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DEVELOPMENT OF A SURFACE ROUGHNESS PREDICTION SYSTEM FOR MACHINING OF HOT CHROMIUM STEEL (AISI H11) BASED ON ARTIFICIAL NEURAL NETWORK

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ABSTRACT

An attempt have been made to apply the principles of artificial neural networks (ANN) towards developing a prediction model for surface roughness during the machining of high chromium steel through face milling process. Now a days, hot chromium steel is prominently used in die and mould industry as well as in press tools, helicopter rotor blades, etc. Initially, Taguchi design of experiments was applied while conducting the experiments to reduce the time and cost of experiment. Multilayer perceptron (MLP) network using Feed Forward Error Back propagation was chosen as the neural network architecture to describe the process model. The experiments were conducted on a C.N.C milling machine using carbide cutters. Pearson correlation coefficient was also calculated to analyze the correlation between the system inputs and selected system output i.e. surface roughness. The results of ANN modeling were substantiated by testing and validation of the resulting surface roughness values and the results have been encouraging. The outputs of Pearson correlation coefficient also showed a strong correlation between the feed per tooth and surface roughness, followed by cutting speed.

Keywords: prediction model, surface roughness, chromium steel, machining, face milling, feed forward, ANN.

1. INTRODUCTION

Modern manufacturing often caters to rapidly changing product specifications with the increasing need for productivity, flexibility and quality requirements. Machining is the most widely used manufacturing process for shaping the material. The requirement for precision in machining emphasizes the importance of the surface roughness parameters and a better control over its value. Hence the quality of surface is very critical in the evaluation of machine tool productivity with consistency in maintaining surface finish. In addition, surface roughness of the workpiece will also decide the efficiency of distribution and adhering of lubricant, application of coatings, fatigue resistance, friction and wear [10]. The quality of finish mainly depends on the interaction between the work, cutting tool and the machining system

Due to the above reasons, there have been a series of attempts by researchers to develop efficient prediction systems for surface roughness prior to machining. But face milling being a complex and dynamically varying system with number of intervening factors becomes a non linear system. This explains the difficulty in arriving at a very accurate prediction system.

Artificial neural network technique is a modeling approach that can be applied to a physical process nonlinear in nature and having a large number of processing elements grouped into layers. Initially, the network is trained using a set of data patterns, i.e. a set of inputs and known outputs. Once the training is over, the ANN system can predict the output corresponding to the given set of inputs. In this paper, a multi layer perceptron neural network model is developed to predict surface roughness during face milling operation of Hot Chromium steel. Three numbers of inputs (cutting speed, feed per tooth, axial depth of cut) were considered for the development of the network. Best performance was achieved in the prediction by fine tuning the ANN system parameters.

2. REVIEW OF LITERATURE

Engineered components must satisfy surface texture requirements and, traditionally, surface roughness (arithmetic average, Ra) has been used as one of the principal methods to assess quality. The surface roughness value is a result of the combination of cutting parameters and tool wear. Moreover, surface finish influences mechanical properties such as fatigue behavior, wear, corrosion, lubrication, and electrical conductivity. Thus, measuring and characterizing surface finish can be considered as one of the means of predicting machining performance.

Luong and Spedding [1] applied neural network technology for the prediction of machining performance in metal cutting. Their network was trained using data from a machining data handbook. They concluded that the network was able to determine conditions for a given material and required depth of cut, and to predict the performance of the process in terms of cutting forces, surfacefinish, and tool life. Also they recognized that there is a lack of guidance on network design. For the prediction of surface roughness, Benardos and Vosniakos [2] used a feed forward ANN. The experimental data was obtained after face milling Al alloy normally used in aerospace applications. They concluded that an ANN can be used reliably, successfully, and very accurately for the modeling of surface roughness formation mechanism and the prediction of its value in face milling.

In 2005, Bisht *et al*., [3] developed a back propagation neural network for the prediction of flank wear in turning operations. In their case, they included the chip width in addition to the existing inputs (cutting speed, feed rate, depth of cut, and cutting forces). They concluded that the back propagation neural network could be trained for the effective prediction of flank wear during turning operations.

Pal and Chakraborty [4] predicted the surface roughness in a turning process by using a back propagation neural network. A large number of experiments were performed on mild steel using a high-speed cutting tool. They showed the efficacy of a back propagation neural network for predicting surface roughness in turning.

