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Prediction of surface roughness for end milling process using Artificial Neural Network

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ABSTRACT
In machining, surface quality is one of the most commonly specified customer requirements in which the major indication of surface quality on machined parts is surface roughness. The aim is prediction of surface roughness by using artificial neural networks. The neural network model can be effectively find the best cutting parameters value for a specific cutting condition in milling operation and achieve minimum surface roughness. In the present work an experimental investigation of the end milling of M.S material up to 30 HRC with carbide tool by varying feed, speed and depth of cut and the surface roughness was measured using Mitutoyo Surface Roughness Tester. The neural network design and development was done using MATLAB. Neural Network Fitting Tool Graphical User Interface is used to establish the relationship between the surface roughness and the cutting input parameters(spindle speed, feed and depth of cut). The result from this research is useful to be implemented in industry to reduce time and cost in surface roughness prediction.

***Keywords* - End milling, Surface roughness, Neural Networks, GUI, MATLAB**

1. INTRODUCTION
Among different types of milling processes, end milling is one of the most vital and common metal cutting operations used for machining parts because of its capability to remove materials at faster rate with a reasonably good surface quality. Also, it is capable of producing a variety of configurations using milling cutter. Surface roughness is a key factor in the machining process while considering machining performance and that is why in many cases, industries are looking for maintaining the good surface quality of the machined parts. Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost and quality. It describes the geometry of the machined surface and combined with the surface texture, it can play an important role on the operational characteristics of the part. It also influences several functional attributes of a part, such as light reflection, heat transmission, coating characteristics, surface friction, fatigue resistance etc. However, the mechanism behind the formation of surface roughness is very dynamic, complicated and process dependent; therefore it is very difficult to calculate its value through analytical formulae. Various theoretical models that have been proposed are not accurate enough and apply only to a limited range of processes and cutting conditions. Therefore, machine operators usually use ANN approaches to set-up milling machine cutting conditions in order to achieve the desired surface roughness

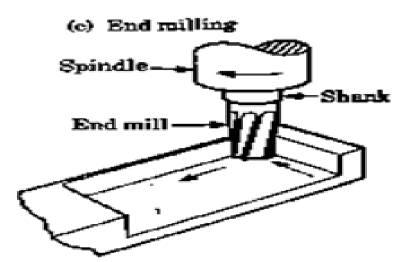

Fig.1.1 End milling operation[12]

