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Workpiece Surface Temperature for In-process Surface Roughness Prediction using Response Surface Methodology

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Abstract: As manufacturing technology has been moving to the stage of full automation over the years, one of the fundamental requirements is the ability to accurately predict the output performance of machining processes. The focus of present study is to predict surface roughness using the workpiece surface temperature of a turning workpiece with the aid of an infrared temperature sensor. Relationship between the workpiece surface temperature and the cutting parameters and also between the surface roughness and cutting parameters were found out for indirect measurement of surface roughness through the surface temperature of the workpiece. A 3^3 full factorial design was used in order to get the output data uniformly distributed all over the ranges of the input parameters. Response Surface Method (RSM) and analysis of variance (ANOVA) are used to get the relation between different response variables (Surface roughness and workpiece surface temperature) and the input parameters (speed, feed and depth of cut). Based on variance analysis for the second order RSM model, most influential design variable is feed rate and depth of cut on surface roughness and workpiece surface temperature respectively and the experimental results show that the workpiece surface temperature can be sensed and used effectively as an indicator of the cutting performance.

Key words: Machining process, surface roughness, cutting temperature, workpiece surface temperature, turning operation

INTRODUCTION

With increasing demands for higher productivity and quality, there has been increased interest in monitoring all aspects of the machining process. Among various process conditions, surface finish is a very important factor determining the quality of a piece. Many surface roughness prediction systems were designed using a variety of sensors including dynamometers for force and torque (Lin *et al*., 2001; Azouzi and Guillot, 1996), accelerometers for mechanical vibrations (Abouelatta and Madl, 2001; Choudhury and Sharat, 1993; Jang *et al*., 1996), AE sensors for acoustic emission (Kirby *et al*., 2006; Manoharan *et al*., 2007; Sundaram *et al*., 2008) and current probes for current/power measurement of spindle and feed motors (Collacott, 1975). The purpose of using these sensors in machining processes is to increase part quality while decreasing cost and time of manufacture. Nevertheless, only a few reliable systems have as yet been established for industrial application. For example, many sophisticated methods proposed in the literature were designed to obtain a high success rate using multiple sensor signals (Varghese and Radhakrishnan, 1994; Risbood *et al*., 2003), but their cost has made them economically non-viable for industrial applications. Other, more simplistic, methods are fast to use but are unfortunately often more sensitive to changes in cutting conditions and less sensitive to tool wear. More details about predicting surface roughness in machining are presented in reference (Benardos and Vosniakos, 2003).

Surface roughness measurement presents an important task in many engineering applications and many life attributes can be determined by how well the surface finish is maintained.

To ensure that a part is machined with the desired surface, an in-process measuring system must be designed and implemented. This system would ideally be able to measure the surface in-process in real time. Surface roughness measurement is divided into two categories. One is direct measurement of machined surface and the other is indirect measurement. In the direct measurement, a machined surface is directly probed by light scattering, fringe field capacitance, ultrasonic sensing (Coker and Shin, 1996), etc. Stylus type gage is the most common direct measuring instrument. Those direct methods are impractical for the application of the in-process

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measurement. The in-direct methods are more practical to be implemented in the in-process measurement. In the in-direct methods, surface roughness is derived using parameters of machining process like cutting force and tool vibration.

The cutting temperature is a key factor which directly affects cutting tool wear, workpiece surface integrity and machining precision according to the relative motion between the tool and work piece (Ming *et al*., 2003). The amount of heat generated varies with the type of material being machined and cutting parameters especially cutting speed which had the most influence on the temperature (Liu *et al*., 2002). Several attempts have been made to predict the temperatures involved in the process as a function of many parameters. Additionally, many experimental methods to measure temperature directly, only a few systems have as yet been used this temperature as an indicator for machine performance monitoring and for industrial application. Therefore, design and develop control system to control these temperature lead to better surface finish as machine performance parameter. More details about cutting temperature prediction and measurement methods presented in reference (Da Silva and Wallbank, 1999).

Because no researcher previously used the workpiece surface temperature as an indicator of the cutting performance, this research proposes an in-process workpiece surface temperature monitoring in order to achieve a good trade-off between cost and performance, with a high reliability and a reduced computing time and using sensors that do not disturb the machining process and presents in-process monitoring and control of surface roughness during machining process via temperature sensing.