In 2006, Basak *et al*., [5] developed radial basis neural network models when turning AISI D2 cold-worked tool steel with ceramic tool. They identified the best values of cutting parameters for a desired value of surface roughness.

In 2006, Zhong *et al*., [6] predicted surface roughness heights Ra and Rt of turned surfaces using a neural network. The experiments were conducted using aluminum and copper rods of 19 mm diameter. Their study showed the effect of the neural network and hyperbolic tangent and sigmoid activation functions on the accuracy of the network.

The determination of best cutting parameters leading to a minimum surface roughness in end milling mold surfaces used in biomedical applications was done by Oktem *et al*., [7]. For their research, they coupled a neural network and a genetic algorithm (GA) providing good results to solve the optimization of the problem.

In 2007, Lin *et al*., [8] developed a surface prediction model for high-speed machining of 304L stainless steel, Al 6061-T6, SKD11, and Ti-4Al-4V. For this purpose, the finite element method and neural network were coupled, and they concluded that surface roughness may quickly be determined from the prediction model developed when the process parameters are set.

In 2007, Jesuthanam *et al*., [9] proposed the development of a novel hybrid neural network trained with GA and particle swarm optimization for the prediction of surface roughness. The experiments were carried out for end milling operations, and they found that the proposed hybrid neural network is competent in terms of computational speed and efficiency over the neural network model.

In 2009, Patricia Munoz-Escalona *et al*., [10] proposed the artificial neural network model for surface roughness prediction for face milling of Al 7075-T735 and they got best result with Feed Forward Neural Network (FFNN). Result shows a strong correlation between the chip thickness and surface roughness followed by the cutting speed.

From the literature review, it was observed that majority of the work in the area of ANN application has been for turning operation when compared to face milling operation. Due to this fact and also considering the importance of face milling operation for machining of hot chromium steel which is widely used in mould and die industry, the Feed Forward multi layer perceptron neural network model is developed in this research. This helps the manufacturing industry in predicting the desired surface roughness for a specific environment while selecting the right combination of cutting parameters.

3. EXPERIMENTAL PROCEDURE

The face milling operation is carried out on Spark DMT -250 high speed CNC machining center supplied by Ace Manufacturing Systems Limited, India.

Hot Chromium steel (AISI H11) is used as the work material due to its importance in the field of mold and die industry. Face milling cutter with 5 no's of carbide inserts has been used under dry cutting condition. Further details regarding the work piece cutter, and milling parameters are presented below:

3.1 Work piece characteristics

H-11 is the basic 5% chromium hot work steel. The 1.5% molybdenum imparts very high harden ability to this grade, enabling it to harden throughout large sections using a still air quench. It has good resistance to softening at elevated temperatures, but it's outstanding characteristics is its high toughness. A slight modification of this grade has been widely used for aircraft and structural applications requiring good ductility and notch strength at high strength levels. Advanced practices for melting, hot working, and annealing have been developed which enable H-11 to be consistently supplied with a fine uniform annealed structure. This steel is readily heat treated to produce a uniformly fine grained microstructure. The structural uniformity results in longer die life. This is used in Die castings dies, punches, piercing tools, mandrels, extrusion tooling, forging, helicopter rotor blades.

Table-1. Chemical composition of AISI H11.

	C	Mn	Si	Cr	Ni	Mo	V	Cu	P	S
Weight %	0.33-0.43	0.20 -0.50	0.80 - 1.20	4.75 - 5.50	<0.3	1.10- 1.60	0.3 -0.6	<0.25	<0.03	<0.03

3.2 Tool and tip characteristics

A standard insert holder of 50 mm diameter with five cutting edges (inserts) was used for the experiments. As tool insert, SDMRT 1205 (tool nose radius of 0.2 mm), was used, as recommended by the tool suppliers for Hot chrome steel under dry cutting condition.

3.3 Cutting Parameters

Cutting speed, feed per tooth, and the axial depth of cut were the variables chosen for the study because from previous research it was observed that these variables had more influence on surface roughness and tool life. Low, medium, and high levels were selected for each of the cutting parameter to have a wide range of combinations. Also the selected values are recommended from the tool supplier when cutting hot chrome tool steel under dry cutting conditions. Selected cutting parameters are shown in Table-2.

Table-2. Selected cutting parameters.

