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Predictive modelling of cnc milling process using regression based artificial neural network (ann)

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Abstract

This paper is aimed to construct a predictive surface roughness model in CNC pocket milling process based on the response surface based (RSM) artificial neural network (ANN). Milling parameters such as cutting speed, feed rate and depth of cut are designed using RSM based rotatable central composite design (CCD). The AISI 1050 medium carbon steel is machined by a flat end 8 mm high speed steel (HSS) tool with the zig-zag cutting path under air flow condition. Experiments have been established according to CCD design matrix. The effects of the main machining parameters on the surface roughness has been determined. Finally, 3:6:8:1 ANN model is constructed. The experimental results were trained in an ANN program and the results were compared with experimental values. It is observed that the experimental results coincided with ANN results.

Keywords: CNC milling, artificial neural network, modelling, prediction.

1. INTRODUCTION

In manufacturing technology, requirements of higher surface roughness have vital importance for quality and efficient manufacturing especially in aerospace and automotive industry. Because roughness is an indicator of surface irregularities [1]. Because of the fact that roughness is usually undesirable for the machine parts, it is also difficult task and expensive for control during manufacturing processes [1]. Decreasing roughness of a surface, which requires high controlled automation, will usually raise the manufacturing cost [1]. Therefore, there is a close relationship between the manufacturing cost of a component and its performance in application. Metal-based industries always have the problems with increasing the productivity and the quality of the machined parts. Since, quality of machining can be expressed by surface roughness, there has been an increasing trend for monitoring all aspects of the machining process in order to reduce and control the surface roughness [1]. Surface finish directly affects the quality so that higher the surface finish results in higher quality. Generally, in machining processes surface finish mainly depends on the machining factors such as cutting speed, depth of cut and feed rate. Tool variables which are tool material, nose radius, rake and shear angle, cutting edge geometry are also affect the surface roughness [2,3]. Most of the operators use “trial and error method” or use machine handbook to find the suitable cutting set-up in order to decrease the surface roughness on a required levels.

There are various studies based on statistical regression or neural network techniques have been constructed to develop a relationship between the cutting performance and selected cutting parameters [2,3]. Ozcelik and Bayramoglu [4] developed a statistical model for surface roughness estimation in a high-speed flat end milling process under wet cutting conditions, using machining variables such as spindle speed, feed rate, depth of cut, and step over. Baek et al. [5] selected the optimal feed rate using a bisection method. Peigne et al. [6] studied effects of the cutting vibratory phenomena and their impacts on the surface roughness of the machined surface. Franco et al. [7] developed a numerical model for predicting the surface profile and surface roughness in face milling with round insert cutting tools. Kishawy et al. [8] researched the effect of flood coolant, and dry cutting, on tool wear, surface roughness and cutting forces. Souza et al. [9] analyzed the two face milling cutter systems in high speed cutting of gray cast iron under a predetermined cutting condition. Ryua et al. [10] studied plane surface generation mechanism in flat end milling using a flat end mill. Mantle and Aspinwall [11] studied the surface integrity produced by end mill tool using a Taguchi orthogonal array. Wang and Chang [12] analyzed the effect of cutting conditions and tool geometry on surface roughness during slot end milling process. Lou and Chen [13] described a new approach for recognition systems to predict surface roughness. Gologlu and Sakarya [14] investigated the optimum cutting characteristics of DIN 1.2738 mould steel using high-speed steel end mills. Benardos and Vosniakosa [15] presented a neural network modeling approach for the prediction of surface roughness (R_a) in CNC face milling using Taguchi design of experiment method. Shamsuddin and et al. [16] presented a comparison of milling cutting path strategies for thin-walled aluminum alloys fabrication. Ertakin et al. [17] identified the most influential and common sensory features for dimensional accuracy and surface roughness in CNC milling operations using three different material types.

This paper is aimed to construct a predictive surface roughness model in CNC pocket milling process based on the response surface based (RSM) artificial neural network (ANN). A 3:6:8:1 ANN model has been developed to predict the effect of CNC milling parameters such as cutting speed (v, rpm), rate of feed (f, mm/min) and depth of cut (d, mm) on the surface roughness (R_a, μm) of pocket milled AISI 1050 steel plate.

2. EXPERIMENTAL PROCEDURE AND DETAILS

As shown in Figure 1, the pocket milling experiments were carried out on a *FANUC C-TEK CNC* horizontal machining center using 8 mm High Speed Steel (*HSS*) end mill cutting tools for the pocket milling of AISI 1050 medium carbon steel plate which has the dimensions of 472x184x40 mm. The opened pockets were made under constant step over value which is the half of the tool diameter as 4 mm [3]. Forty pockets with the dimensions of 30x30 mm were opened on the steel plate according to recommended depth of cut given in design matrix. The percent chemical composition and mechanical properties of workpiece material used in this study is listed in Table 1.

