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Construction of a surface roughness prediction model for high speed machining

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Abstract

In manufacturing environment prediction of surface roughness is very important for product quality and production time. For this purpose, the finite element method and neural network is coupled to construct a surface roughness prediction model for high-speed machining. A finite element method based code is utilized to simulate the high-speed machining in which the cutting tool is incrementally advanced forward step by step during the cutting processes under various conditions of tool geometries (rake angle, edge radius) and cutting parameters (yielding strength, cutting speed, feed rate). The influences of the above cutting conditions on surface roughness variations are thus investigated. Moreover, the abductive neural networks are applied to synthesize the data sets obtained from the numerical calculations. Consequently, a quantitative prediction model is established for the relationship between the cutting variables and surface roughness in the process of high-speed machining. The surface roughness obtained from the calculations is compared with the experimental results conducted in the laboratory and with other research studies. Their agreements are quite well and the accuracy of the developed methodology may be verified accordingly. The simulation results also show that feed rate is the most important cutting variable dominating the surface roughness state.

Keywords: High speed machining; Surface roughness; Neural network

1. Introduction

Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost. It describes the geometry of the machined surface and combined with the surface texture, which is process dependent, can play an important role on the operational characteristics of the part including surface friction, wearing, heat transmission, the ability to distribute and hold a lubricant, the ability to accept a coating, and the ability to resist fatigue. Consequently, the desired surface roughness value is usually specified for an individual part, and specific processes are selected in order to achieve that specified finish. Surface specification can also be a good reference point in determining the stability of a production process, because the stability of the machine is contingent on the quality of the operating part.

The mechanism behind the formation of surface roughness is very complicated and process dependent, therefore it is very difficult to calculate its value through analytical formula simply. Consequently, there is a need for a tool that will allow the evaluation of the surface roughness value before the machining of the part and which, at the same time, can be easily used in the production-floor environment contributing to the minimization of required time and cost. Moreover, it could be used for the determination of the appropriate cutting conditions in order for a specific surface roughness to be achieved.

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Gökkaya and Nalbant [1] investigated the effects of three insert radii of cutting tools coated with three layers of coating materials, five depths of cut and five feed rates on the surface quality depending on various processing parameters through the turning experiments of AISI 1030 steel workpieces. Colak, et al. [2] devoted to predicting surface roughness with a new approach method called gene expression programming (GEP). Three milling parameters such as spindle speed, feed rate and depth of cut have been selected. Based on these three milling parameters and another important parameter on surface roughness they investigated how to use GEP for surface roughness prediction. Öktem et al. [3, 4] presented an approach for determination of the best cutting parameters leading to minimum surface roughness in end milling mold surfaces of an ortez part used in biomedical applications by coupling neural network and genetic algorithm. A number of machining experiments based on statistical three-level full factorial design of experiments method were also conducted in order to collect surface roughness values. An effective fourth order response surface (RS) model was developed utilizing experimental measurements in the mold cavity. RS model was further interfaced with the GA to optimize the cutting conditions for desired surface roughness. Ozcelik and Bayramoglu [5] presented the development of 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. First- and second-order models were developed using experimental results of a rotatable central composite design, and assessed by means of various statistical tests. Kirby [6] discussed the development of an in-process surface roughness adaptive control system for a CNC turning operation, using fuzzy-nets modeling and tool vibrations measured with an accelerometer. Fuzzy-nets models for prediction of surface roughness and adapted feed rate were trained using feed rate, spindle speed, tangential vibration and measured surface roughness data collected during experimental runs. Özel and Karpat [7] utilized neural network modeling to predict surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish hard turning. Regression models were also developed in order to capture process specific parameters. Hocheng and Hsieh [8] studied the surface roughness obtained from the diamond turning of a phosphor-bronze lens mold with various tool nose radii, spindle speeds, feed rates and cutting depths. The surface roughness was measured in the time domain using a stylus-type surface roughness meter and then transformed into the frequency domain using the fast Fourier transform. A relationship between the root-mean-square summation of the surface roughness and cutting conditions was found. Risbood et al. [9] presented a strategy for surface roughness and dimensional deviation prediction based on the measurement for cutting forces and vibrations in cylindrical turning operation. Due to non-linear dependence of surface finish and dimensional deviation on the process parameters, tool-work combination and rigidity of machine tool, neural network were used for prediction. A neural network modelling approach was presented for the prediction of surface roughness in CNC face milling [10]. The data used for the training and checking of the networks' performance derived from experiments conducted on a CNC milling machine according to the principles of Taguchi design of experiments method. An in-process based surface recognition system to predict the surface roughness of machined parts in the end milling process was developed in the research [11] to assure product quality and increase production rate by predicting the surface finish parameters in real time. In this system, an accelerometer and a proximity sensor were employed as in-process surface recognition sensors during cutting to collect the vibration and rotation data, respectively.