Level	V, cutting speed m/min	fz, feed per tooth mm per tooth	ap, axial depth of cut, mm
Low (1)	78	0.08	0.5
Medium (2)	157	0.12	1
High (3)	235	0.16	1.4

3.4 Work piece

In our experiments, 90 x 63 x 25 mm rectangular bars of Hot Chromium steel specimens are used as shown in Figure-1.

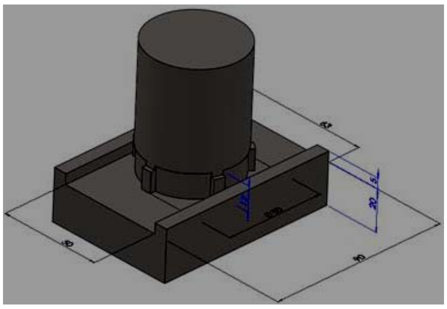

Figure-1. Scheme of the cutting process.

3.5 Design of experiments: Taguchi method

DOE is an efficient method of experimental planning which incorporates the orthogonal arrays (OAs), developed by Taguchi, to successfully design and conduct fractional factorial experiments that can collect all the statistically significant data with the minimum possible number of repetitions. Although a three-level factor is considered as a small OA, due to cost and time saving the L27 array was selected, and Table-3 shows the OA for the three cutting parameters selected. The values 1 to 3 indicate the levels of the three cutting parameters as defined in Table-2.

Table-3. L 27 orthogonal array for the experiments.

Trail	V in m/min	F_z in mm per tooth	a_p in mm	Trail	V in m/min	F_z in mm per tooth	a_p in mm
1	1	1	1	15	2	2	3
2	1	1	2	16	2	3	1
3	1	1	3	17	2	3	2
4	1	2	1	18	2	3	3
5	1	2	2	19	3	1	1
6	1	2	3	20	3	1	2
7	1	3	1	21	3	1	3
8	1	3	2	22	3	2	1
9	1	3	3	23	3	2	2
10	2	1	1	24	3	2	3
11	2	1	2	25	3	3	1
12	2	1	3	26	3	3	2
13	2	2	1	27	3	3	3
14	2	2	2				

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3.6 Roughness measurements

Surface roughness (Ra) was measured with the help of MITUTOYO Surf test SJ-301 (stylus tip: type Diamond, 90º / 5μm) instrument. The sample size used for this case was 12.5 mm in the X direction and for each of the experiments, three sample readings are taken and their average value was considered.

3.7 Normalization

Normalization is the process of mapping the given data in to a range of limits, zero and one in this case.

Normalization of data is required during computations since logistic sigmoid function is used as threshold function of neurons. Normalization is given by:

$$\delta = \frac{\mathbf{d} - \mathbf{d}_{\mathbf{minimum}}}{\mathbf{d}_{\mathbf{maximum}} - \mathbf{d}_{\mathbf{minimum}}}$$

Where δ = normalized data; d = input data; $\mathbf{d}_{\mathbf{minimum}}$ = min. value in the table; $\mathbf{d}_{\mathbf{maximum}}$ = max. Value in the table.

Table -4. Training data set for ANN model.

Trail No.	V in m/min	F_z in mm per tooth	a_p in mm	Ra in μm	Trail No.	V in m/min	F_z in mm per tooth	a_p in mm	Ra in μm
1	78	0.08	0.5	2.43	12	157	0.12	1	1.66
2	78	0.08	1	2.04	13	157	0.16	0.5	2.02
3	78	0.08	1.4	1.88	14	157	0.16	1	1.7
4	78	0.12	0.5	2.59	15	157	0.16	1.4	1.54
5	78	0.12	1.4	1.64	16	235	0.08	0.5	1.01
6	78	0.16	0.5	1.6	17	235	0.08	1.4	1.54
7	78	0.16	1	1.9	18	235	0.12	0.5	1.82
8	78	0.16	1.4	1.39	19	235	0.12	1	1.54
9	157	0.08	1	1.57	20	235	0.12	1.4	1.89
10	157	0.08	1.4	1.41	21	235	0.16	1	1.51
11	157	0.12	0.5	2.85	22	235	0.16	1.4	1.52

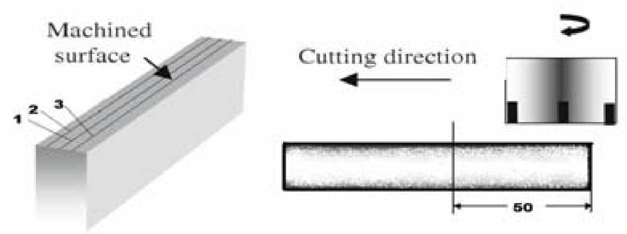

Figure-2. Scheme indicating areas where surface roughness measured.

