Surface Roughness Prediction in Machining Castamide Material Using ANN

Şeref Aykut

Department of Mechanical Engineering, Faculty of Engineering Architecture
Bitlis Eren University, 13000 Bitlis, Turkey
e-mail: saykut@bitliseren.edu.tr

Abstract: Castamide, a kind of casting polyamide, is widely used in industry because of its light weight and high corrosion resistance, and because of its impact-resistant, oil-free and silent operation. The scope of its usage has been increasing. It is used in the packaging, textiles, chemicals, leather, construction and heavy machinery manufacturing sectors. Particularly, in the manufacture of machine parts like gears surface roughness of which is crucial, it has superseded many metals because it is important to be able to predict the surface roughness to get more qualified materials. The aim of this study is to predict the surface roughness of Castamide material after machining process using ANN (artificial neural network). In this study, experiments on Castamide were done in CNC milling using high speed steel and hard metal carbide tools. The cutting parameters (cutting speed, feed rate and depth of cut) were changed and the average surface roughness (Ra, μm) values were obtained. In the experiments, the effects of cutting tools with the same diameters, but with different cutting edges and tool materials on average surface roughness were also investigated. The data were used to train and test a dynamic ANN model. It is quite clear from the model results that the surface roughness predicted by the ANN model matches well with the training data as well as the test data. The developed model has managed to is to the surface roughness with correlation rate of 83.6% and minimum error rate of 0.02.

Keywords: Surface roughness; Castamide; ANN; End milling; Cutting edge

1 Introduction

End milling is one of the most fundamental and commonly encountered chip removal operations occurring in a real manufacturing environment. In this machining process, the surface finish is a key factor in evaluating and determining the quality of a part. In practice, a desired surface roughness value is usually designated, and the appropriate cutting parameters are selected to achieve the desired quality of a specified part. Typically, surface inspection is carried out through manually inspecting the machined surfaces and using surface profilometers with a contact stylus at fixed intervals. Being a post-process

operation, this procedure is both time-consuming and-labor intensive. In addition, a number of defective parts can be produced during the period of surface inspection, thus leading to additional production cost. Another disadvantage is that the accuracy of surface measurements might be significantly influenced by serious interference or vibration from the surroundings [1].

The usage of engineering plastics has increased in today's designs due to its light weight, low cost and strength. It is used in almost all fields of industry [2]. One of the most commonly used engineering plastics is polyamide. The type which is obtained by casting, using mechanical techniques and improved with specific additives, is called cast-polyamide or Castamide, to use its industrial special name. Castamide takes the place of many metals due to its being a cheap, easily-processed, lightweight, high-resistance, abrasion-resistant and quiet working engineering material. It is preferred because of being cheaper than metals such as aluminum, copper and brass.

Many studies have been carried out since the 1960s to discover the different characteristics of polyamides, during the time they have been used as an engineering material. Some of these studies are based on their friction condition [3]. Friction forces of dry Castamides which do not contain any lubricant are lower than other metals. In order to decrease this friction force even more, different lubricants are added in Castamide materials [4-7].

With the inclusion of lubricant in the Castamide materials, the operating life of machine elements such as frictional beds, shafts, slides and cams are extended. Castamide materials are processed with metal cutting. The workability of different polyamide types, the cutting force and surface roughness observations are other areas of the experiment. A lot of parameters, such as cutting types, cutting speed, depth of cut, material used, etc. can be effective on the cutting force and surface quality [2, 8].

There are various studies aimed at determining the relationship between surface roughness and cutting conditions. Wang has studied the effect of special cutting conditions for micro cutters on the formation of surface roughness by using a miniature bench and composing a mathematical model of these effects [9]. Davim has studied the difference between processing conditions of turn bench and surface roughness formation of glass-fiber-reinforced and non-reinforced PA66 polyamide materials [2]. In some studies, the processing of rough metals, such as cobalt alloy, and change in their cutting parameters are analyzed or optimized by using techniques such as the Taguchi method on the experimental results [10, 11]. The observation of surface roughness values by using optimization methods and predictions based on artificial mind techniques can be made. Ozcelik and Bayramoglu have designed a model based on the predictability of surface roughness value with statistical methods [12]. While most formulas are developed by studying the relationship between the controlled cutting conditions that are created and surface roughness, in some conditions the shape of chip waste formed

during treatment is observed as well [13]. Generally in the metal cutting processes, cutting conditions, cutting tool geometry, cutting tool type, the usage or non-usage of coolant, the rigidity of work bench used, the cutting method used and the material type used all have effects on average surface roughness. Cutting parameters, i.e. feed rate, depth of cut, cutting speed, cutting edge and the number of cutting tool, also have effects on cutting [14, 15].