Experimental theory: The temperature was picked up by the infrared thermometer based on Steffen-Boltzman law by the following Eq. 1:

$$E = \varepsilon\sigma T^4 \ (\mathrm{W\ m^{-2}}) \qquad (1)$$

where, ε is the emissivity of the material radiation element, σ the Steffen-Boltzman constant, 5.67×10^{-8} W m^2 K^4, T the surface temperature of radiation element (K) and E the radiation energy of radiation element per unit (W).

The radiation energy could be received and measured on the radiation element of the material by an infrared thermometer and then the surface temperature of the radiation element could be calculated according to the Steffen-Boltzman law if the emissivity of the radiation element was known. This was a visual, simple and non-contact method to measure the temperature by an infrared thermometer.

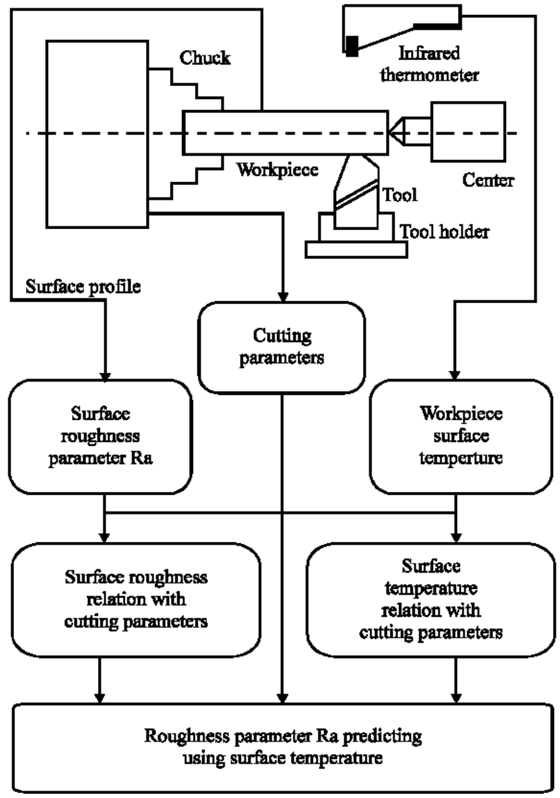

Fig. 1: Schematic diagram of the experimental setup

Experimental procedure and conditions: A schematic diagram of the experimental set-up is shown in Fig. 1. The experiments were performed using OKUMA CNC turning machine supported with Spindle Drive motor 11 KW and 6000 rpm maximum speed (CAD/CAM Lab./Mechanical and Manufacturing Department/Universiti Malay). All tests were performed dry. Experimental planning was prepared by using cutting parameters and test conditions that were advised for a couple of tool-workpiece by tool manufacturer.

For workpiece surface temperature measurement, handheld infrared thermometer type (OS534E) with built-in laser circle to dot switchable and RS-232 output used. The infrared thermometers have been used in more reports than any other method and there are advantages in the use of infrared sensor (Longbottom and Lanham, 2005):

- Non-contact
- Can respond to rapid changes in temperature
- Enable the easy measurement of high temperatures without disturbing the heat distribution
- Not affected by cutting process

The amount of standard surface roughness parameter (Ra) carried out using surface roughness tester model Mpi

Table 1: Workpiece specifications

Item	Values
Chemical composition	
C	0.20
Si	0.15
Mn	0.72
P	0.011
S	0.023
Mechanical properties	
Yield strength	245 N mm^{-2}
Tensile strength	400 N mm^{-2}

Mahr Perthometer S2 (produced by Mahr GMbH, Germany). Three measurements were made and averaged for each test.

This set-up was connected to computer using necessary hardware and software for data acquisition. The relationship between the workpiece surface temperature and the cutting parameters were examined.

Workpiece material: The workpiece specimens were medium carbon steel AISI 1020 and 250 mm long and 50 mm diameter. The mechanical properties and chemical compositions of the machined workpiece material are given in Table 1. An CNMG 432 TT5100 insert with Sandvik tool holder PCLNR 2525M/12 universal turning machine tool was used in the experiments.