3.8 Artificial neural network

Artificial Neural networks are used to establish the nonlinear relationship between the input and output variables. It consists of a number of elementary units called neurons. A neuron is a simple processor which takes one or more inputs and produces an output. Each input has an associated weight that determines the intensity of the input. A network can be trained to perform certain tasks where the data is fed into the network through an input layer. This is processed through one or more intermediate hidden layers and finally it is fed out of the network through an output layer as shown in Figure-3. A standard MLP neural network was developed using the NN toolbox of Lab View software. Feed forward neural network with error back propagation algorithm was adopted for the NN system. Combinations of the number of neurons in the hidden layer, number of hidden layers, spread parameter and learning rate parameters were suitably chosen.

3.8.1 Feed forward neural network with error back propagation algorithm (EBPA)

FFNN with EBPA, which is one of the most popular multi-layer architectures proving to be an excellent universal approximation of nonlinear functions, has been adopted for our work. Its ability to map complex input-to-output relationships with acceptable error best demonstrates its suitability. The mean square error was calculated based on the summation of all the squares of error during training and this summation is divided by the set of trials.

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$$Mean\ square\ error = \frac{1}{N}\sum_{i=0}^{p}\sum_{j=0}^{q}(Oa - Op)^2$$

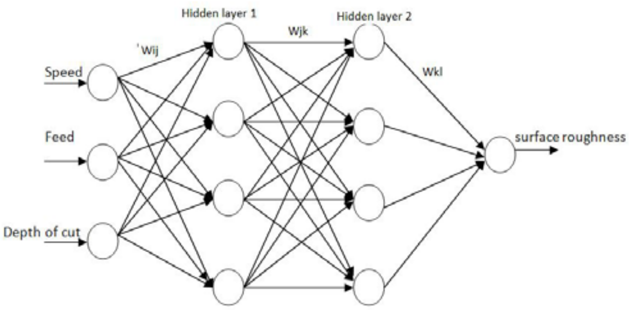

Figure-3. Architecture of the adopted feed forward neural network.

3.9 Neural network configuration

From among the 27 no. of experimental trials conducted on the CNC machine, 22 data sets were chosen for training session and the remaining were used for testing and validation. During the training of the network, the computed output is compared with the target output, and then the Mean square Error is calculated. The NN architecture was developed considering cutting parameters as input variables and the surface roughness as the output variable. The predicted surface roughness obtained from developed ANN was compared with experimental (measured) values of surface roughness.

Based on trial and error, architecture consisting of two hidden layers with four neurons in each layer is adopted. The three layer architecture neural network (input layer, hidden layer, and output layer) are Tan-sigmoid activation function was applied to hidden layers and pure-line activation function was applied to output layer. A learning rate of 0.01 was chosen. The stopping criterion for the neural network learning process was fixed as an error tolerance of 0.0001 to 0.00015 or the number of iterations as 10000, whichever happens earlier. Figure-4 shows the configuration for the neural network adopted in this research work with the criterion of error limitation.

