Asian Journal of Scientific Research

ISSN 1992-1454

Asian Journal of Scientific Research 4 (3): 255-263, 2011
ISSN 1992-1454 / DOI: 10.3923/ajsr.2011.255.263

Development of Surface Roughness Prediction Model for High Speed End Milling of Hardened Tool Steel

[1]Afifah Mohd. Ali, [1]Erry Yulian T. Adesta, [2]Delvis Agusman, [1]Siti Norbahiyah Mohamad Badari and [1]Muataz Hazza Faizi Al-Hazza

[1]Department of Manufacturing and Materials Engineering, Faculty of Engineering, International Islamic University Malaysia, 53100 Gombak, Kuala Lumpur, Malaysia

[2]Department of Mechanical Engineering, Faculty of Engineering, Universitas Tarumanagara, Jakarta, Indonesia

Corresponding Author: Erry Yulian Triblas Adesta, Department of Manufacturing and Materials Engineering, Faculty of Engineering, International Islamic University Malaysia, 53100 Gombak, Kuala Lumpur, Malaysia Tel: +60 3 6196 4452 Fax: +60 3 6196 4477

ABSTRACT

The quality of the surface plays a very important role in the performance of milling as a good-quality milled surface in a variety of manufacturing industries including the aerospace and automotive sectors where good quality surface significantly improves fatigue strength, corrosion resistance, or creep life. This study discussed the issue of surface machined quality and the effort taken to predict surface roughness. For this purpose, hardened material AISI H13 tool steel with hardness of 48 Rockwell Hardness (HRC) was chosen for work material. Machining was done at High Cutting speed (Vc) from 150 up to 250 m min^{-1}, feedrate (Vf) 0.05-0.15 mm rev^{-1} and depth of cut (DOC) 0.1-0.5 mm. The analysis and observation of the surface roughness were done by using optical surface roughness machine. Response Surface Methodology (RSM) Model was used to design the prediction model with parameters generated by using Central Composite Face (CCF) methods. A prediction model developed with 90% accuracy with the conclusion of feedrate as the main contributor to surface roughness followed by cutting speed. Therefore, RSM has been proven to be an efficient method to predict the surface finish during end-milling of H13 tool steel using TiAlN coated carbide tool inserts under dry conditions.

Key words: AISI H13, central composite face, surface quality, coated carbide, prediction method, hot work tool steel

INTRODUCTION

In the recent past, the dimensional accuracy and the surface finish of any manufacturing process have become very important where manufactured part quality is determined by their form errors and the surface finish. Surface finish is important factor in evaluating the quality of products. Surface roughness is mostly used as an index to determine the surface finish in machining process. Surface roughness also affects several functional attributes of parts, such as contact causing surface friction, wearing, light reflection, heat transmission, ability of distributing and holding a lubricant, coating, or resisting fatigue (Lou *et al*., 1999). Therefore, the desired finish surface is usually specified and the appropriate processes are selected to reach the required quality.

Realizing the need of the industry, numerous research and study to predict the surface roughness have been conducted in order to improve the manufacturing process while reducing the cost of production. Many researchers have actively performed the research to predict the surface roughness and many methodology and approaches have been introduced. Among the approaches are the followings (Benardos and Vosniakos, 2002):

- Machining theory based approaches (Lim *et al.*, 1995; Gologlu and Sakarya, 2008; Tang *et al.*, 2009) and Experimental investigation approaches (Lou *et al.*, 1999; Lee *et al.*, 2001; Xu *et al.*, 2003)
- Designed experiments approaches (Hafiz *et al.*, 2007; Vivancos *et al.*, 2005; Ghani *et al.*, 2004; Mansoura and Abdalla, 2002; Reddy *et al.*, 2008)
- Artificial Intelligent (AI) approaches (Dhokia *et al.*, 2008; Ho *et al.*, 2009)

Benardos and Vosniakos (2002) in his review claim that the Response Surface Methodology (RSM) and Taguchi techniques for Design of Experiments (DoE) seem to be the most wide-spread methodologies for the surface roughness prediction problem. Therefore, among the researches that applied these methods are described in the next paragraph.