2. Basic theory

If the cutting condition of feed rate level is not set too large and the cutting tool used having edge radius, an idealized machined surface profile left after the cutting operation exhibits a saw-tooth type in a series manner along the longitudinal direction, which is very similar to nose arc shape of the tool edge as indicated in Fig. 1. The maximum and arithmetic average surface roughness may be derived, respectively, as follows:

$$R_{max} = \frac{0.125 f^2}{r} \tag{1}$$

$$R_a = \frac{0.0321 f^2}{r} \tag{2}$$

3. Problem statement and method of approach

Finite element software code, AdvantEdge, released by Third Wave System is utilized for high-speed machining simulation while abductive neural network is adopted to synthesize the numerous data acquired from the results of machining simulation. A basic 2D cutting model and the sampling length for surface roughness calculation are shown in Fig. 2. The initial height and length of the workpiece in this model are set as 2 and 7 mm along the vertical and horizontal directions, respectively, while sampling length for surface roughness calculations is adopted as 2.5 mm. Carbide is selected as the tool material in simulation. There are four kinds of workpiece materials utilized in this study and their yielding stresses are shown in Table 1. In addition, the influence of four cutting variables such as cutting speed, feed rate, rake angle and edge nose radius of the tool on surface roughness are analyzed in this study. Setting levels of these variables are shown in Table 2. Hence, there are five process variables, one of these variables was set at four levels and for the others each variable was set at three levels. Therefore, $324(4\times3\times3\times3\times3)$ combinations of process parameters are constituted totally and were all performed in the simulation.

The basic sampling lengths adopted for surface roughness measurements in international standard are 0.08, 0.25, 0.8, 2.5, 8 and 25 mm, respectively. The surface roughness value can not be obtained directly from the simulation results by AdvantEdge software. A file owning node coordinates without node number may only be gotten after each case simulation instead. Hence, 2.5mm sampling length is adopted for surface roughness estimation on the deformed grid pattern after cutting simulation just as mentioned above. The data related to deformed grid pattern of surface waviness is obtained within a zone; x, y coordinates are from 8.5 to 11 mm and from 1.8 to 2 mm, respectively. The searching increment along the x direction is set as 0.0001 mm for each advancing step. After the coordinates belonging to each surface pattern point are found, trapezoidal area within each increment interval above or below datum line is calculated and summed up together. If the sum of the total areas is positive, then the datum line is shifted up a small altitude. Conversely, the center-line is shifted down if the sum of the total areas is negative. This adjustment procedure is performed repeatedly until this datum line setting is ascertained. The arithmetic average surface roughness can be calculated from the deformed grid pattern consequently if the datum line has been set properly. The flow chart related to the determination procedures for this kind of surface roughness is summarized in Fig. 3.

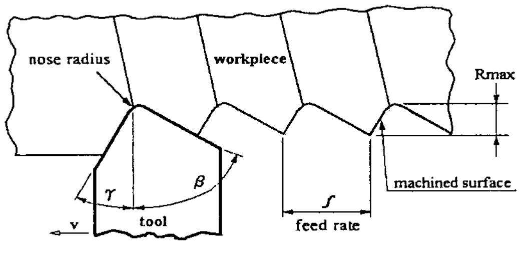


Fig. 1. An idealized machined surface profile left after cutting operation with an edge radius tool.

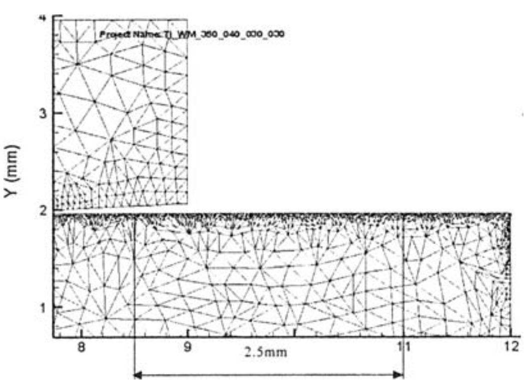


Fig. 2. A basic 2D cutting model and the sampling length for surface roughness calculation.