2. LITERATURE REVIEW

Chen and Savage [2001] used fuzzy net-based model to predict surface roughness under different tool and work piece combination for end milling process. Speed, feed and depth of cut, vibration, tool diameter, tool material, and work piece material are used as input variables for fuzzy system. The authors found that the predicted surface roughness is within an error of 10%[6]. Prakasvudhisarn et al. [2009] proposed an approach to determine optimal cutting condition for desired surface roughness in end milling. The approach consists of two parts: machine learning technique called support vector machine to predict surface roughness and particle swarm optimization technique for parameters optimization. The authors found that PSO shows consistent near-optimal solution with little effort[5].Metin Kök (2010) has suggested an experimental investigation of the effects of cutting speed, size and volume fraction of particle on the surface roughness in turning of 2024Al alloy composites reinforced with Al_2O_3 particles. A plan of experiments, based on Taguchi method, was performed machining with different cutting speeds using coated carbide tools K10 and TP30. The objective was to establish a correlation between cutting speed, size and volume fraction of particle with the surface roughness in workpieces. These correlations were obtained by multiple linear regression. The analysis of variance was also employed to carry out the effects of these parameters on the surface roughness. The test results revealed that surface roughness increased with increasing the cutting speed and decreased with increasing the size and the volume fraction of particles for both cutting tools. The average surface roughness values of TP30 cutting tools were observed to be lower than those of K10 tools. For the average surface roughness values of TP30 tool, cutting speed was found to be the most effective factor while the volume fraction of particle was the most effective factor for those of K10 tool. A good agreement between the predicted and experimental surface roughness was observed within a reasonable limit[8].Brezocnik et al. [2004] proposed a GP approach to predict surface roughness in end milling process. The genetic programming is an evolutionary computation method that was first introduced by Koza [1992] in the year 1992. It aims to find out computer programs (called as chromosomes) whose size and structure dynamically changes during simulated evolution that best solve the problem. Cutting parameters, viz., spindle speed, feed, and depth of cut as well as vibration between tool and work piece, were used to predict the surface roughness and the authors found that the model that involves all these variables accurately predict the surface roughness[3].Lo [2003] used ANFIS to predict the surface roughness in end milling process. Spindle speed, feed rate, and depth of cut were considered as input parameters. The ANFIS was modeled using triangular and trapezoidal membership functions. The average error of prediction of surface roughness for triangular membership function was found lower, around 4% [1]. Reddy and Rao [2005] developed an empirical surface roughness model for end milling of medium carbon steel, whose parameters were optimized using GA also Reddy and Rao used genetic algorithm to optimize tool geometry, viz., radial rake angle and nose radius and cutting conditions, viz., cutting speed and feed rate to obtain desired surface quality in dry end milling process[4]. S. Saikumar et al (2011) has reported High-speed machining centers are used for end-milling operations of a variety of parts, dies, and molds needed in power and transport industries. Different approaches are used for rough and finish end milling, since desired productivity and quality are important in the respective cases. In the present work, a feed rate adaption control system is proposed by integrating different requirements of high-speed end milling. Hardened EN 24 steel which is being widely used in the production of dies, molds, and other parts is taken as a candidate work material for implementation of the proposed control system. Based on extensive experimentation, investigations have been carried out on high speed rough and finish end-milling operations, and the details are reported by the authors (Saikumar and Shunmugam, Int J Adv Manuf Technol, under review). In this paper, relevant response surface and artificial neural network models have been used, and suitable reference parameters are obtained for the proposed control system. In the case of rough end-milling, material removal volume is taken as the objective, and the reference values for cutting force and cutting time are used. Only a reference cutting force is used for finish end-milling in which surface roughness is considered as the objective. Implementation details of the proposed PC-based control system are presented. The results obtained for a newly devised H–A–S–H test (short run) along with those for long-run tests are presented and discussed[9]. Masoud Farahnakian (2011) has suggested polymer nanocomposites have emerged relatively as a new and rapidly developing class of composite materials and attracted considerable investment in research and development worldwide. An increase in the desire for personalized products has led to the requirement of the direct machining of polymers for personalized products. In this work, the effect of cutting parameters (spindle speed and feed rate) and nanoclay (NC) content on machinability properties of polyamide-6/nanoclay (PA- 6/NC) nanocomposites was studied by using high speed steel end mill. This paper also presents a novel approach for modeling cutting forces and surface roughness in milling PA-6/NC nanocomposite materials, by using particle swarm optimization-based neural network (PSONN) and the training capacity of PSONN is compared to that of the conventional neural network. In this regard, advantages of the statistical experimental algorithm technique, experimental measurements artificial neural network and particle swarm optimization algorithm, are exploited in an integrated manner. The results indicate that the nanoclay content on PA-6 significantly decreases the cutting forces, but does not have a considerable effect on surface roughness. Also the obtained results for modeling cutting forces and surface roughness have shown very good training capacity of the proposed PSONN algorithm in comparison to that of a conventional neural network[7]. Amir Mahyar Khorasani1et al[2011] (ANN) for modeling and predicting tool life in milling parts made of Aluminum (7075) material was developed. Given the accuracy that was achieved it is safe to conclude that all the significant factors were included in the (DOE) process. extended towards three different steps. The first step is using Taguchi (DOE) and different combinations of cutting parameters for building database. The second step is modeling tool life by using (ANN). Third step is validation by carrying out the experimental tests. In generating the (ANN) model statistical (RMS) was utilized. The accuracy error was found to be insignificant (3.034%). It was found that (ANN) prediction correlates very well with the experimental results. Finally the correlation for training and test was obtained 0.96966 and 0.94966 respectively and mean square error was calculated 3.1908% for test data[10]. C. C. Tsao (2010) has discussed The grey–Taguchi method was adopted in this study to optimize the milling parameters of A6061P-T651 aluminum alloy with multiple performance characteristics. A grey relational grade obtained from the grey relational analysis is used as

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the performance characteristic in the Taguchi method. Then, the optimal milling parameters are determined using the parameter design proposed by the Taguchi method. Experimental results indicate that the optimal process parameters in milling A6061P-T651 aluminum alloy can be determined effectively; the flank wear is decreased from 0.177 mm to 0.067 mm and the surface roughness is decreased from 0.44 µm to 0.24 µm, leading to a multiple performance characteristics improvement in milling qualities through the grey–Taguchi method[15].