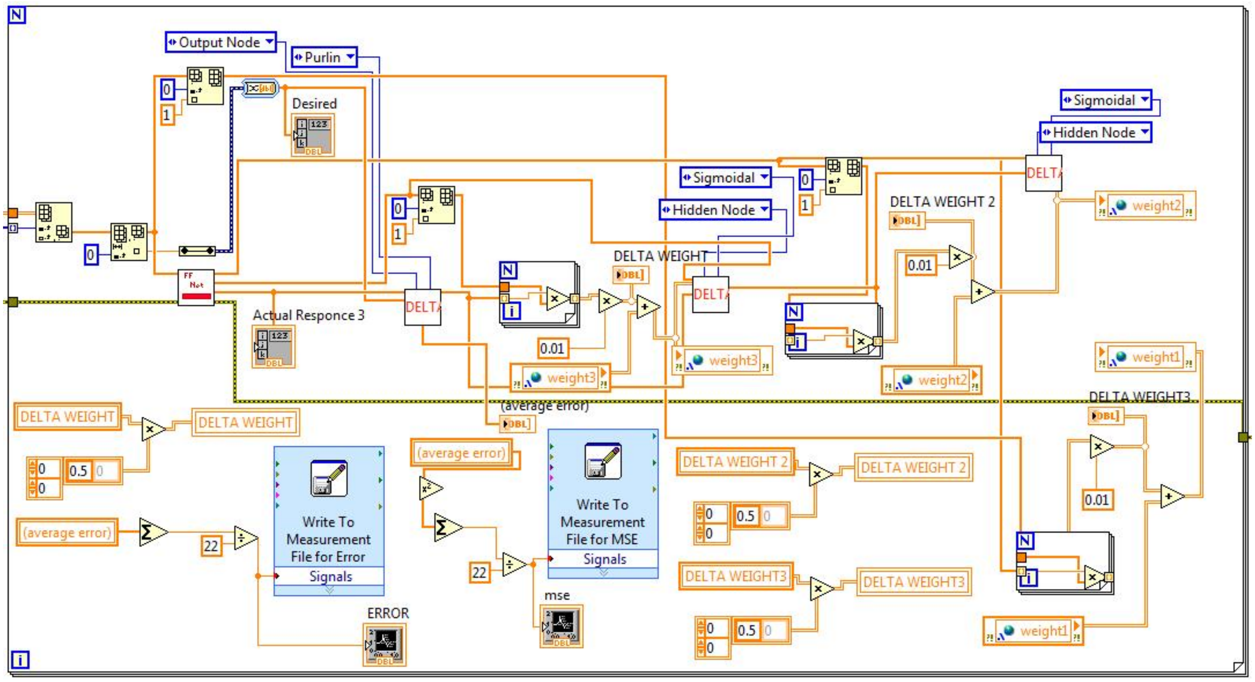

Figure-4. Lab VIEW Circuit diagram.

3.9.1 Pearson correlation coefficient

To analyze the mapping of surface roughness against the system input variables i.e., (cutting speed, feed per tooth, and axial depth of cut), a correlation among these parameters is arrived at. A correlation is a statistical technique which can show whether and how strongly pairs of variables are related. The main result of a correlation is called correlation coefficient (or r). There are several correlation techniques but the most common one is the Pearson correlation and this is the one which has been adopted in our work.

4. RESULTS AND DISCUSSIONS

After conducting experiments the data were applied for the neural network based prediction system and the prediction results are tabulated in Table-5. This table shows the predicted surface roughness obtained for training data set based on 3-4-4-1 FFNN architecture. Figure-5 shows plotting of the above results. It can be observed from the table that the prediction results for surface roughness are quite accurate in most of the cases. For thereof the training data set a larger error value of up to 19% is observed. Again the neural network model is verified with test data and the results of predicted surface

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roughness values are plotted in Figure-6 along with the prediction for validation data gathered through experiments. The results are found to be within acceptable limits. Larger deviation in prediction for surface roughness in few of the cases cited above may be due to in homogeneity in work piece composition, small discrepancy in tool setting/work piece setting and tool or machining condition. From Figure-8 it can be observed that the neural network predicted the output with an average mean square error of $1.27\,e^{-7}$ along with minimum mean square error of 0.01%.

Table-5. Training data of experimental verses predicted surface roughness.

Trial No.	Experimental Ra	Predicted Ra	% of Error	Trial No.	Experimental Ra	Predicted Ra	% of Error
1	2.43	2.4627306	-1.34694	12	1.66	1.5626026	5.867313
2	2.04	2.0062657	1.653642	13	1.87	1.9839442	-6.09327
3	1.88	1.8332942	2.484351	14	1.7	1.5721085	7.523029
4	2.59	2.5624862	1.062309	15	1.54	1.5444625	-0.28977
5	1.64	1.6110291	1.766518	16	1.01	0.988277	2.150796
6	1.6	1.5757632	1.5148	17	1.31	1.5141968	-15.5875
7	1.9	1.87825	1.144737	18	1.54	1.781052	-15.6527
8	1.39	1.3539029	2.596914	19	1.54	1.5484852	-0.55099
9	1.57	1.5437886	1.669516	20	1.89	1.5297839	19.05905
10	1.41	1.5076579	-6.92609	21	1.51	1.5733344	-4.19433
11	2.85	2.8374075	0.441842	22	1.52	1.5753446	-3.64109