Cutting parameters used with three levels for each, cutting speeds used were (950, 1150 and 1400 RPM). Feed rate (0.05, 0.1 and 0.15 mm rev^{-1}) and depth of cut (0.5, 1.0 and 1.5 mm).

RESULTS AND DISCUSSION

A series of experiments was conducted to obtain the surface temperature of the workpiece by the aid of the infrared thermometer. A 3^3 full factorial design was used in order to get the output data uniformly distributed all over the ranges of the input parameters. In this way 27 experiments were carried out with different combinations of the levels of the input parameters. On the first step regression equations models using RSM method were found out to get the relation between different response variables (surface roughness Ra and workpiece surface temperature T) and the input parameters (speed S, feed F and depth of cut D) using software for statistical analysis, called MINI-TAB. The software required the cutting conditions and responses from the experiments and developed the regression equations for each desired output using RSM method.

Surface roughness prediction models: The original and full quadratic terms were used in each model and then keep each interaction or square term if it appears significant individually. Also, each model term was examined to find its effect on the coefficient of multiple determination R^2 and adjusted R^2. In general, the R^2 measures percentage of the variation of measured response around predicted response that is explained by the regression equation. However, adding a variable to the model always increased R^2, regardless of whether or not that variable statistically significant. Thus, some experimenter rather using adjusted R^2 (Ryan, 2000). When variables are added to the model, the adjusted R^2 will not necessarily increase. In actual fact, if unnecessary variables are added, the value of adjusted R^2 will often decrease. For that, some terms were included in some models and excluded from others.

Surface roughness regression equation is:

$$Ra = 2.62-0.00192S-16.6F+3.43D+131F^2-1.71D^2 \quad (2)$$

Workpiece surface temperature regression equation is:

$$T = 56.2+0.00042\, S-62.0\, F+20.8\, D \quad (3)$$

According to two regression models above we observed that the adjusted R^2 reaches a maximum value of 0.819 for the model that includes the linear and square terms (curvilinear model) for surface roughness prediction and maximum value of 0.786 for the model that includes only the linear terms (simple linear model) for surface temperature prediction, respectively. Thus, there is a direct linear relationship between the cutting parameters and the workpiece surface temperature.

On the next step another regression equation were found out to get the relation between surface roughness as a response variable and consider the workpiece surface temperature as input variable in addition to other input parameters (S, F and D).

Surface roughness regression equation includes workpiece surface temperature as input parameter is:

$$Ra = -57.5+0.0505S+306F+12.1D+0.938T+0.000003S^2-0.280S*F-0.0032\, S*D-0.000971S*T+118F^2+120F*D-5.82F*T-0.375D*T+0.00210T^2-0.106S*F*D+0.00511\, S*F*T+0.000224\, S*D*T \quad (4)$$

In this regression model the maximum value of 0.882 for the adjusted R^2 was reached for the model that includes the linear, second order and third order terms (curvilinear model) and reflect how significantly affect the response variable (Ra).

Table 2, 3 and 4 summarizes the statistical results of the estimated regression models. The predictor column shows the independent variables that are used in the

Table 2: Statistical analysis for regression model Eq. 2

Predictor	Coef	SE Coef.	T	p
Constant	2.6162	0.6508	4.02	0.001
S	-0.0019247	0.0002856	-6.74	0.000
F	-16.639	9.016	-1.85	0.079
D	3.4335	0.9016	3.81	0.001
FF	130.56	44.62	2.93	0.008
DD	-1.7109	0.4462	-3.83	0.001

S = 0.273237
R^2 = 0.854
R^2 (adj) = 0.819

Source	DF	SS	MS	F	p
Analysis of variance					
Regression	5	9.1647	1.8329	24.55	0.000
Residual Error	21	1.5678	0.0747		
Total	26	10.7325			

Table 3: Statistical analysis for regression model Eq. 3

Predictor	Coef	SE Coef.	T	p
Constant	56.221	6.502	8.65	0.000
S	0.000419	0.004844	0.09	0.932
F	-61.98	21.84	-2.84	0.009
D	20.774	2.184	9.51	0.000