Table 1. Various workpiece materials and their yielding stresses.

Workpiece material	304L stainless steel	Al 6061-T6	SKD11	Ti-4Al-4V
Yielding stress (MPa)	430	282	486	1050

Table 2. Setting levels for cutting variables.

Speed (m/min), V	350	450	550	Rake angle (deg),α	-3	3	5
Feed rate (mm/rev),f	0.02	0.04	0.06	Edge radius((mm), r	0.03	0.05	0.07

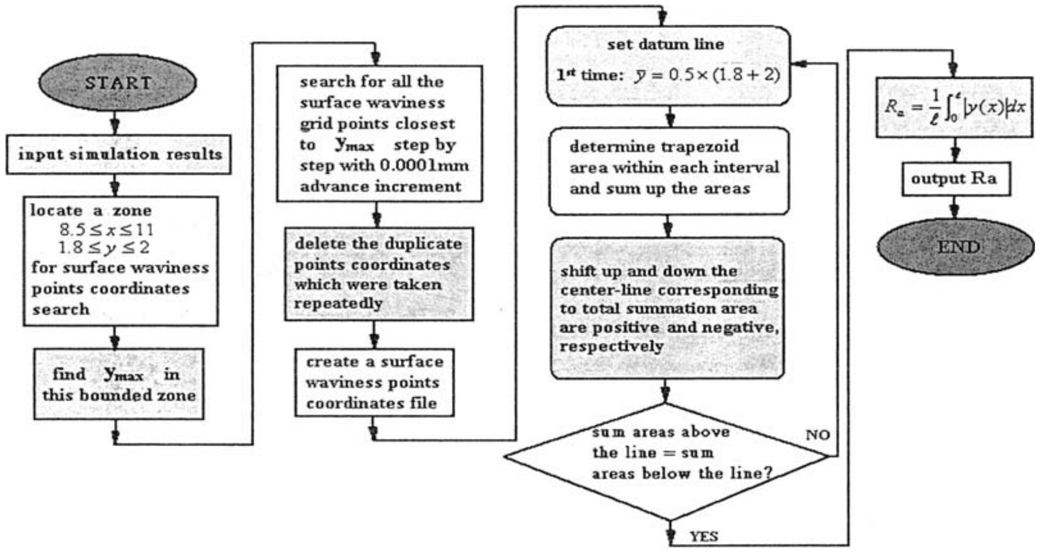


Fig. 3. Flow chart of the determination procedures for CLA surface roughness calculations.

4. Results and discussion

In order to validate the accuracy of the surface roughness determined from the deformed grid pattern, the milling experiments were undertaken in the laboratory. The arithmetic mean surface roughness after three times experimental measurements for each case is shown in Table 3 and comparisons of their average results with numerical calculations under different combinations of cutting conditions are shown in Fig. 4. Furthermore, the calculation results of surface roughness, R_a, for 304L workpiece in this study ranging from 1.025 to 3.814 μm are very close to the measured results of 1.287–3.870 μm in Chien and Chou [12] which only accounted for the cutting speed, feed rate and depth of cut. In addition, the experimental result in Huang [13] pertaining to R_a ranging from 0.91-5.73 μm under the cutting speeds of 93-140 m/min, feed rates of 0.1-0.3 mm/rev and SKD61 workpiece material is also very close to the results of 0.576–3.199 μm with SKD11 workpiece material in this study. These relative comparisons are all shown in Fig. 5.

Based on the training database regarding to process variables combinations and their corresponding surface roughness obtained from the simulations, the abductive network can be developed for predicting the surface roughness. A four-layer network shown in Fig. 6 is built, which is created by 324 machining data sets as mentioned above. The network developed is

Table 3. Arithmetic mean surface roughness after three times experimental measurements for each case.