Among researches using designed experiments approaches in performing their prediction are Hafiz *et al.* (2007) who developed the prediction of surface roughness for AISI H13 by using PCBN insert through application of RSM, CCD model. They found that feedrate is the common factor that contributes to surface roughness. Vivancos *et al.* (2005) in the other hand presented a model for the prediction of surface roughness in high-speed side milling of hardened die steels by using RSM. Suhail *et al.* (2011) on the other hand applied full factorial RSM to predict surface roughness using the work piece surface temperature of a turning work piece with the aid of an infrared temperature sensor. Ghani *et al.* (2004) applied Taguchi method for the optimization of surface roughness during the end milling of AISI H13 tool steel. They found that roughness value tends to decrease with increasing cutting speed and decreasing feedrate. In this research, two objectives has been fulfilled where they are: To study the relationship of the parameters to the surface roughness with hypothesis of feedrate as the major contributor to surface roughness and to develop a prediction model for surface roughness by using RSM (CCF). Based on the previous researches, it is expected for a high accuracy of model will be presented.

MATERIALS AND METHODS

A series of cutting tests were carried out to verify the surface generation model presented. Machining was conducted using vertical milling centre type MAZAK machine (Model Nexus 410A-II) through dry cutting. Machining was done at high Cutting Speed (Vc) from 150 up to 250 m min^{-1}, feedrate (Vf) 0.05-0.15 mm rev^{-1} and Depth of Cut (DOC) 0.1-0.5 mm. Parameters used was based on the parameters suggested by Sandvik as the choice of optimized cutting parameters is very important for controlling the required surface quality (Suhail *et al.*, 2010), The experiments for this research were performed on AISI H13 at hardness of 48 HRC as work material. The chemical compositions of the material are presented in Table 1.

Tool used was indexable tool holder Sandvick Coromill R490 (http://www.sandvik.com/) while for the insert, PVD coated TiAlN carbide insert was chosen for machining as PVD cutting tools perform better than CVD cutting tools (Habeeb *et al.*, 2008). While TiAlN is chosen for economical purpose. Three cutting parameters with three levels of each parameter used in this research are presented in the Table 2.

Table 1: Chemical composition of work material as provided by supplier

Chemical composition	C	Si	P	S	Cr	Mo	V	Mn
%	0.32-0.40	0.80-1.20	0.011	0.002	4.55-5.50	1.00-1.50	0.80-1.20	<0.50

Table 2: Three levels of parameters

	Level of parameter		
Parameters	Low	Centre	High
Cutting Speed (m min^{-1})	150	200	250
Feedrate (mm rev^{-1})	0.05	0.10	0.15
Depth of cut (mm)	0.10	0.30	0.50

Parameters for these experiments were generated by using Response Surface Methodology (RSM) and the analysis and prediction of surface roughness also generated from the same design. The details of the prediction model are described below. Surface roughness of the material after the machining was taken by using optical surface roughness measurement machine (Model: Wyto 1100) is used. This research was conducted within January 2009 to December 2010.

Prediction model

Mathematical model postulation: The theoretical surface roughness is generally dependent on cutting tool geometry, tool material, workpiece geometry, workpiece material, cutting conditions, cutter run-out, mode of milling and machine-tool rigidity, etc. However, an empirical relationship can be formed between surface roughness and the main independent variables, namely, cutting speed (v), Axial Depth of Cut (a) and Feed (f) which is given as follows (Hafiz *et al*., 2007):

$$Ra = C\,v^k a^l f^m \tag{1}$$

where, C is a model constant and k, l and m are the model parameters. Eq. 1 can be represented in linear form by using natural logarithm:

$$\ln Ra = \ln C + k \ln v + l \ln a + m \ln f \tag{2}$$

The second-order linear model of Eq. 2 can be represented as follows (Kadirgama *et al*., 2009):

$$\begin{aligned}\hat{y}_2 = y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{11}x_1^2 b_{22}x_2^2 \\ + b_{33}x_3^2 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 a\end{aligned} \tag{3}$$