Several modeling techniques of input–output and in-process parameter relationship using ANN sets offer a distribution-free alternative and have attracted the attention of manufacturing practitioners and researchers alike when they run into difficulties in building empirical models in metal cutting process control. These techniques can offer a cost effective alternative in the field of machine tool design and manufacturing approaches, and have thus received wide attention in recent years [16].

A few applications of ANN-based input-output relationship modeling for metal cutting processes are reported in literature. The literature is rich with relevant investigations on choosing the best machining parameters for low surface roughness during different machining processes. Lee et al [17] used abductive network modeling for the drilling process to predict surface roughness. Chien and Chou [18] presented an ANN approach to predict the surface roughness of AISI 304 stainless steel, the cutting forces and the tool life. Then the genetic algorithm was introduced to find the optimum cutting conditions for the maximum material removal rate under the constraints of the expected surface roughness. Risbood et al [19] utilized a neural network to predict surface roughness and dimensional deviation based on the cutting forces and vibrations in turning of rolled steel bars containing about 0.35% carbon.

Nabil and Ridha [20] developed an approach that combined the design of experiments (DOE) and the ANN methods to establish accurate models for ground surface roughness parameter prediction. Erzurumlu and Oktem [21] have developed an ANN and surface response model to predict surface roughness in milling mould parts. A statistical design consisting of 243 experiments was adopted to collect the Ra measurement data. An effort has been made to predict surface roughness in the end milling process by using an ANN model based on the design experiments of Oktem et al [22].

Topal [23] discovered the role of the step-over ratio in surface roughness prediction studies in flat-end milling operations. Machining experiments were performed under various cutting conditions by using sample specimens. The surface roughness of these specimens was measured. Two ANN structures were constructed. The Zain et al. [24] model for surface roughness in the milling process could be improved by modifying the number of layers and nodes in the hidden layers of the ANN network structure, particularly in order to predict the value of the surface roughness performance measure. As a result of the prediction, the recommended combination of cutting conditions to obtain the best surface roughness value is a high speed with a low feed rate and a radial rake angle.

The ANN model of Zain et al. [25] predicted the surface roughness performance measured in the machining process by considering the Artificial Neural Network as the essential technique for measuring surface roughness. The ANN technique predicted the value for surface roughness; a real machining experiment is referred to.

This study investigates the application of dynamic ANN to predict the surface roughness values. Feed speed, cutting speed, depth of cut and tool type are selected as the inputs of the model while the surface roughness is the output variable. The obtained results show that the used ANN model has given similar values to experimental data with sufficient accuracy.

2   The Importance of the Study

In this study, the cutting parameters of Castamide materials on a CNC vertical machining bench are changed under control, and the average surface roughness values are experimentally observed. In the experimental studies, Castamide samples and cutters in the same diameters and of different types are processed. In order to detect the average surface roughness (Ra) value, experiments were carried out by changing the cutting speed (V_c), the feed speed (f) and the depth of cut (a_p). The experiments on Castamide were done in CNC milling using high speed steel and hard metal carbide tools. In the experiments, the effects on the average surface roughness of cutting tools with the same diameters but with different cutting edges and tool materials were also investigated. The measured data were used to train and test a dynamic ANN model. It is quite clear from the model results that the surface roughness predicted by the ANN model matches well with the training data, as well as with the test data.