Cutting speed	Feed rate	Rake angle	Edge radius	R_{a1}	R_{a2}	R_{a3}	$\bar{R}_a$
350	0.02	5	0.05	0.8	2.0	2.2	1.67
450	0.04	5	0.05	1.3	0.8	1.3	1.13
550	0.06	5	0.05	1.2	0.7	1.1	1.0

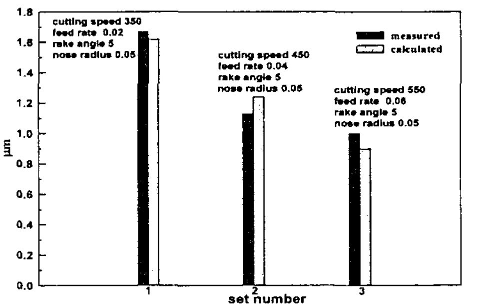


Fig. 4. Comparison of R_a between calculations and measurements in this study.

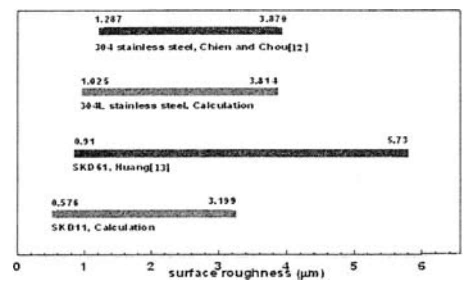


Fig. 5. Comparison of Ra among Chien et al. [12], Huang [13] and calculations of this study.

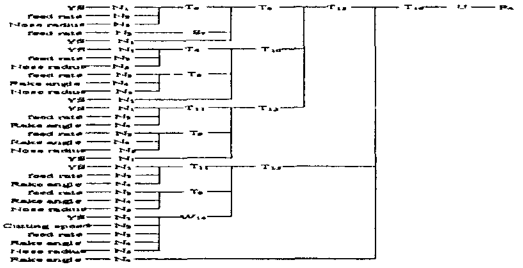


Fig. 6. Abductive network for predicting surface roughness.

Table 4. Pearson correlation coefficient among surface roughness and process parameters relations.

	YS	Cutting Speed	Feed	Rake Angle	Tool Radius	Ra
YS	1.000	-.202	-.185	-.059	-.081	-.329
Cutting Speed	-.202	1.000	.172	.147	.085	.224
Feed	-.185	.172	1.000	.338	.285	.879
Rake Angle	-.059	.147	.338	1.000	.141	.355
Tool Radius	-.081	.085	.285	.141	1.000	.293
Ra	-.329	.224	.879	.355	.293	1.000

the optimal structure based on the principle of the predicted square error criterion [14] and can be utilized to determine the surface roughness under various combinations of process parameters in a continuous manner. The PSE deduced from the statistical synthesis is 0.0465066.

In order to clarify the matching extent between surface roughness and the process parameters, Pearson correlation coefficients among these parameters are determined from statistical calculation and listed in Table 4 in detail. It indicates that there exists a strongest correlation between feed rate and surface roughness since they have a largest correlation coefficient value. A secondary correlation between rake angle and surface roughness is found also from the coefficient value. The above two positive values of correlation coefficient represent the correlation factors are distributed along the same orientation trend. But it exists a negative correlation coefficient value between surface roughness and yielding stress, and this represents a correlation between them along the opposite orientation trend, and the correlation extent is a little weaker than rake angle. Consequently, the effect of process parameter on the surface roughness, feed rate plays a most important role in high-speed machining operations.

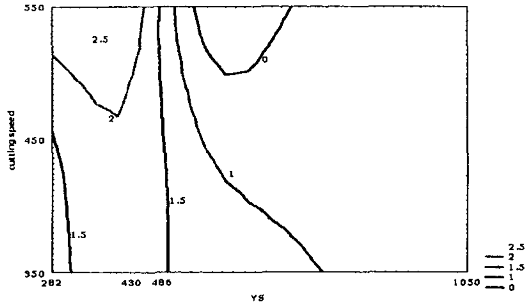
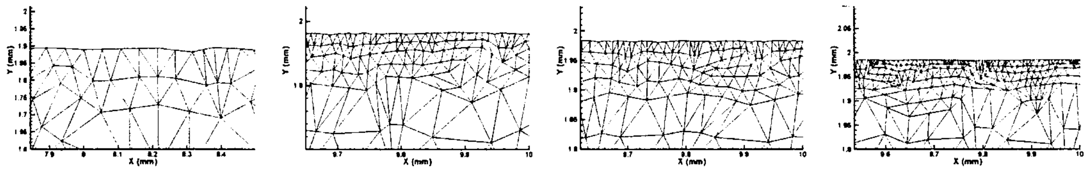


Fig. 7. The relationship among yielding stress, cutting speed and surface roughness.