Where:

$\hat{y}_2$	=	The estimated response based on the second-order equation
y	=	The measured surface roughness on a logarithmic scale
x_0	=	1(dummy variable)
x_1, x_2, x_3	=	Logarithmic transformations of cutting speed, feedrate and depth of cut, respectively
b_0, b_1, b_2 and b_3	=	The parameters to be estimated
ε	=	The experimental error

The second order response equation considers the influence of single factor along with their quadratic and interactive effects over the responses. Thus, it gives more effective prediction of the responses. In this model, x_1, x_2 and x_3 represent cutting speed, feed rate and depth of cut, respectively.

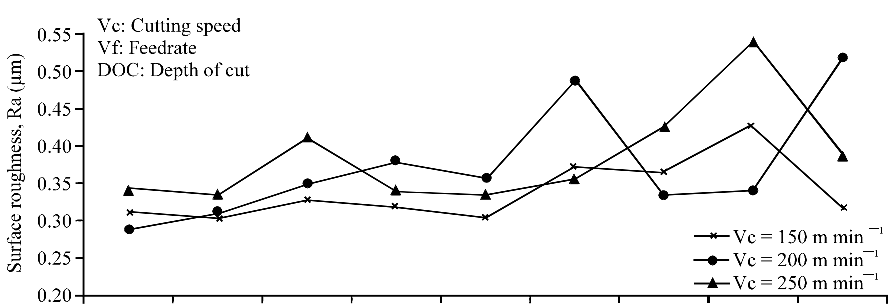
RESULTS AND DISCUSSION

In this research, experiments were performed using full factorial model to observe the relationship of the parameters to the surface roughness. For prediction model using CCF model, 20 parameters are selected by the design to produce the surface roughness prediction model. A CCF design is one type of CCD model in RSM. It is chosen as it provides relatively high quality predictions over the entire design space and do not require using points outside the original factor range.

The analysis of the result was done in two steps. Step 1 was the analysis on the relationship between the parameters and their contributions to the surface roughness and step 2, the surface roughness prediction model analysis.

Step 1

Parameters: Based on the data collected, graph on the relationship of the parameters to the surface roughness are presented in Fig. 1. From this graph the relationship between the parameter and surface roughness can be seen. The graph has shown a trend of increasing surface roughness with the increment of feedrate especially for cutting speed 150 and 250 m min^{-1}. The second factor after the feedrate was the cutting speed where the surface roughness also increased as the cutting speed increased. However, when it reach certain point the surface roughness start to decrease again. This result suits the result as reported by Novakova *et al.* (2009) as when cutting speed is increased and reaches certain point, surface roughness will improve and reduced. The same conclusion for feedrate and cutting speed also reported by Mansoura and Abdalla (2002) in their research where they stated that the increment of feedrate will increase the surface roughness whilst inclement of cutting speed will decrease the surface roughness. However, the depth of cut gives very little effect to the surface roughness.



	Vf = 0.05 DOC = 0.1	Vf = 0.10 DOC = 0.1	Vf = 0.15 DOC = 0.1	Vf = 0.05 DOC = 0.3	Vf = 0.10 DOC = 0.3	Vf = 0.15 DOC = 0.3	Vf = 0.05 DOC = 0.5	Vf = 0.10 DOC = 0.5	Vf = 0.15 DOC = 0.5
Vc = 150 m min^{-1}	0.24	0.23	0.26	0.25	0.23	0.32	0.31	0.39	0.25
Vc = 200 m min^{-1}	0.21	0.24	0.29	0.33	0.30	0.47	0.27	0.28	0.51
Vc = 250 m min^{-1}	0.28	0.27	0.37	0.28	0.27	0.30	0.39	0.54	0.34