3   Experimental Design

In the study, a TAKSAN trademark TMC700VC CNC vertical machining centre was used. The bench is composed of a system that can be programmed in ISO format with 15 kW of power, in metrical and inch units, and can do linear and circular interpolation in three cycles. The control unit is FANUC serial O-M. The bench table moves automatically in the directions of X, Y, Z. The tools are set to CNC milling machine. Then, the part is mounted on the table of the milling machine. Later, NC codes are transmitted to the CNC and the parts are measured after the machining process. These processes are shown in the figure below. The used CNC vertical machining centre and schematic picture of experiment setting can be shown in Fig. 1.
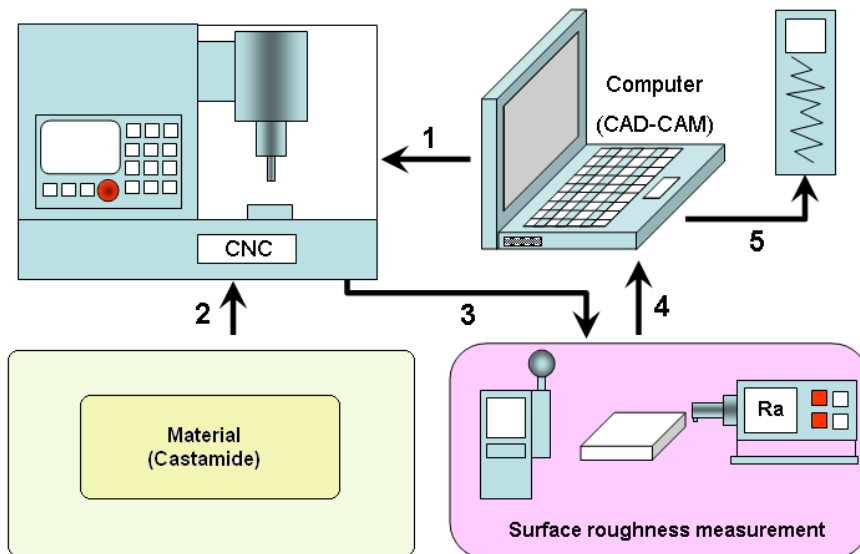
Figure 1
Schematic picture of experiment setting

For the measurement of roughness, a MarSurf PS1 portable surface roughness measurement unit was used. The measurement needle has a diameter of 2 µm and an average pressure force of 0.7 mN. The measurement scanning length was adjusted to 5.6 mm.

3.1 The Cutting Tool and Conditions

3.1.1 The Cutting Tool

In the cutting process, 14 mm end milling cutter tools made of high speed steel (HSS) and hard metal carbide were used. An HSS cutting tool, a cutting tool with four cutter edges in DIN standards, can easily do machining in profile processing, and in the process of high strength steel and other hard processed steels. It has four cutter edges and a 30° helix angle. Hard metal carbide cutter tools are produced in the DIN 81800 standard, with four cutter edges, a 30° helix angle, WC (Tungsten Carbide) rate of 87.7%, a cobalt rate of 12.3%, a TRS (Transverse rupture strength) MPa, a 92.5 HRA hardness, a 0.5 µm grain size and high corrosion and effect ability. The cutting tools are bound to a spindle with the help of pincers. In the milling process, the average surface roughness is obtained with the help of cutting parameters: cutting speed, feed speed, depth of cut, type of cutting equipment and Castamide material.

3.1.2　　The Machining Conditions

The experimental work was done on a CNC milling machine. The surface roughness was investigated by the effect of the cutting rate, the feed rate and the cutting depth. Cutting speeds were 100, 120, 140 m/min; the feed rates were 75, 100, 125 mm/min; and the cutting depths were selected as 1.0; 1.5; 2.0 mm. Prefeasibility parameter values were selected as recommended for polyamide material [26, 27]. A sample taken out of a dry container was brought to the experiment in desired process parameters after serially connected to the bench. The cutting conditions can be seen in Table 1.

Table 1

Cutting conditions for end milling

Terms of cutting condition	Unit	Value
Cutting speed	(m/min)	100, 120 and 140
Feed rate	(mm/min)	75, 100 and 125
Depth of cut	(mm)	1,0; 1,5 and 2,0
Dimension of cutting tool	(mm, ¬)	14
Tool and the number of cutting edge	-----	CARBIDE (4), HSS (4) and HSS (6)
Material	-----	Castamide
Coolant	-----	Dry

3.2　　Workpiece Material

The Castamide material in 46 mm plates used in the experiments was supplied by Polimersan. It is called POLIKES[®] (PA6 G) in the firms product catalogue. The plates were cut in the dimensions of 112*82*46 mm. The mechanical and physical features of the PA6G used in the expiraments are shown in Table 2.