According to the Pearson correlation analysis, surface roughness and yielding stress exhibit a negative correlation between them. That is, this two process parameters will distribute along the opposite orientation trend. Hence, the magnitude of surface roughness is increased as the yielding strength of the workpiece material is decreased under the same cutting conditions as shown in Fig. 7. The larger cutting forces are induced during the machining process as a larger yielding strength of workpiece material is machined and the plough depth of cut is naturally reduced. It causes the level of surface roughness is small. Fig. 8 indicates the deformed grid patterns of surface waviness for different workpiece materials, the magnitude of yielding strength is in order as Ti, SKD11, 304L and Al. But the surface roughness obtained after machining is in a fully reverse order.

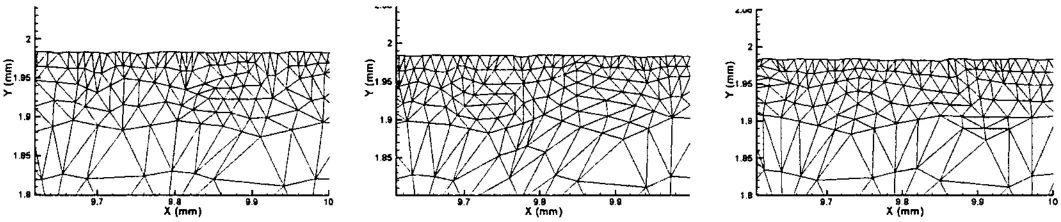
Fig. 9 shows the deformed grid pattern of surface waviness for different cutting speeds under the conditions of f=0.02 mm/rev, α=3° and r= 0.07 mm for SKD11 workpiece. Usually, the surface roughness is getting better when the cutting speed is increased, but an irregular relationship among them is found in this study when the cutting speed is greater than 450 m/min. This phenomenon may be changed with the materials of tool and workpiece utilized in machining and this specific speed may be called as a transition speed. In general, surface quality increases when the cutting speed increases.

Fig. 10 shows the relationship among yielding stress, feed rate and surface roughness and Fig. 11 shows the deformed grid pattern of surface waviness for different feed rates under the conditions of V=350 m/min, α=3° and r= 0.07 mm with Ti workpiece. The tool feeding marks will be left on the machined surface after cutting tool passed; the greater feed rate is the more obvious tool path marks are left. Hence,



(a) Al: R_a= 0.783 μm (b) 304L: R_a= 0.637 μm (c) SKD11: R_a= 0.616 μm (d) Ti: R_a= 0.380 μm

Fig. 8. Deformed grid pattern of surface waviness for different workpiece materials under the conditions of V=350 m/min, f=0.02 mm/rev, α =3° and r= 0.07 mm.



(a) V=350 m/min: R_a=0.878 μm (b) V=450 m/min: R_a=0.574 μm (c) V=550 m/min: R_a=0.685 μm

Fig. 9. Deformed grid pattern of surface waviness for different cutting speeds under the conditions of f=0.02mm/rev, α =3° and r= 0.07mm for SKD11 work piece.

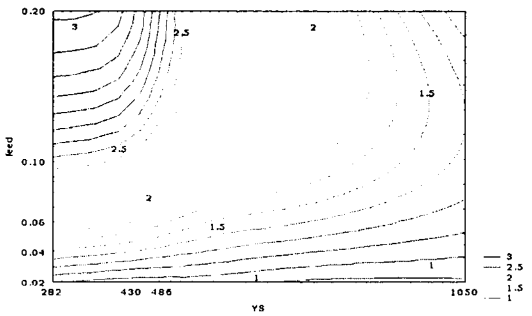
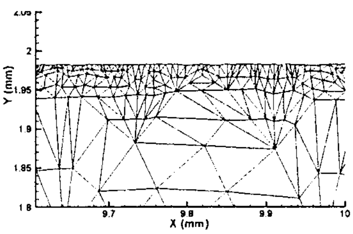


Fig. 10. Relationship among yielding stress, feed rate and surface roughness.

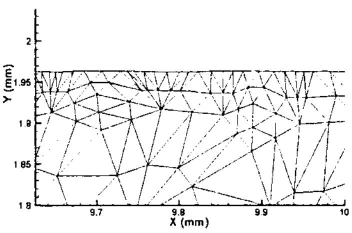
the level of surface roughness is proportional to the process parameter of feed rate as shown in the figures.