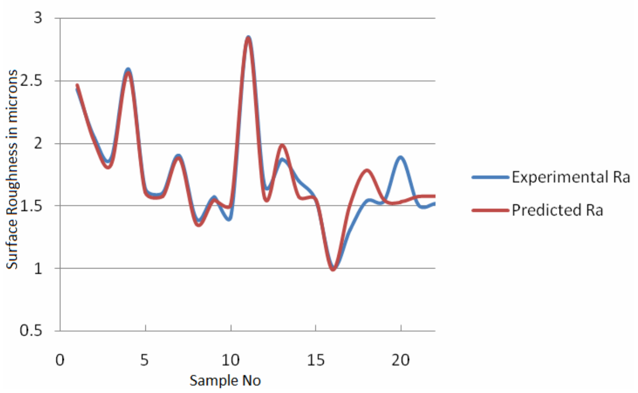

Figure-5. The results of the measured and predicted values of surface roughness for the 3-4-4-1 FFNN architecture.

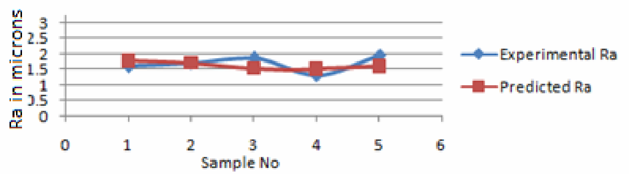

Figure-6. The plot of test and validation data of experimental and predicted surface roughness.

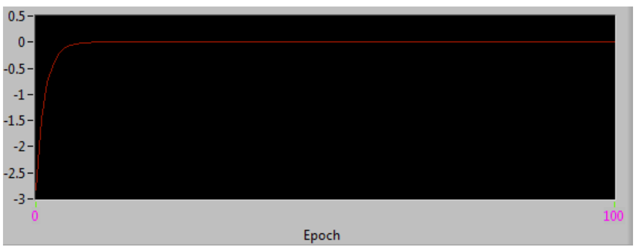

Figure-7. The absolute error Vs epoch number.

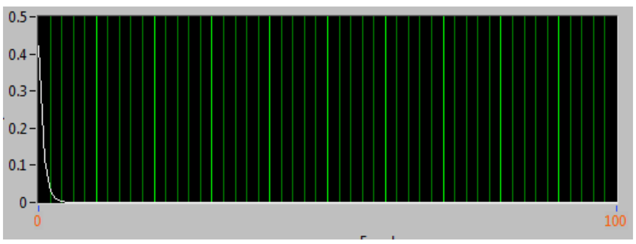

Figure-8. The mean square error Vs epoch number.

4.1 Pearson correlation coefficient analysis

From Table-6 it can be observed that there is a strong correlation between feed and the surface roughness variables, since a correlation coefficient value of 0.028 was obtained. It means that as the feed increases the surface roughness value increases. If we consider the second largest correlation value between speed and the surface roughness -0.35063, in this case, it is a negative correlation, which means that the magnitude of surface roughness is increased as the cutting speed is decreased. This may be justify due to the fact that at higher cutting speed built up edge which are formed at the tip of the cutting edges are vanishing and hence resulting in better surface finish. This result is also in agreement with previous research works carried out in this field [11, 12].

Table-6. The pearson correlation coefficient obtained for each of the input and output parameters.

	Surface finish	Cutting speed	Feed	Doc
Surface finish	1	-0.35063	0.028334	-0.40311
Cutting speed	-0.350632652	1	0	0
Feed	0.028333952	0	1	0
Doc	-0.40311	0	0	1

5. CONCLUSIONS

In this study the ANN model with three inputs has been developed to predict surface roughness values during face milling operation for the machining of AISI H11 material. It can be observed that adoption of neural network modeling for complex problems involving non linearity will offer an easier yet accurate solution. Based on accurate which were obtained it can also be concluded that all required significant factors have considered in the DOE process. From the Pearson correlation analysis it is observed that most important cutting parameter affecting the machined surface quality.

The above result can be made more generic by making use of different cutting tools, work material combination and using the ANN model over this experimental data.

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