Table 2

Mechanical and physical features of tested material

Properties of Castamide	Unit	Value
Specific gravity	gr/cm^3	1,15
Thermal elongation	$1/K*10^5$	8-9
Pulling resistance	N/mm^2	55-85
Breaking resistance	N/mm^2	88-90
Breaking elongation	%	10-40
Elastic module	N/mm^2	3900-4200
Water absorption	%	6-7
Resistance as per volume	$\Omega*cm$	$>10^{15}$
Resistance as per surface	Ω	$>10^{12}$
Dielectric resistance	KV/mm	80-100
Rockwell	HRC	M88
Ball notch 358/30	N/Mm^2	110-160

4   The Artificial Neural Network and the Prediction of Surface Roughness

There are various simple surface roughness amplitude parameters used in industries, such as roughness average (Ra), root-mean-square (rms) roughness (Rq), and maximum peak-to-valley roughness (Ry or Rmax), etc. [28]. The parameter Ra was used in this study. The average roughness (Ra) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation length (Fig. 2). Therefore, the Ra is specified by the following equation;

$$Ra = \frac{1}{L} \int_0^L |Y(x)| dx \tag{1}$$

where Ra is the arithmetic average deviation from the mean line, L is the sampling length and Y the ordinate of the profile curve. The average surface roughness Ra was measured within the sampling length of 5.6 mm.
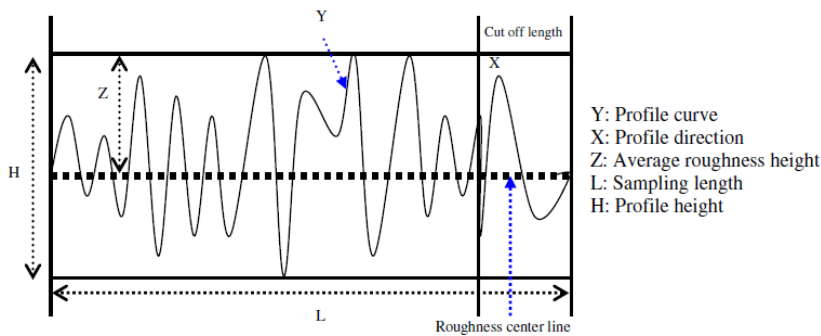

Figure 2
Surface roughness profile [29]

The obtained database (Table 3) by the surface roughness of milled specimens was used to train and test the neural network model. A four-layer network having one input layer, two hidden layers and one output layer were formed for the present study. The input layer had 6 neurons and the output layer was determined by the output parameter (surface roughness, Ra). The number of neurons in the hidden layer is optimized to achieve optimum output accuracy. The number of hidden neurons depended on both input vector size and the number of input classifications (first hidden layer had 2 neurons and second hidden layer had 2 neurons). Too few neurons could lead to under-fitting whereas too many neurons could result in over-fitting.

Fig. 3 shows the schematic layout of the neurons within the network, each arrow representing a link between neurons, or a synapse. Each of these synapses has a weight attached to it which governs the output of the neuron. By adjusting the

values of these synaptic weights, the outputs of the neural network can be altered. Training involves adjusting the synaptic weights within the network until the mean of absolute error between the predicted and experimental output values has been minimized.
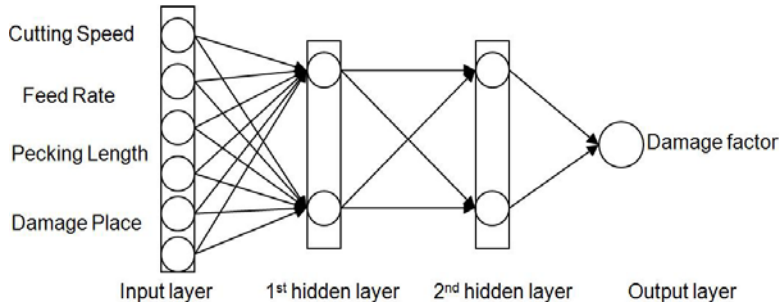