Table 1. Chemical and mechanical properties of AISI 1050 medium carbon steel

Chemical composition (% weight)	C	P	S	Mn	Cr	Si
	0.47	0.04	0.04	0.80	0.11	0.10
Mechanical properties	Yield strength (MPa)		Tensile strength (Mpa)		Elongation (%)	Brinell Hardness (HB)
	580		690		15	197

Figure 1. CNC pocket milling process [3]

The machining processes run in vertical mode. As shown in Figure 2, *zig-zag* cutter path strategy by using *VISICAD* software was applied to obtain the different machining set up according to the given design matrix [3].

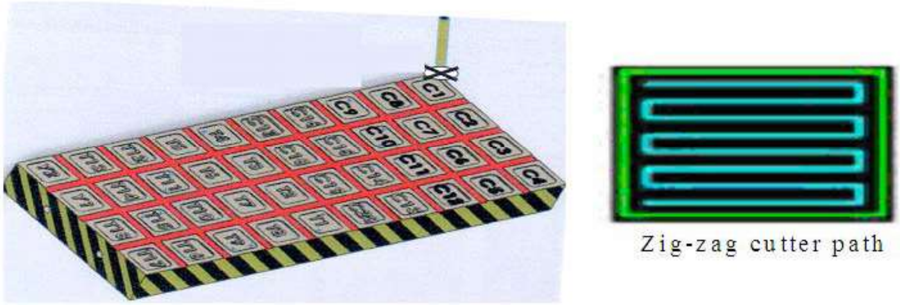

Figure 2: *VISICAD* Simulation and cutter path strategy [3]

Phynix TR-100 model surface roughness tester was used to measure the surface roughness of the machined samples. Cut off length (λ) is chosen as 0.3 for each roughness measurement [3]. Average of six measurements of surface roughness is entered to use in the design matrix which forms the train set of ANN.

2.1 Selection of Experimental Design Matrix

In this study, for planning the experiments Response Surface Methodology (RSM) with Central Composite Design (CCD) is used for the modelling of CNC pocket milling process to create a training set for artificial neural network (ANN). According to the obtained experimental data, the levels of the three main milling parameters investigated in this study are given in Table 2. These values are calculated using Eq. (1) given below.

$$X_i = \frac{X_i - X_o}{\delta X} \tag{1}$$

where X_o is the value of X_i at the center point, and δX represents the step change [3,18-21].

Table 2. CCD design of CNC milling parameters and their levels

	Factor	Range and level				
		-1.682	-1	0	+1	+1.682
v:cutting speed (rpm)	x_1	514.79	975	1650	2325	2785.21
f: feed rate (mm/min)	x_2	155.69	275	450	625	744.31
d: depth of cut (mm)	x_3	0.74	1.25	2.00	2.75	3.26

Thus, RSM was used for obtaining a relationship between factors and the response and for optimizing the response [18]. Table 3 depicts a complete 2^3 factorial design with *four center points* in cube, and *six axial points* and *two center points* in axial [3,18]. The experiments were carried out in three replicates and six blocks in order to fit the second-order polynomial model [18,22]. The repeated runs such as center and axial points are used only one time in the training set.

2.2 Artificial Neural Network (ANN)

Computers are an integral part of day to day activities in engineering design and engineers have utilized various applications to help them improve their design [23,24]. ANN mimics some basic aspects of the brain functions [23-27]. ANN is based on the neural structure of the human brain, which processes information by means of interaction between many neurons [23,26]. In the past fifteen years there has been a constant increase in interest of neural network modeling in different fields of materials science. There are several applications of neural networks such as back-propagation network (BPN) and general regression neural network (GRNN) [28,29]. In general, BPN seems to be the most utilized neural network. A feed forward neural network based on back propagation is a multilayered architecture made up of one or more hidden layers placed between the input and output layers. Layers include several processing units known as neurons [28]. The basic unit in the ANN is the neuron. The neurons are connected to each other with a weight factor. A network is usually trained using a large number of inputs while monitoring corresponding output data [23,24].

The ANN BPN architecture used for modeling and prediction of CNC parameters is illustrated in Figure 3, and comprises many simple processing neurons organized in a sequence of layers: input, intermediate (hidden) and output layers [23,24]. The simulation problem consists of finding a satisfactory relationship between a set of neurons representing the input data and associated known output. The selection of the input parameters is a very important aspect of neural network modeling [23]. All relevant input parameters must be represented as the input data of the neural network. In this study cutting speed, feed rate and depth of cut were used as inputs while surface roughness was used as an output.

The 3:6:8:1 multilayer ANN model with BPN architecture is shown in Figure 3.