Hasan Kurtaran et al (2005) has discussed optimum cutting parameters of Inconel 718 are determined to enable minimum surface roughness under the constraints of roughness and material removal rate In doing this, advantages of statistical experimental design technique, experimental measurements, artificial neural network and genetic optimization method are exploited in an integrated manner. Cutting experiments are designed based on statistical three-level full factorial experimental design technique. A predictive model for surface roughness is created using a feed forward artificial neural network exploiting experimental data. Neural network model and analytical definition of material removal rate are employed in the construction of optimization problem. The optimization problem was solved by an effective genetic algorithm for variety of constraint limits. Additional experiments have been conducted to compare optimum values and their corresponding roughness and material removal rate values predicted from the genetic algorithm. Generally a good correlation is observed between the predicted optimum and the experimental measurements. The neural network model coupled with genetic algorithm can be effectively utilized to find the best or optimum cutting parameter values for a specific cutting condition in end milling Inconel 718[14].

3. Experimental study

For developing models on the basis of experimental data three main machining parameters are considered to predict surface roughness of M.S material using carbide tool. The available literature reveals that spindle speed, feed rate and axial depth of cut are primary machining parameters on which surface roughness depends. These factors are considered for experimentation study. In this study factorial method is used. DOE of all three factors and their unique factor level combinations (4Vc X 7f X 3doc) results in a total 84 observation End mill cutter with 12 mm diameter having 4 flutes with carbide tipped is used for machining M.S material work piece. Among the range of spindle speed, feed, and depth of cut available possible in the machine the following three levels are considered as shown in table I. The machining was carried out on Vertical milling machine, The M.S material work piece is clamped on vice mounted on the table of the machine. The machining process and work tool motion of the end milling process respectively. The machining is carried out by selecting proper spindle speed and feed rate during each experimentation. Experiment was carried out by varying the depth of cut.

Factors	**Levels**	**Factors level values**
SPEED(m/min.)	4	80,100,120,140
FEEDRATEPER TOOTH(mm/min.)	7	0.03, 0.035, 0.040, 0.045, 0.05, 0.055, 0.06, 0.065
DEPTH OF CUT(mm)	3	0.1, 0.2 ,0.3

Table I Level of experimen

Surface roughness values of work pieces were measured by Mitutoyo Surface Roughness Tester by a proper procedure while measuring instrument and measurements are repeated three times.

Table II shows the experimental result.

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SR. NO	FEED (mm/rev.)	CUTTING SPEED VC (m/min)	Depth of cut (mm)	Experimental ROUGHNESS VALUE Ra (µm)
1	0.03	80	0.1	0.21
2		80	0.2	0.22
3		80	0.3	0.25
4		100	0.1	0.2
5		100	0.2	0.21
6		100	0.3	0.22
7		120	0.1	0.19
8		120	0.2	0.21
9		120	0.3	0.22
10		140	0.1	0.18
11		140	0.2	0.19
12		140	0.3	0.2
13	0.035	80	0.1	0.23
14		80	0.2	0.24
15		80	0.3	0.25
16		100	0.1	0.19
17		100	0.2	0.21
18		100	0.3	0.22
19		120	0.1	0.19
20		120	0.2	0.2
21		120	0.3	0.21
22		140	0.1	0.19
23		140	0.2	0.21
24		140	0.3	0.23
25	0.04	80	0.1	0.26
26		80	0.2	0.28
27		80	0.3	0.3

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28		100	0.1	0.23
29		100	0.2	0.24
30		100	0.3	0.24
31		120	0.1	0.19
32		120	0.2	0.2
33		120	0.3	0.23
34		140	0.1	0.2
35		140	0.2	0.21
36		140	0.3	0.21
37	0.045	80	0.1	0.28
38		80	0.2	0.29
39		80	0.3	0.29
40		100	0.1	0.26
41		100	0.2	0.25
42		100	0.3	0.23
43		120	0.1	0.25
44		120	0.2	0.24
45		120	0.3	0.21
46		140	0.1	0.23
47		140	0.2	0.22
48		140	0.3	0.2
49	0.05	80	0.1	0.29
50		80	0.2	0.3
51		80	0.3	0.3
52		100	0.1	0.28
53		100	0.2	0.3
54		100	0.3	0.31
55		120	0.1	0.27
56		120	0.2	0.29

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57		120	0.3	0.29
58		140	0.1	0.25
59		140	0.2	0.27
60		140	0.3	0.28
61	0.055	80	0.1	0.3
62		80	0.2	0.31
63		80	0.3	0.31
64		100	0.1	0.29
65		100	0.2	0.3
66		100	0.3	0.3
67		120	0.1	0.28
68		120	0.2	0.29
69		120	0.3	0.31
70		140	0.1	0.27
71		140	0.2	0.28
72		140	0.3	0.28
73	0.06	80	0.1	0.34
74		80	0.2	0.35
75		80	0.3	0.33
76		100	0.1	0.31
77		100	0.2	0.3
78		100	0.3	0.32
79		120	0.1	0.29
80		120	0.2	0.3
81		120	0.3	0.31
82		140	0.1	0.27
83		140	0.2	0.29
84		140	0.3	0.31