Figure 3

ANN model

Table 3

Sample training and testing data set

a_p	V_c	f	Tool	Ra	Train	a_p	V_c	f	Tool	Ra	Train
2	100	100	CARBIDE–4	0,588	Training	2	125	200	CARBIDE–4	0,644	Testing
1	100	100	HSS–4	0,811	Training	2	125	100	HSS–4	0,945	Testing
2	125	100	CARBIDE–4	0,915	Training	1,5	75	150	HSS–4	1,293	Testing
1,5	125	150	CARBIDE–4	1,003	Training	1,5	100	200	CARBIDE–4	1,369	Testing
1	100	200	HSS–4	1,05	Training	1,5	125	100	CARBIDE–4	1,374	Testing
1	75	100	HSS–6	1,058	Training	1	75	200	HSS–4	1,449	Testing
1	75	150	HSS–4	1,204	Training	1	75	150	CARBIDE–4	1,473	Testing
2	100	200	CARBIDE–4	1,239	Training	1,5	75	150	CARBIDE–4	1,512	Testing
1,5	125	200	CARBIDE–4	1,25	Training	1	125	150	HSS–4	1,617	Testing
1,5	125	200	HSS–4	1,256	Training	2	75	150	CARBIDE–4	1,619	Testing
1,5	100	150	HSS–6	1,264	Training	1	75	200	CARBIDE–4	1,646	Testing
1,5	100	100	HSS–4	1,277	Training	1,5	75	100	HSS–4	1,836	Testing
1	100	200	CARBIDE–4	1,307	Training	1	125	100	CARBIDE–4	1,874	Testing
1,5	75	100	HSS–6	1,313	Training	2	100	150	CARBIDE–4	2,056	Testing
2	100	200	HSS–4	1,313	Training	2	75	200	HSS–4	2,086	Testing

For the present study, the input variables were discrete and set values while the values of output variables were in a range. Since three different tools were used, the names of the tools were accepted as the value of the variable: hard metal CARBIDE-4, HSS-4 and HSS-6. The cutting speed and feed rate have discrete values (75, 100, 125 m/min and 100, 150, 200 mm/min). 81 data sets were used. 56 data sets (approximately 70%) were used to train the model and 25 data sets were used to test the model.

5   Results and Discussion

For each input pattern, the predicted value of surface roughness was compared with the respective experimental Ra (µm) value. It was found that the predicted average surface roughness were close to the experimental values. Fig. 4 shows the graph of the predicted and the experimental values of the surface roughness for training patterns. The maximum error was 1.59 and the minimum error was 0.015. The absolute error was found to be less than 20% for most cases.
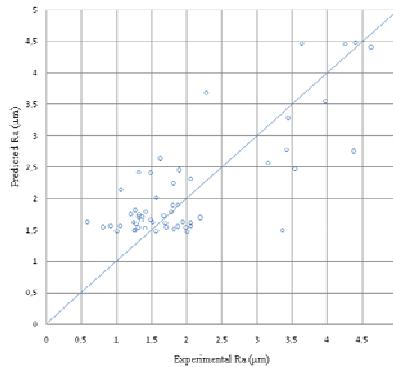

Figure 4
Predicted Ra values for training data sets

The network was then tested with the 25 test data points which were not used for the training purpose. The comparison of the predicted and the experimental values of surface roughness for the test data sets are presented in Fig. 5. From the test results, it can be observed that the predicted values are close and follow almost the same trend as the experimental values. While the maximum error was 1.18, the minimum error was 0.024. The absolute error was found to be less than 20% for most cases. In conclusion, our model has managed to cover experimental data with a 83.6% correlation factor.
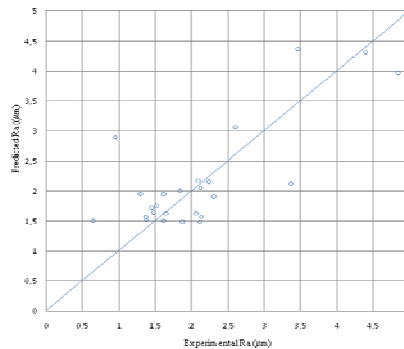