S = 4.63336
R^2 = 0.811
R^2(adj) = 0.786

Source	DF	SS	MS	F	p
Analysis of variance					
Regression	3	2114.98	704.99	32.84	0.000
Residual error	23	493.77	21.47		
Total	26	2608.74			

Table 4: Statistical analysis for regression model Eq. 4

Predictor	Coef	SE Coef.	T	P
Constant	-57.47	24.61	-2.34	0.042
S	0.05054	0.01918	2.63	0.025
F	305.8	177.8	1.72	0.116
D	12.11	13.12	0.92	0.378
T	0.9376	0.4982	1.88	0.089
SS	0.00000258	0.00000273	0.94	0.367
SF	-0.2804	0.1436	-1.95	0.079
SD	-0.00324	0.01122	-0.29	0.779
ST	-0.0009711	0.0003376	-2.88	0.016
FF	118.39	57.04	2.08	0.065
FD	120.19	66.19	1.82	0.099
FT	-5.825	3.187	-1.83	0.098
DT	-0.3749	0.1317	-2.85	0.017
TT	0.002099	0.002543	0.83	0.428
SFD	-0.10622	0.05471	-1.94	0.081
SFT	0.005108	0.002615	1.95	0.079
SDT	0.0002241	0.0001164	1.92	0.083

S = 0.220591
R^2 = 0.955
R^2-Sq(adj) = 0.882

Source	DF	SS	MS	F	p
Analysis of variance					
Regression	16	10.24593	0.64037	13.16	0.000
Residual error	10	0.48661	0.04866		
Total	26	10.73254			

regression analysis. The coefficients column gives the estimated coefficients of the regression and their respective t statistics as well as their significance levels (or p-values). The estimated R-Sq for the first model Table 2 is 0.854, indicating that 85.4% of the variance of dependent variable is explained by the variance of the independent variables. High R^2-Sq values for the regression equations reveal reliable estimation for predicted responses. The F statistic is 24.55 is the computed statistic value within the 95% confidence interval and p-value ($p<0.05$) from the analysis of variance for the regression model indicate that the estimated equation is robust and adequate.

Table 5 shows the averaged surface roughness and workpiece surface temperature values measured by experiment (RaEx and TEx) and the respective values of surface roughness and workpiece surface temperature predicted (RaPr, TPr and RaTPr) using the above models equations Eq. 2, 3 and 4, respectively.

Table 5 also shows the percentage error between the predicted and the experimental values of surface roughness (Ra) and surface temperature (T). It was considered that less than 20% error is reasonable, considering that there is inherent randomness in metal cutting process (Risbood *et al*., 2003). The table shows that in 21 cases, the error in prediction was less than 20% and only in five cases, the error was more than 25%, with a maximum error of 31.75%. That for the predicted surface roughness (RaPr) was obtained from Eq.2. while for predicted surface roughness (RaPrT) obtained from Eq. 4 which includes the surface temperature (T) terms, the most error values in the prediction was less than 10% and only in five cases was more than 10% with maximum error of 18.19%. Figure 2 and 3 show the plots of predicted versus actual surface roughness. It is seen that most of the points in Fig. 3 lie very close to the line for perfect prediction.

Study of factors affecting surface roughness: The first regression equation Eq. 2 and p-value (Table 2) show that the calculated t statistic for feed rate (F) at -1.85 is highly significant and has the largest effect on surface roughness according to its coefficient value (-16.639) which accords with common cutting theory (Stephenson and Agapiou, 1997). The second regression equation Eq. 3 and p-value Table 3 show that the calculated t statistic for depth of cut (D) at 9.51 is highly significant and feed rate also has the largest effect on the workpiece surface temperature according to its coefficient value (-61.98) followed by Depth of cut (D) and last by speed (S) which is not significant and the analysis of variance revealed that the model is adequate according to p-value ($p<0.05$).