Fig. 12 shows the relationship among yielding stress, rake angle and surface roughness and Fig. 13 shows the deformed grid pattern of surface waviness for different rake angles under the conditions of V=350 m/min, f=0.02 mm/rev and r=0.07 mm with Al workpiece. The surface roughness is increased as the rake angle of the tool is increased when a smaller yielding strength workpiece material was machined. Larger rake angle with sharpness edge plow ability may make a deeper cut when a softer workpiece material is cut.

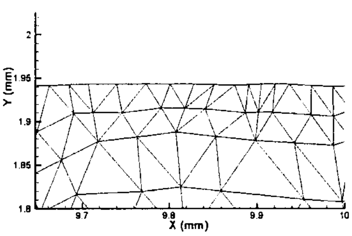
From the Pearson correlation analysis, surface roughness and edge radius exhibit a negative correlation between them. This phenomenon may be verified from the interpretations of Figs. 14 and 15.



(a) f=0.02 mm/rev: R_a=0.380 μm



(b) f=0.04 mm/rev: R_a=0.761 μm



(c) f=0.06 mm/rev: R_a=0.784 μm

Fig. 11. Deformed grid pattern of surface waviness for different feed rates under the conditions of V=350 m/min, α =3° and r= 0.07mm with Ti work piece.

During the cutting process, tool edge front was subject to a greater compressive stress when the edge radius is smaller and this kind of tool tip tends to be easily worn. Moreover, a larger frictional constraint will be created between tool and workpiece interface for the smaller edge radius case, which promotes the action of tool feeding more critically. Hence, a much wavier machined surface is naturally generated. Superposition actions of feed and tool edge radius coupling always cause an intensively adverse effect on the surface roughness generation.

5. Conclusion

Surfaces are exposed to the environment and thus are subject to environmental attack. They also may come into contact with tools and dies during processing or other components during their service life. Consequently, their geometric and material properties can significantly affect friction, wear, fatigue, corrosion, and electrical and thermal conductivity. Measuring and describing surface features and their characteristics are among the most important aspects of manufacturing processes. From the above analyses, the following conclusions can be drawn:

Neural network developed in this study can be used to predict the surface roughness more effectively. Surface roughness may quickly be determined from the prediction model developed when the process parameters are set.

From the Pearson correlation analysis, feed rate is the most important process parameter affecting the machined surface quality, and tool rake angle plays a

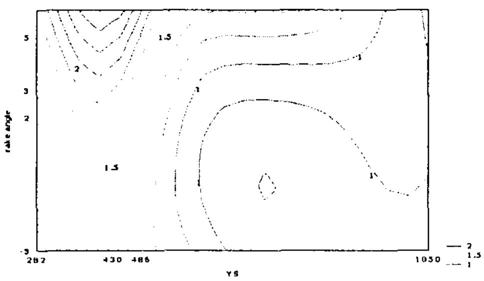


Fig. 12. Relationship among yielding stress, rake angle and surface roughness.

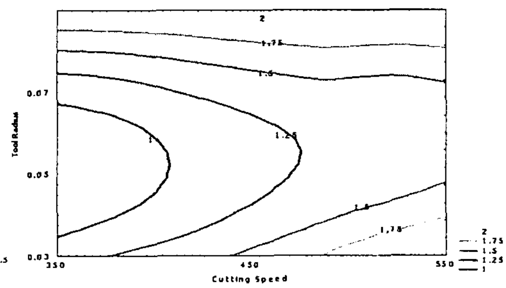
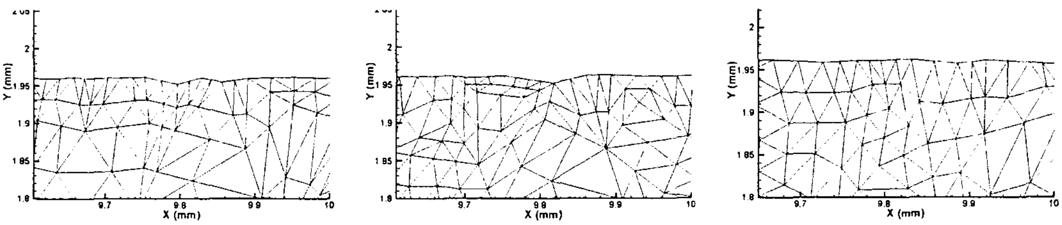
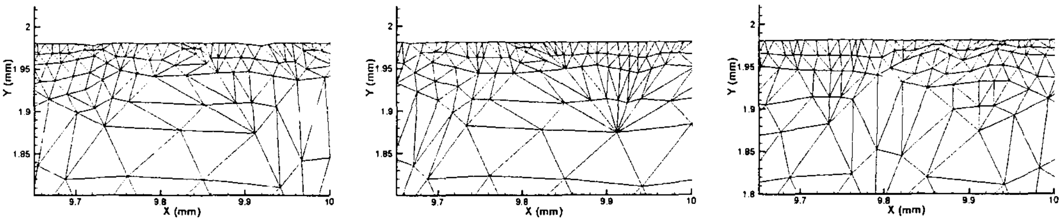