Figure 5
Predicted Ra values for testing data sets

It is quite obvious from the results of the ANN predictive model that the predicted accuracy was good and the predicted results matched well with the experimental values. The prediction of the surface roughness of Castamide is important for applications. It was earlier established that the cutting parameters (feed rate, depth of cut, cutting speed, cutting edge number of cutting tool) have an impact on cutting. The obtained results hereby are in compliance with the earlier findings. The difference may be due to the type of investigated materials. Obtained surface roughness quality varies between 0.5 and 5. This change makes it hard to find a good correlation among cutting parameters, tool type and surface roughness. In addition, considering that tool type also affected the results, there is a high correlation for CARBIDE-4 and HSS-6 datasets. 83.6% correlation becomes 90-99% when only one tool type is considered. As the correlation between the machining and the surface roughness is strongly dependent on the material being machined, there is an imminent need to develop a generic predictive platform to predict surface roughness. The present investigation is a step in this regard. The proposed model is helpful in the judicious selection of the various machining parameters to minimize surface roughness.

Conclusions

An ANN-based predictive model for surface roughness in the process of milling of Castamide was developed. The model served as a tool to calculate the surface roughness for various sets of input parameters. Prior knowledge of the potential roughness could help engineers to select the optimum process parameters as well as the tool type for smooth surfaces on Castamide.

- The cutting speed, feed rate, depth of cut, and two types of tools were used as the input parameters, and the surface roughness was used as the output.

- The predicted values using ANN were found to be in close agreement with the training as well as the testing data. For both training and testing data, the obtained error was less than 20 percent in most cases.

- A more generic ANN model incorporating input variables at a greater number of levels can be developed and validated. The experimental data available in literature can be incorporated in the model to increase its applicability. An ANN model for predicting surface roughness can also be used in conjunction with an optimization tool to find the best drilling parameters, to reduce the damage prior to milling and at the start of any milling process of Castamide.

References

[1]   Tsai, YH., Chen, JC., Lou, SJ., An In-Process Surface Recognition System Based on Neural Networks in End Milling Cutting Operations, International Journal of Machine Tools & Manufacture 39 (1999) 583-605

[2]   Davim, J. P., Silva, L. R., Festas, A., Abrão, A. M., Machinability Study on Precision Turning of PA66 Polyamide with and without Glass Fiber Reinforcing, Materials and Design 30 (2009) 228-234

[3]   Adams, N., Friction and Deformation of Nylons, J. Appl. Polym. Sci. 7 (1963) 2075-2103

[4]   Samyna, P., Baets, P., Schoukens, G., Van Driessche, I., Friction, Wear and Transfer of Pure and Internally Lubricated Cast Polyamides at Various Testing Scales, Wear 262 (2007) 1433-1449

[5]   Palabiyik, M., Bahadur, S., Mechanical and Tribological Properties of Polyamide 6 and High Density Polyethylene Polyblends with and without Compatibilizer, Wear 246 (2000) 149-158

[6]   Samyn, P., Tuzolana, T. M., Effect of Test Scale on the Friction Properties of Pure and Internal-lubricated Cast Polyamides at Running-In, Polymer Testing 26 (2007) 660-675

[7]   Liu, C. Z., Wu, J. Q., Li, J. Q., Ren, L. Q., Tong, J., Arnell, R. D., Tribological Behaviours of PA/UHMWPE Blend under Dry and Lubricated Condition, Wear 260 (2006) 109-115

[8]   Mata, F., Reis, P., Davim, J. P., Physical Cutting Model of Polyamide Composites (PA66 GF30), Mater Sci Forum (2006) 514-516:643-7

[9]   Wang, W., Kweon, S. H., Yang, S. H., A Study on Roughness of the Micro-End-milled Surface Produced by a Miniatured Machine Tool, The International Journal of Advanced Manufacturing Technology (2005);162-13:702-708

[10]   Bağcı, E., Aykut, Ş., A Study of Taguchi Optimization Method for Identifying Optimum Surface Roughness in CNC Face Milling of Cobalt-based Alloy (stellite 6), Int J Adv Manuf Technol (2006) 29:940-947