Fig. 1: Graph of parameters Vs surface roughness

Step 2

Prediction model: Machining or material removal with tools of geometrically define cutting edges is one of the oldest and indispensable processes for shaping components in manufacturing industry. It has long been recognized that improving the technological performance of machining operations as assessed by the surface finish and dimensional accuracy enhances the economic viability of machining operations. It has also been realized that reliable quantitative predictions of the various technological performance measures, preferably in the form of models (equations), are essential for developing constrained optimization analysis. The present work focused on the prediction of surface roughness in end milling by using RSM. RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. RSM also quantifies relationships among one or more measured responses and the vital input factors (Patwari *et al.*, 2010), An analytical model has been developed incorporating those factors that are significant.

From the second order Eq. decribed in material and methods section, a prediction model from the RSM design is obtained as below.

Surface roughness:

$$Ra = \frac{-0.85070+0.012027x_1-5.80409x_2+1.33955x_3-0.0000294545x_1^2+0.54545x_2^2}{-1.71591x_3^2+0.004\,x_1x_2+0.00025\,x_1x_3-2.75x_2x_3} \quad (4)$$

Calculation of predicted surface roughness were done and presented in Table 3 together with the percentage of accuracy for the experimental result to the predicted surface roughness. From the accuracy percentage calculation in this table, the average percentage was 90% where the deviation between the experimental result and prediction data is only 10%. Therefore, the model can be accepted for application. Hafiz *et al.* (2007) who also applied RSM as the medium for prediction of surface roughness, also manage to get up to 95% confident interval in the research and Ozcelik and Bayramoglu (2006) managed to get 94% accuracy shows that RSM is a reliable model to predict the surface roughness of the machined surface.

From the data collected, the graph of comparison for the predicted value and experimental value of surface roughness are presented in Fig. 2. From this graph, a close prediction value with the actual data can be seen clearly.

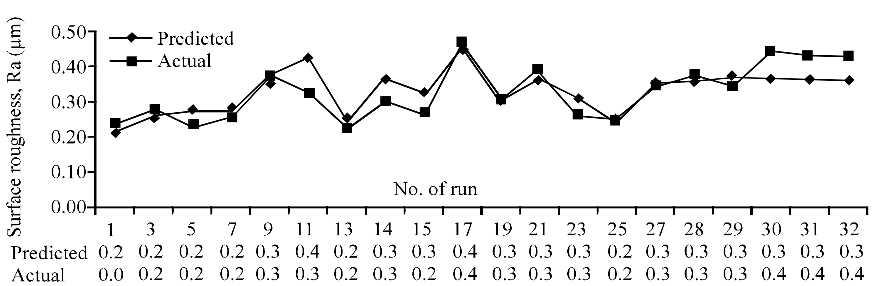


Fig. 2: Comparison between experimental results and values predicted by 2nd order mathematical model for logarithm of surface roughness

Table 3: The design of experiment, comparison of predicted surface roughness with experimental surface roughness and model accuracy

Factor 1	Factor 2	Factor 3	Predicted	Experimental	
Cutting speed (m min^{-1})	Feedrate (mm/tooth)	Depth of cut (mm)	Surface roughness (μm)	surface roughness (μm)	Accuracy (%)
150	0.05	0.1	0.21	0.24	88
250	0.05	0.1	0.26	0.28	93
200	0.10	0.1	0.28	0.24	87
150	0.15	0.1	0.28	0.26	94
250	0.15	0.1	0.36	0.37	98
200	0.05	0.3	0.42	0.33	78
150	0.10	0.3	0.25	0.23	91
200	0.10	0.3	0.36	0.30	83
250	0.10	0.3	0.32	0.27	83
200	0.15	0.3	0.45	0.47	96
150	0.05	0.5	0.30	0.31	96
250	0.05	0.5	0.35	0.39	90
200	0.10	0.5	0.31	0.27	87
150	0.15	0.5	0.25	0.25	100
250	0.15	0.5	0.35	0.34	98
200	0.10	0.3	0.36	0.37	98
200	0.10	0.3	0.36	0.35	97
200	0.10	0.3	0.36	0.44	78
200	0.10	0.3	0.36	0.43	81
200	0.10	0.3	0.36	0.43	81
Average accuracy					90