Table 3. CCD experimental plan and comparison of experimental results [3]

Experiment run no	Experimental design			Experimental plan		
	v (rpm)	f (mm/min)	d (mm)	x_1	x_2	x_3
1	0	0	0	1650	450	2.00
2	+1	+1	+1	2325	625	2.75
3	-1	-1	+1	975	275	2.75
4	+1.682	0	0	2785.21	450	2.00
5	0	0	0	1650	450	2.00
6	+1	+1	-1	2325	625	1.25
7	0	+1.682	0	1650	744.31	2.00
8	0	0	0	1650	450	2.00
9	0	0	-1.682	1650	450	0.74
10	0	0	0	1650	450	2.00
11	0	0	0	1650	450	2.00
12	0	0	+1.682	1650	450	3.26
13	+1	-1	-1	2325	275	1.25
14	0	-1.682	0	1650	155.69	2.00
15	-1.682	0	0	514.79	450	2.00
16	-1	-1	-1	975	275	1.25
17	+1	-1	+1	2325	275	2.75
18	-1	+1	-1	975	625	1.25
19	-1	+1	+1	975	625	2.75
20	0	0	0	1650	450	2.00

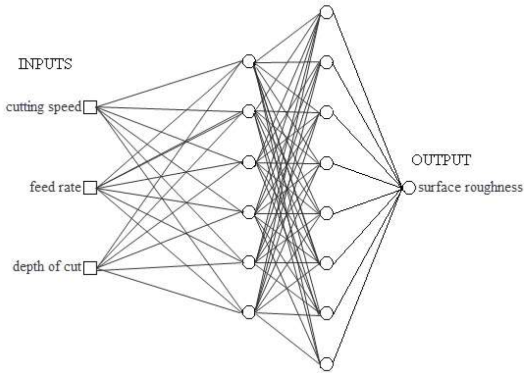

Figure 3: The constructed 3:6:8:1 multilayer ANN model with BPN architecture

2.3 The Training of the Network

Generally, there are three different learning strategies for the neural network training. *Firstly*, the trainer could tell the network what it have to learn (*Supervised Learning*), *secondly*, the trainer could indicate whether or not the output is correct without telling what the network have to learn (*Reinforcement Learning*) and *finally*, the network may learns without any intervention of the trainer or user (*Unsupervised Learning*). The learning set consists of the input parameters and the output parameters used in training the network. The required outputs take place in this set in the case of supervised learning, while in other cases, they are not found in it [23-25]. In the present study, a supervised learning approach was used. The neural network tool box of MATLAB R2010a is used in the modelling. As given in Table 4, RSM experimental plan of 15 results was used to train the ANN model.

Table 4. RSM based ANN training set

train no	v (rpm)	f (mm/min)	d (mm)	Experimental R_a (μm)
1	1650	450	2.00	2.33
2	2325	625	2.75	4.59
3	975	275	2.75	4.61
4	2785.21	450	2.00	2.31
5	2325	625	1.25	1.24
6	1650	744.31	2.00	2.35
7	1650	450	0.74	0.95
8	1650	450	3.26	6.55
9	2325	275	1.25	1.02
10	1650	155.69	2.00	2.09
11	514.79	450	2.00	2.88
12	975	275	1.25	1.28
13	2325	275	2.75	4.42
14	975	625	1.25	1.16
15	975	625	2.75	4.21

3. RESULTS AND DISCUSSION

The comparisons of experimental results with the ANN predictions have been studied in terms of percentage error for the validation set of experiments. From the Table 5, it is clear that for our set of data the neural network predicts the surface roughness very close to experimental values. In the prediction of surface roughness values the average errors for ANN is found to be as *0.89%*.

Table 5. Validation set of data used for ANN confirmation

Test no	Cutting speed (rpm)	Feed rate (mm/min)	Depth of cut (rpm)	(Ra)experimental	ANN	
					(Ra)predicted	Error (%)
1	1588.02	203.60	1.04	0.84	0.84	0.00
2	2156.97	515.53	0.80	0.90	0.94	4.44
3	1364.86	182.04	0.98	0.87	0.87	0.00
4	1725.93	734.35	0.76	0.92	0.92	0.00
5	1748.45	628.61	0.76	0.93	0.93	0.00
					Average error: 0.89 %	

Figure 4 shows the comparison between experimental surface roughness vs predicted surface roughness. It is clear from this graph that, predicted values are close to the experimental values. Also, in accordance with the statistical analysis, the correlation coefficient of R^2 is obtained as *0.858*. Therefore, it is evident that for our limited set of data the neural network with back propagation algorithm predicts nearer to the experimental values.

4. CONCLUSION

This study is focused on the prediction of surface roughness in CNC milling process using RSM based ANN method in combination with BPN algorithm. Close relationship between the experimental and predicted results showed that constructed ANN-BPN method is successfully implemented in predicting surface roughness. This study again supported that ANN method is fast and has capacity to learn from small and limited experimental training set of data.

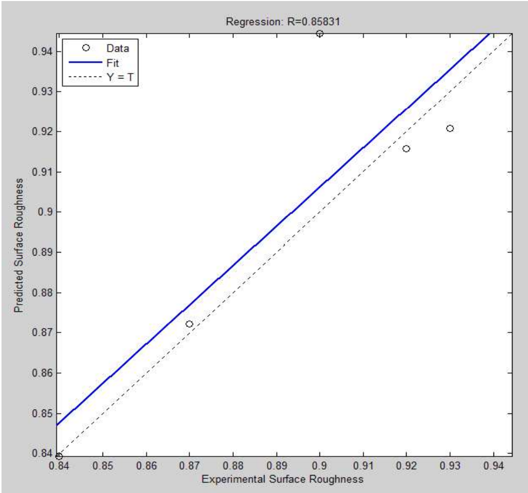

Figure 4: Comparison of experimental and predicted surface roughness

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