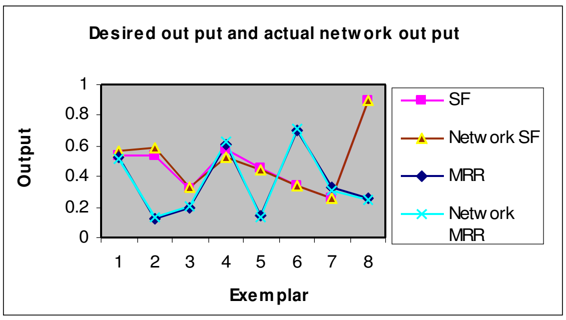
Table 7. Co relation between desired output and ANN output

Stainless Steel		
Performance	SF	MRR
MSE	0.00686	0.00382
Min Abs Error	0.00273	0.0242
Max Abs Error	0.15481	0.0736
R	0.97136	0.984

Mild Steel		
Performance	SF	MRR
MSE	0.00585	0.00312
Min Abs Error	0.00183	0.00267
Max Abs Error	0.15490	0.09779
R	0.92907	0.9869



(a) Stainless steel plate.



(b) Mild steel plate

Fig.6. Desired out put and ANN predicted output

4 CONCLUSION

Following conclusions are derived from the parametric study of abrasive water jet cutting on MRR and surface roughness using the artificial neural network.

- Experimental investigations have been carried out for the surface roughness and MRR in abrasive water jet cutting of stainless steel and mild steel. The effects of different operational parameter on surface roughness and MRR have been investigated. As a result of this study, it is observed that these operational parameters have direct effect on surface roughness and MRR.
- Experimental results show that as feed rate increases MRR and surface roughness increases in mild steel as well as in stainless steel. With increase in SOD surface roughness is increase while MRR decrease. Therefore to achieve an overall good cutting performance optimum parameters are required to be selected.
- Parametric study indicates that there exists unique combination of network parameters like momentum and learning rate for MSE. Optimal parameter values are required to be finding out by trail and error.
- It is observed from the results that a correlation of experimental and the BPN model is nearer to 1 which shows that the developed neural network model is capable of making the prediction of the MRR and surface finish with reasonable accuracy.

REFERENCES

[1] Hascalik, A., Caydas, U., Gurun, H. “Effect of travers speed on abrasive waterjet machining of Ti-6Al-4 alloy”.Meter.Des.28,1953-1957, 2007.

[2] Momber, A., Kovacevic, R. “Principles of Abrasive Waterjet Machining”. Springer-Verlag, London, 1998.

[3] Hashish M. “A model for abrasive waterjet (A machining”. Transactions of ASME Journal of Engineering Materials and Technology, vol. III1,54-162, 1989.

[4] Siores E., Wong W C K., Chen L., Wager J G.“Enhancing abrasive waterjet cutting of ceramics by head oscillation techniques”. Ann CIRP, 45[1], 215-218, 1996.

[5] Wang J. “Abrasive Waterjet Machining of Engineering Materials”. Uetikon-Zuerich [Swizerland]: Trans Tech Publications, 2003.

[6] M.A. Azmir, A.K. Ahsan. “Investigation on glass/epoxy composite surfaces machined by abrasive waterjet machining”. Journal of Materials Processing Technology, vol.198, 122-128, 2008.

[7] C. Ma, R.T. Deam. “A correlation for predicting the kerf profile from abrasive waterjet cutting”. Experimental Thermal and Fluid Science, vol.30, 337-343, 2006.

[8] Kovacevic R. “Monitoring the depth of abrasive waterjet penetration”. International Journal of Machine Tools & Manufacture, vol 32(5),725-736, 1992.

[9] Hashish, M. “Optimization factors in abrasive waterjet machining”. Transaction of ASME J. Eng. Ind. 113, 29-37, 1991.

[10] John Rozario Jegaraj J., Ramesh Babu N. "A soft computing approach for controlling the quality of cut with abrasive waterjet cutting system experiencing orifice and focusing tube wear", Journal of Materials Processing Technology, vol.185, 217–227, 2007.

[11] Manikya Kanti K., Rao Srinivasa “Prediction of bead geometry in pulsed GMA welding using back propagation neural network” Journal of materials processing technology 200 (2008) ,300–305

[12] Erdal Karadeniz,Ugur Ozsarac , Ceyhan Yildiz “The effect of process parameters on penetration in gas metal arc welding processes” Materials and Design 28 (2007), 649–656

[13] Hakan Ates “Prediction of gas metal arc welding parameters based on artificial neural networks” Materials and Design 28 (2007) ,2015–2023

[14] Gandhi A.H., “Simulation of three roller plate Bending process for real material behavior using Artificial Neural Network-: A Parametric study”, M.E. Dissertation report submitted to South Gujarat University, 2003.

[15] Uhrig Isoukalus “Fuzzy and Neural Approches in engineering” ’96 publication John Wiley and sons.

[16] Weilong Hu, Z.R. Wang, “Theoretical analysis and experimental study to support the development of a more valuable roll-bending process”. International journal of machine tool and manufacture, 41 (2001),731-747.

[17] Inamdar M., Date P. P, Narasimhan K., Maiti S. K. and Singh U. P. “Development of an Artificial Neural Network to Predict Springback in Air Vee Bending” Journal of Advance manufacturing Technology. (2000) 16,376–381

[18] Inamdar M., Date P. P, Desai U.B. “ Studies on the prediction of springback in air vee bending of metallic sheets using an artificial neural network” Journal of Materials Processing Technology 108 (2000) ,45-54.

[19] Bhatt Dhaval, Desai Chinmay, Raval H.K. and Dave A.K. ,”prediction of the spring back in air V-bending ANN for the real material behavior (power law)”, 6th Internation conference on Engineering Design and Automation, Aug4-7,2002,Hawai.

[20] Forcellese A., Gabriell F, Ruffini R. “Effect of the training set size on spring back control by neural network in an air bending process” Journal of Material processing Technology ,1998.