Fig. 14. Relationship among cutting speed, edge radius and surface roughness.



(a) α =3°: R_a=1.549 μm (b) α =5°: R_a=1.895 μm (c) α =7°: R_a=1.483 μm

Fig. 13. Deformed grid pattern of surface waviness for different rake angles under the condition of V=350m/min, f=0.02 mm/rev and r= 0.07 mm with Al workpiece.



(a) r=0.03 mm: R_a=0.819 μm (b) r=0.05 mm: R_a=0.460 (c) r=0.07 mm: R_a=0.412 μm

Fig. 15. Deformed grid pattern of surface waviness for different edge radii under the conditions of V=350 m/min, f=0.02 mm/rev and α =3° with Al workpiece.

secondary role determining the surface roughness states.

Reference

[1] H. Gökkaya and M. Nalbant, The effects of cutting tool geometry and processing parameters on the surface roughness of AISI 1030 steel, *Mater. Des.* 28 (2007) 717-721.

[2] O. Colak, C. Kurbanoğlu and M.C. Kayacan, Milling surface roughness prediction using evolutionary programming methods, *Mater. Des.* 28 (2007) 657-666.

[3] H. Oktem, T. Erzurumlu and F. Erzincanli, Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm, *Mater. Des.* 27 (2006) 735-744.

[4] H. Öktem, T. Erzurumlu and H. Kurtaran, Application of response surface methodology in the optimization of cutting conditions for surface roughness, *J. Mater. Process. Technol.* 170 (2005) 11-16.

[5] B. Ozcelik and M. Bayramoglu, The statistical modeling of surface roughness in high-speed flat end milling, *Int. J. Mach. Tools Manuf.* 46 (2006) 1395-1402.

[6] E.D. Kirby, J.C. Chen and J.Z. Zhang, Development of a fuzzy-nets-based in-process surface roughness adaptive control system in turning operations, *Expert Syst. Appl.* 30 (2006) 592-604.

[7] T. Özel and Y. Karpat, Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, *Int. J. Mach. Tools Manuf.* 45 (2005) 467-479.

[8] H. Hocheng and M.L. Hsieh, Signal analysis of surface roughness in diamond turning of lens molds, *Int. J. Mach. Tools Manuf.* 44 (2004) 1607-1618.

[9] K.A. Risbood, U.S. Dixit and A.D. Sahasrabudhe, Prediction of surface roughness and dimensional deviation by measuring cutting forces and vibrations in turning process, *J. Mater. Process. Technol.* 132 (2003) 203-214.

[10] P.G. Benardos and G.C. Vosniakos, Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments, *Robot. Comput. Integr. Manuf.* 18 (2002) 343-354.

[11] Y.H. Tsai, J.C. Chen and S.J. Lou, An in-process surface recognition system based on neural networks in end milling cutting operations, *Int. J. Mach. Tools Manuf.* 39 (1999) 583-605.

[12] W.T. Chien and C.T. Chou, The predictive model for machinability of 304 stainless steel, *J. Mater. Process. Technol.* 118 (2001) 442-447.

[13] T.S. Huang, The investigation on the predictive model for the cutting forces and the optimized cutting parameters based on cutting SKD61, M.S. dissertation NPUST, Taiwan (2001).

[14] A.R. Barron, Predicted square error: A criterion for automatic model selection, self-organizing methods in modeling: GMDH type algorithms, edited by Farlow, S. J. Marcel-Dekker, New York (1984).