Then last regression equation Eq. 4 which includes the workpiece surface temperature as input variable shows clearly better regression model and reveal that feed rate effect the surface roughness significantly followed by depth of cut and last by surface temperature and the

Table 5: Predicted and experimental data

S	F	D	Ra Ex	Ra Pr	Error (%)	T Ex	T Pr	Error (%)	Ra PrT	Error (%)
1400	0.05	0.5	1.001	0.705	29.55	66.54	64.095	3.67	0.961	3.98
1150	0.05	0.5	1.099	1.186	-7.94	55.89	63.990	-14.49	1.068	2.75
950	0.05	0.5	1.219	1.571	-28.89	62.96	63.907	-1.50	1.240	-1.72
1400	0.10	0.5	1.249	0.852	31.75	65.31	60.996	6.60	1.265	-1.30
1150	0.10	0.5	1.330	1.333	-0.26	61.92	60.892	1.65	1.300	2.20
950	0.10	0.5	1.499	1.718	-14.64	63.80	60.808	4.68	1.606	-7.16
1400	0.15	0.5	1.867	1.652	11.49	55.86	57.898	-3.64	2.018	-8.13
1150	0.15	0.5	2.127	2.133	-0.31	58.00	57.793	0.35	1.967	7.48
950	0.15	0.5	2.277	2.518	-10.60	62.00	57.709	6.91	2.344	-2.94
1400	0.05	1.0	0.934	1.138	-21.92	75.87	74.482	1.82	0.899	3.73
1150	0.05	1.0	1.485	1.619	-9.08	76.78	74.377	3.12	1.613	-8.67
950	0.05	1.0	2.697	2.004	25.66	76.57	74.294	2.97	2.460	8.75
1400	0.10	1.0	1.309	1.286	1.75	69.18	71.383	-3.18	1.364	-4.23
1150	0.10	1.0	1.394	1.767	-26.77	69.81	71.279	-2.10	1.647	-18.19
950	0.10	1.0	2.067	2.152	-4.11	68.16	71.195	-4.45	2.060	0.29
1400	0.15	1.0	1.879	2.086	-11.01	60.80	68.285	-12.31	1.764	6.11
1150	0.15	1.0	2.697	2.567	4.81	64.88	68.180	-5.08	2.399	11.01
950	0.15	1.0	3.109	2.952	5.04	71.05	68.096	4.15	3.161	-1.68
1400	0.05	1.5	0.798	0.716	10.16	84.00	84.869	-1.03	0.743	6.85
1150	0.05	1.5	1.066	1.198	-12.38	87.65	84.764	3.29	1.176	-10.40
950	0.05	1.5	1.422	1.583	-11.32	82.00	84.681	-3.26	1.560	-9.74
1400	0.10	1.5	0.699	0.864	-23.62	85.00	81.770	3.79	0.700	-0.27
1150	0.10	1.5	1.479	1.345	9.03	82.62	81.665	1.15	1.265	14.45
950	0.10	1.5	2.019	1.730	14.30	78.10	81.582	-4.45	1.838	8.96
1400	0.15	1.5	1.413	1.664	-17.77	87.00	78.671	9.57	1.435	-1.61
1150	0.15	1.5	2.195	2.145	2.26	67.89	78.567	-15.72	2.434	-10.92
950	0.15	1.5	2.682	2.530	5.65	85.00	78.483	7.66	2.722	-1.52

S: Cutting speed (RPM); TEx: Experimental workpiece surface temperature (°C); F: Feed rate (mm rev^{-1}) RaEx: Experimental Surface roughness (μm); D: Depth of cut (mm); TPr: Predicted workpiece surface temperature (°C); RaPrT: Predicted equation includes temperature (μm) RaPr: Predicted surface roughness (μm)

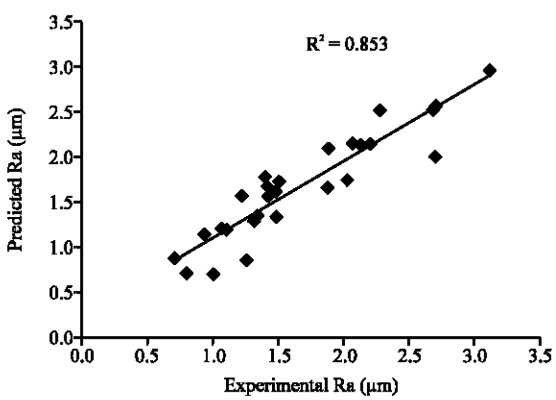

Fig. 2: Experimental surface roughness vs predicted surface roughness correlation plot