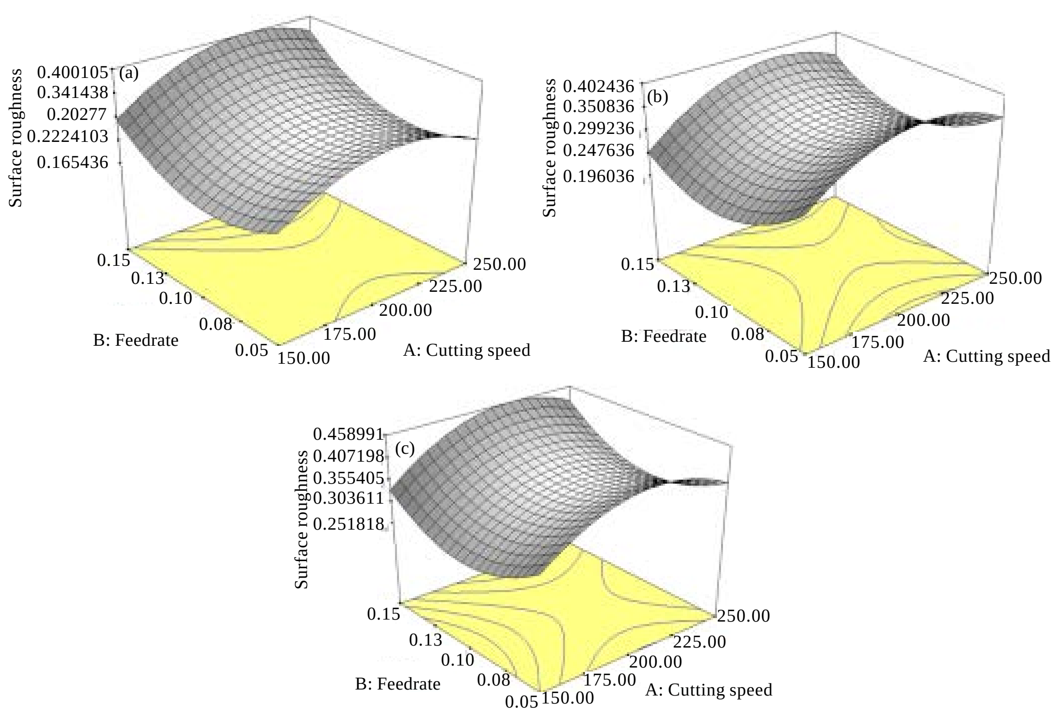


Fig. 3: Surface roughness as the function of cutting speed and feedrate

Figure 3 shows the contours of experimental results and predicted surface roughness values generated by the 2nd order CCF model. Figure 3a, b and c show the logarithmic roughness as the function of x_1 and x_2, for the minimum, middle and maximum values of x_3 Based on Fig. 3, it is observed that surface roughness decrease when feedrate is decreased while for cutting speed, surface roughness increase with increase of cutting speed. However, the graphs shows an increasing trend when it reach certain point. This graph also shows that feed plays the most influencing factor contribute to surface roughness followed by cutting speed and finally depth of cut. Same conclusion also reported by Abdullah *et al.* (2008), Axinte and Dewes (2002), Hafiz *et al.* (2007), Onwubolu (2005) and Jaharah *et al.* (2009), as feed possesses the most significant effect on roughness followed by cutting speed. However, axial depth of cut appears to have very little effect over roughness value. An increment of cutting speed and decrement of feed will result in better surface quality in terms of roughness.