Table II Experimental data

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SR. NO	FEED PER TOOTEH	CUTTING SPEED VC (m/min)	DOC (mm)	experimental ROUGHNESS VALUE Ra (µm)	ANN ROUGHNESS VALUE Ra (µm)	Error	Error %
1	0.03	80	0.1	0.21	0.212917	-0.00292	1.38894
2	0.03	80	0.2	0.22	0.232296	-0.0123	5.58927
3	0.03	100	0.1	0.2	0.187708	0.012292	6.145831
4	0.03	100	0.2	0.21	0.220786	-0.01079	5.13629
5	0.03	120	0.1	0.19	0.185403	0.004597	2.419305
6	0.03	120	0.2	0.21	0.202975	0.007025	3.3454
7	0.035	100	0.3	0.22	0.226249	-0.00625	2.8404
8	0.045	80	0.1	0.28	0.272137	0.007863	2.808156
9	0.045	120	0.2	0.24	0.246086	-0.00609	2.53591
10	0.055	140	0.1	0.27	0.289599	-0.0196	7.25887
11	0.06	100	0.1	0.31	0.282894	0.027106	8.743766
12	0.06	120	0.2	0.3	0.304228	-0.00423	1.40927
13	0.06	120	0.3	0.31	0.314916	-0.00492	1.58579

TABLE III Comparison of ANN predictions with experimental data

4. Neural Network modeling

Neural network is a highly flexible modeling tool with the ability to learn the mapping between input and output parameters [13]. An artificial neural network (ANN) is capable of learning from an experimental data set to describe the nonlinear and interaction effects more effectively. The network consists of an input layer used to present data, output layer to produce ANN's response, and one or more hidden layers in between. The network is characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

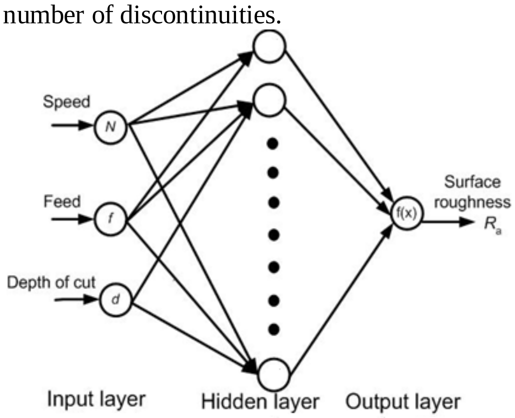

Fig.-2 Neural Network

The knowledge is presented by the interconnection weight, which is adjusted during the learning stage using the back propagation learning algorithm to minimize the mean square between the actual output of the network and the desired output pattern. Here it is used to develop surface roughness prediction model for end milling process. From 84experiments were conducted 58 experimental datasets are used to train ,13 used for verification and 13 for testing purpose. Before applying the neural network for modeling the architecture of the network has to be decided; i.e. the number of hidden layers and the number of neurons in each layer and transfer function for each layer. As there are 3 inputs to produce one output, the number of neurons in the input and output layer has to be set to 3 and 1 respectively. Considering one hidden layer the number of neurons in the hidden layer is optimized. Table III shows the established tested experimental result and the NN model prediction. It was observed that the prediction based on an ANN model is quite close to the established observation. The average prediction error for data set is found to be 3.5% and maximum prediction error is 8.743766%. In all cases, maximum error tolerance was kept constant. It was observed that the average prediction error was minimized. The transfer functions used in this are Tan Sigmoid between input and hidden layer and pureline between hidden and output layer.

5. Conclusion

In doing this, experimental measurements, artificial neural network is exploited in an integrated manner. The goal is prediction of surface roughness in milling process by using artificial neural networks and roll of main parameters (spindle speed, feed rate and depth of cut). Generally a good correlation is observed between the predicted and the experimental measurements. This survey will help in another

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important factor that greatly influences production rate and cost. So, as a whole, there is a need for allow the evaluation of the surface roughness before the machining of the part and which, at the same time, can be easily used in the production floor environment for contributing to the minimization of required time and cost and the production of desired surface quality.

- Identifies minimum surface roughness value 0.18μm was obtained at the value of 0.03 mm/tooth, 140 m/min and 0.1 for feed rate, cutting speed and depth of cut respectively.
- Identifies maximum surface roughness value 0.35μm was obtained at the value of 0.06 mm/rev, 80 m/min and 0.2 mm for feed rate, cutting speed and depth of cut respectively.
- Surface roughness increase as feed rate increase.
- These model can be used to prediction of surface roughness in end milling process.

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