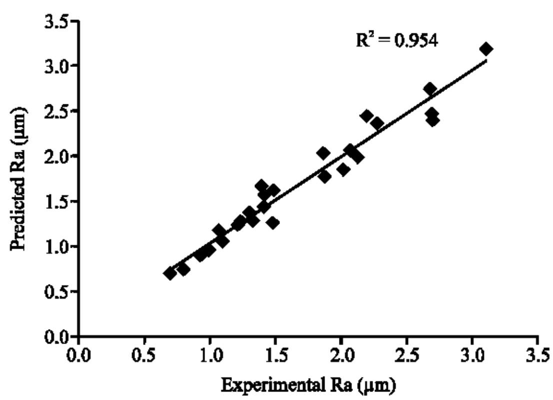

Fig. 3: Experimental vs predicted surface roughness correlation plot (model includes T)

interaction between surface temperature (T) and cutting speed (S) was significant according to (p-value<0.05) and the interaction between (T) and (D) as well.

For more understand and clarify how the cutting parameters interaction is affect the surface roughness and surface temperature, the contour plots for the results from these experiments are shown in Fig. 4-8. Figure 4 shows that workpiece surface temperature value increases when depth of cut increase with all range of cutting speed and there is no interaction effect between cutting speed and depth of cut, but there is an interaction between depth of cut and feed rate in Fig. 5 where an increase in feed rate and depth of cut lead to an increase in surface temperature.

In the same way for surface roughness, Fig. 6 shows clearly that surface roughness improved when feed rate decreases and cutting speed increases which accords with Doniavi *et al.* (2007) finding, while it is improved with high and low levels of depth of cut as Fig. 7 revealed. Also the interaction effect between the cutting speed and the depth of cut on surface roughness is clear from Fig. 7.

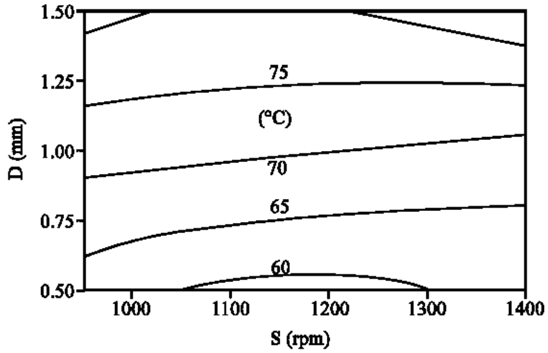

Fig. 4: Contour plot of workpiece surface temperature vs cutting speed and depth of cut

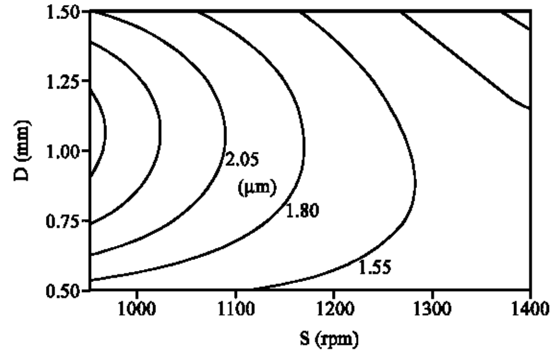

Fig. 7: Contour plot of surface roughness vs cutting speed and depth of cut

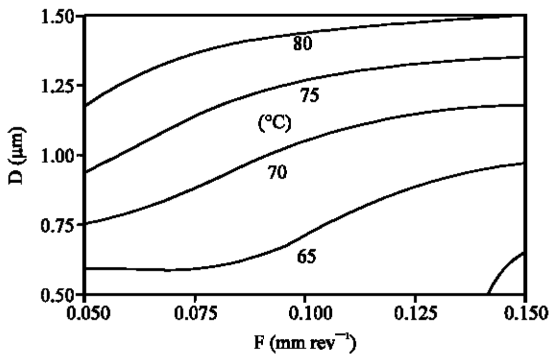

Fig. 5: Contour plot of workpiece surface temperature vs feed rate and depth of cut