This can be related to other condition such as tool wear which is not considered in this research. The response surface plot is a good tool to estimate the region of optimum response which is basically similar to the 3-D wire frame plot. Therefore, Eq. 2 is valid for end milling of AISI H13 tool steels under dry condition using TiAlN inserts with the following range of cutting speed, feedrate and depth of cut as below:

$$\text{Cutting speed} = 150 \text{ m min}^{-1} \leq Vc \leq 250 \text{ m min}^{-1}$$

$$\text{Feedrate} = 0.05 \text{ mm/tooth} \leq Vf \leq 0.15 \text{ mm/tooth}$$

$$\text{Depth of cut} = 0.1 \text{ mm} \leq a \leq 0.5 \text{ mm}$$

CONCLUSION

This study presented an experimental investigation on surface finish during the high speed end milling of AISI H13 tool steel in order to develop an appropriate roughness prediction model. The general conclusions that can be made from the current study is feed possessed the most significant effect on roughness followed by cutting speed. However, axial depth of cut appears to have very little effect over roughness value. Other than that, the quadratic second order models, developed to predict the surface roughness value, could provide predicted values of surface roughness pretty close to the actual values found in the experiments. The average accuracy percentage calculated in this model is 90%. Finally, the RSM has been proven to be an efficient method to predict the surface finish during end-milling of H13 tool steel using TiAlN coated carbide tool inserts under dry conditions. It also reduces the total numbers of experiment quite significantly.

ACKNOWLEDGMENT

This research study is funded by Research Management Centre (RMC) International Islamic University Malaysia (IIUM) through research grant no: EDW A10-0633 to whom the authors wish to thank for the financial support.

REFERENCES

Abdullah, A.B., L.Y. Chia and Z. Samad, 2008. The effect of feed rate and cutting speed to surface roughness. Asian J. Scientific Res., 1: 12-21.

Axinte, D.A. and R.C. Dewes, 2002. Surface integrity of hot work tool steel after high speed milling-experimental data and empirical models. J. Mater. Process. Technol., 127: 325-335.

Benardos, P.G. and G.C. Vosniakos, 2002. Prediction of surface roughness in CNC face milling using neural networks and taguchi's design of experiments. Robotics Comput. Integrated Manuf., 18: 343-354.

Dhokia, V.G., S. Kumar, P. Vichare and S.T. Newman, 2008. An intelligent approach for the prediction of surface roughness in ball-end machining of polypropylene. Robotics Comput. Integrated Manufact., 24: 835-842.

Ghani, J.A., I.A. Choudhury and H.H. Hassan, 2004. Application of Taguchi method in the optimization of end milling. J. Mater. Process. Technol., 145: 84-92.

Gologlu, C. and N. Sakarya, 2008. The effects of cutter path strategies on surface roughness of pocket milling of 1.2738 steel based on Taguchi method. J. Mater. Process. Technol., 206: 7-15.

Habeeb, H.H., K.A. Abou-El-Hossein, B. Mohamad, J.A. Ghani and K. Kadirgama, 2008. Investigating of tool wear, tool life and surface roughness when machining of nickel alloy 242 with using of different cutting tools. Asian J. Scientific Res., 1: 222-230.

Hafiz, A.M.K., A.K.M.N. Amin, A.N.M. Karim and M.A. Lajis, 2007. Development of surface roughness prediction model using response surface methodology in high speed end milling of AISI H13 tool steel. Proceedings of the 2007 IEEE International Conference on Industrial Engineering and Engineering Management. Dec. 2-4, IEEE, USA., pp: 1868-1872.