[11]   Aykut, Ş., Demetgül, M., Tansel, İ. N., Selection of Optimum Cutting Condition of Cobalt-based Super Alloy with GONN The International Journal of Advanced Manufacturing Technology (2010) 46:957-967

[12]   Ozcelik, B., Bayramoglu, M., The Statistical Modeling of Surface Roughness in High-Speed Flat End Milling, Int J Mach Tools Manuf (2006) 46:1395-1402

[13]   Kishawy, H. A., Dumitrescu, M., Ng, E. G., Elbestawi, M. A., Effect of Coolant Strategy on Tool Performance, Chip Morphology and Surface Quality during High-Speed Machining of A356 Aluminum Alloy, Int J Mach Tools Manuf (2005) 45:219-227

[14]   Ertakin, Y. M., Kwon, Y., Tseng, T. L., Identification of Common Sensory Features for the Control of CNC Milling Operations under Varying Cutting Conditions, Int J Mach Tools Manuf (2003) 43.897-904

[15]   Dabade, U. A., Joshi, S. S., Ramakrishnan, N., Analysis of Surface Roughness and Cross-Sectional Area while Machining with Self-propelled Round Inserts Milling Cutter, J Mater Process Technol (2003) 132:305-312

[16]   Mukherjee, I. Ray, P. K., A Review of Optimization Techniques in Metal Cutting Processes, Computers & Industrial Engineering 50 (2006) 15-34

[17]   Lee, B. Y., Liu, H. S., Tarng, Y. S., 1998. Modeling and Optimization of Drilling Process, J. Mater. Process. Technol. 74, 149-157

[18]   Chien, W. T., Chou, C. Y., 2001. The Predictive Model for Machinability of 304 Stainless Steel. J. Mater. Process. Technol. 118, 442-447

[19]   Risbood, K. A., Dixit, U. S., Sahasrabudle, A. D., 2003. Prediction of Surface Roughness and Dimensional Deviations by Measuring Cutting Forces and Vibrations in Turning Process, J. Mater. Process. Technol. 132, 203-214

[20]   Nabil, B. F., Ridha, A., Ground Surface Roughness Prediction Based upon Experimental Design and Neural Network Models. Int. J. Adv. Manuf. Technol., 2006 31, 24-36

[21]   Erzurumlu, T., Oktem, H., Comparison of Response Surface Model with Neural Network in Determining the Surface Quality of Moulded Parts, Materials & Design 200728, 459-465

[22]   Oktem, H., Erzurumlu, T., Erzincanlı, F. Prediction of Minimum Surface Roughness in end Milling Mold Parts Using Neural Network and Genetic Algorithm, Materials & Design Volume 27, Issue 9, 2006, pp. 735-744

[23]   Topal, EY, The Role of Step over Ratio in Predictionof Surface Roughnessin Flat Endmilling International Journal of Mechanical Sciences 51 (2009) 782-789

[24]   Zain, AM., Haron, H., Sharif, S., Prediction of Surface Roughness in the End Milling Machining Using Artificial Neural Network, Expert Systems with Applications 37 (2010) 1755-1768

[25]   Zain, AM., Haron, H., Sharif, S., Prediction of Surface Roughness in the End Milling Machining Using Artificial Neural Network, Expert Systems with Applications 37 (2010) 1755-1768

[26]   Atakök, G., Kurt, M., Measurement and Evaluation of Force, Vibration, Thermal Changes and Roughness of Polyamide Materials' Machining at CNC Machines, 10. Denizli Malzeme Sempozyumu ve Sergisi, 2004, 895-902

[27]   Xiao, K. Q., Zhang, L. C., The Role of Viscous Deformation in The Machining of Polymers, International Journal of Mechanical Sciences, 2002, pp. 44-52

[28]   Benardos, P. G., & Vosnaikos, G. C. (2003). Predicting Surface Roughness in Machining: a Review. International Journal of Machine Tools and Manufacture, 43, 833-844

[29]   Yang, J. L., & Chen, J. C. (2001) A Systematic Approach for Identifying Optimum Surface Roughness Performance in End-Milling Operation, Journal of Industrial Technology, 45, 110-120