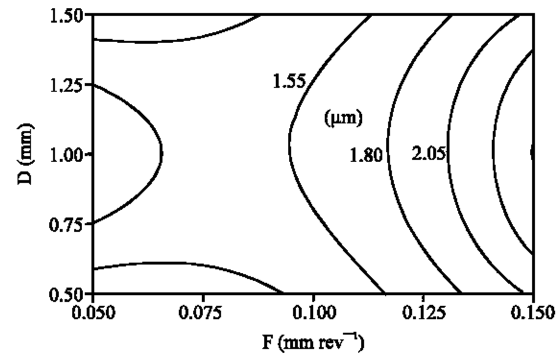

Fig. 8: Contour plot of surface roughness vs feed rate and depth of cut

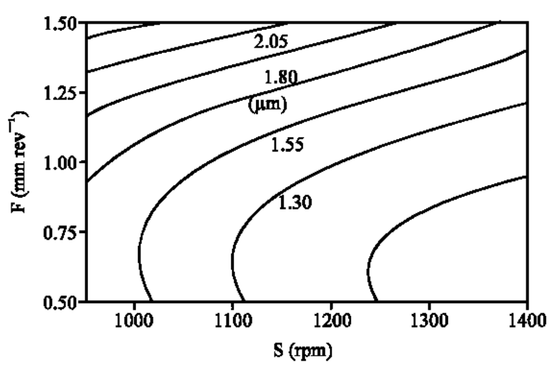

Fig. 6: Contour plot of surface roughness vs cutting speed and feed rate

Figure 8 shows that low level of feed rate (<0.1 mm rev^{-1}) with low level or high level of depth of cut give better surface roughness values (<1.3 µm).

Confirmation experiments: After identifying the most influential parameters and the response surface regression models were obtained, the final step is to verify these models using the experimental tests with different levels for cutting parameters that were not carried out in Table 5. The results of the verification tests are presented in Table 6.

Table 6: Confirmation experiments results

S	F	D	Ra Ex	T Ex	T Pr	Ra Pr	Ra PrT
1000	0.075	0.75	1.97	71.312	67.572	2.039	1.790
1000	0.125	0.75	2.33	69.874	64.473	2.375	2.264
1200	0.075	0.75	1.38	72.104	67.655	1.418	1.405
1200	0.125	0.75	1.83	65.134	64.557	1.763	1.879
1000	0.075	1.25	1.87	80.167	77.959	1.994	1.796
1000	0.125	1.25	2.29	79.883	74.860	2.442	2.270
1200	0.075	1.25	1.42	80.963	78.042	1.292	1.411
1200	0.125	1.25	2.03	71.965	74.944	1.732	1.885
Pearson correlation					88.45%	93.64%	97.49%

The predicted Ra obtained from Eq. 3 and 4 have been compared with the actual Ra using Pearson correlation and a good agreement was obtained between these values according to correlation coefficient as shown in Table 6.

According to above analysis, less costly and easily mountable infrared thermometer can be a fairly good substitute of other sensor like dynamometer (force sensor) for real and in-process machine performance monitoring systems.

CONCLUSION

This study proposes a response surface regression model to predict surface roughness based on cutting parameters (cutting speed, feed rate and depth of cut) and on an in-process signal (workpiece surface temperature) acquired by an infrared thermometer. While, workpiece surface temperature is acquired by an infrared thermometer, it can be used to monitor and predict the surface roughness according to its significant relationship with cutting conditions.

From this work, following conclusions could be reached:

- As expected, workpiece surface temperature signal predict surface roughness fairly well
- Depth of cut has a much greater influence on the workpiece surface temperature and when feed rate increase surface roughness increase and workpiece surface temperature decrease. Thus higher workpiece surface temperature means better surface roughness, which readily reacts to instantaneous changes in the cutting conditions
- Prediction model using cutting parameters with workpiece surface temperature as independent variables and surface roughness as response variable fairly more accurate than prediction model using only cutting parameters as input variables

Finally the experimental results show that workpiece surface temperature can be sensed and used effectively as an indicator of the cutting performance. Thus, it is possible to increase machine utilization and decrease production cost in an automated manufacturing environment.

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