Ho, W.H., J.T. Tsai, B.T. Lin and J.H. Chou, 2009. Adaptive network-based fuzzy inference system for prediction of surface roughness in end milling process using hybrid Taguchi-genetic learning algorithm. Expert Syst. Appl., 36: 3216-3222.

Jaharah, A.G., C.H.C. Hassan and N. Muhamad, 2009. Machined surface of AISI H13 tools steels when end milling using P10 tin coated carbide tools. Eur. J. Sci. Res., 26: 247-254.

Kadirgama, K., M.M. Noor, M.M. Rahman, K.A. Abou-El-Hossein, B. Mohammad and H. Habeeb, 2009. Effect of milling parameters on frictions when milling hastelloy C-22HS: A FEM and statistical method. Trends Applied Sci. Res., 4: 216-228.

Lee, K.Y., M.C. Kang, Y.H. Jeong, D.W. Lee and J.S. Kim, 2001. Simulation of surface roughness and profile in high speed end milling. J. Mater. Process. Technol., 113: 410-415.

Lim, E.M., H.Y. Feng, C.H. Meng and Z.H. Lin, 1995. The prediction of dimensional error for sculptured surface productions using the ball-end milling process. Part 1: Chip geometry analysis and cutting force prediction. Int. J. Mach. Tools Manufact., 35: 1149-1169.

Lou, M.S., J.C. Chen and C.M. Li, 1999. Surface roughness prediction technique for CNC end-milling. J. Ind. Technol., 15: 1-6.

Mansoura A. and H. Abdalla, 2002. Surface roughness model for end milling: A semi-free cutting carbon casehardening steel (EN32) in dry condition. J. Mater. Process. Technol., 124: 183-191.

Novakova, J., L. Petrkovska, J. Brychta, R. Cep and L. Ocenasova, 2009. Influence of high speed parameters on the quality of machined surface. World Acad. Sci. Eng. Technol., 56: 274-277.

Onwubolu, G.C., 2005. A note on surface roughness prediction model in machining of carbon steel by PVD coated cutting tools. Am. J. Applied Sci., 2: 1109-1112.

Ozcelik, B. and M. Bayramoglu, 2006. The statistical modeling of surface roughness in high-speed flat end milling. Int. J. Machine Tools Manufacture, 46: 1395-1402.

Patwari, M.A.U., A.K.M.N. Amin and W. Faris, 2010. Identification of instabilities of the chip formation and it's prediction model during end milling of medium carbon steel (S45C). Am. J. Eng. Applied Sci., 3: 193-200.

Reddy, B.S., G. Padmanabhan and K.V.K. Reddy, 2008. Surface roughness prediction techniques for CNC turning. Asian J. Sci. Res., 1: 256-264.

Suhail, A.H., N. Ismail, S.V. Wong and N.A.A. Jalil, 2010. Optimization of cutting parameters based on surface roughness and assistance of workpiece surface temperature in turning process. Am. J. Eng. Applied Sci., 3: 102-108.

Suhail, A.H., N. Ismail, S.V. Wong and N.A.A. Jalil, 2011. Workpiece surface temperature for in-process surface roughness prediction using response surface methodologyac. J. Applied Sci., 11: 308-315.

Tang, W.X., Q.H. Song, S.Q. Yu, S.S. Sun, B.B. Li, B. Dua and X. Aia, 2009. Prediction of chatter stability in high-speed finishing end milling considering multi-mode dynamics. J. Mater. Process. Technol., 209: 2585-2591.

Vivancos, J., C.J. Luis, J.A. Ortiz and H.A. Gonzalez, 2005. Gonzalez, 2005. Analysis of factors affecting the high-speed side milling of hardened die steels. J. Mater. Process. Technol., 162-163: 696-701.

Xu, A.P., Y.X. Qu, D.W. Zhang and T. Huang, 2003. Simulation and experimental investigation of the end milling process considering the cutter flexibility. Int. J. Mach. Tools Manufacture, 43: 283-292.