

Full Length Research Paper

A surrogate modelling to predict surface roughness and surface texture when grinding AISI 1042 carbon steel

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Accepted 17 January, 2012

The quality of the surface produced during carbon steel is important as it influences the performance of the finished part to a great extent. This paper discusses the optimization of cylindrical grinding when grinding carbon steel (AISI 1042) and effect of three variables (work speed, diameter of workpiece and depth of cut) towards surface roughness with aluminium oxide as grinding wheel. Surrogate modelling was used to minimize the number of experiments and developed mathematical model to predict surface roughness hence optimization of cutting variables was found. This model has been validated by the experimental results of aluminium oxide grinding. Prediction model show that diameter of the workpiece and work speed effect mostly compare with depth of cut. The optimum cutting parameters for minimum Ra are work speed 120 RPM; diameter 18 mm and depth of cut 20 μm . The theoretical analysis yielded values which agree reasonably well with the experimental results.

Key words: Cylindrical grinding, surrogate, AISI 1042, surface roughness.

INTRODUCTION

Surface roughness is one of the most important factors in assessing the quality of a ground component. However, there is no comprehensive model that can predict roughness over a wide range of operating conditions; and after many decades of research, this is an area that still relies on the experience and skills of the machine tool operators, the reason stems from the fact that many variables are affecting the process. Many of these variables are nonlinear, interdependent, or difficult to quantify. Therefore, the models available so far are not fully feasible and experimental investigations can be very exhaustive but with limited applicability (Ali and Zhang, 1999). So, an attempt has been made to develop a theoretical model for the prediction of surface roughness for the grinding of silicon carbide with diamond abrasive. Extensive research has been carried out to predict the surface roughness of the workpiece manufactured by

grinding. On the basis of information available in the literature, theoretical methods of surface roughness evaluation can be classified into empirical and analytical methods. In the empirical method, surface roughness models are normally developed as a function of kinematic conditions (Malkin, 1989).

The empirical model, developed by Suto and Sata (1981), relates surface finish to the number of active cutting edges using the experimental data and it has been found to be having a logarithmic relationship. Although, empirical models have the advantages that they require minimum efforts to develop and are used in all fields of grinding technology but the inherent problem associated with this method is that the model developed under one grinding condition, cannot be used for surface roughness prediction at other conditions that is to say, it can be used for accurate description of the process within the limited range of chosen parameters only. Hence the scope is limited.

Salje et al. (1953) developed the initial grinding force model considering the shear strength as a specific parameter for the workpiece material and the model parameters

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are taken from a characteristic diagram that considers the influences of the respective combination of the material and the grinding wheel. Brach et al. (1988) took the grinding wheel topography into consideration in two dimensional forms. Ono (1961) considered the average grain distance and took the distance between the cutting edges into consideration for the modelling of the grinding forces. Lindsay (1971) developed two grinding models for specific normal force, one for the materials that are easy to grind and the other for the materials that are difficult to grind. Werner (1978) developed a grinding force model taking into account the combined effects of friction and chip formation. His model predicts the effect of workpiece properties on grinding. When the exponent $n = 0$, the phenomenon is purely frictional, while if it is 1 then the phenomenon is purely a chip formation force. Lichun and Jizai (1980) developed a grinding force model from the Werner model that takes friction and chip formation into account; here, they separated out the effects of frictional and chip formation forces. Younis et al. (1987) extended Werner's work taking the combined effect of ploughing, friction and chip formation forces for cylindrical grinding, where the loaded area is found out using a fiber optic system. Huang-Cheng et al. (2008) developed a stochastic grinding force model taking into account the random distribution of the grits in the grinding instead of assuming them to be uniform as done in the previous works. Jinyuan et al. (2008) developed a grinding force model for surface grinding considering friction and chip formation. Here, the average contact pressure and the frictional coefficients are treated as variable parameters, unlike previous research, where these parameters were considered constant. Ghosh et al. (2008) developed a mathematical model that predicts the specific energy consumed during HEDG of bearing steel by monolayer CBN wheel. The model successfully captures the mechanics of grinding under HEDG mode mainly consisting of chip formation, ploughing, primary and secondary rubbing phenomenon. Most of the proposed grinding force models neglected the effect of ploughing, considering it to be very low in comparison with the chip formation force. But if the model is to represent the actual grinding process the effect of ploughing has to be considered. The coefficient of friction in most of the models is taken as constant but in reality it varies with process parameters during the grinding process. On the basis of foundation of the achievements of these researchers, a new grinding force model was developed by incorporating the proposed improvements to the Werner model. The developed model considers the effect of the input process parameters and grain size on the ploughing force component and on the coefficients of friction. Planning of experiments through design of experiments has been used quite successfully in process optimization by Chen and Chen (2007), Fung and Kang (2005), Tang et al. (2007), Vijian and Arunachalam (2006). Yang (2007), Zhang et al. (2007) and as well as,

Kadirgama et al. (2011, 2010). Malkin (1989), Hwang and Malkin (1999) investigated the process monitoring and studied various grinding phenomena such as cutting mechanisms, the specific energy and the interrelationship of the parameters during past decades. In his research, it was seen that the grinding process had very complex cutting mechanisms and also repeatability was difficult to obtain under the same grinding conditions. Shaji and Radhakrishnan (2003) reported a study on the Taguchi method for evaluating process parameters in surface grinding with graphite as lubricant. The effect of the grinding parameters (wheel speed, table speed, depth of cut and the dressing mode) on the surface finish and the grinding force was analyzed. Kwak (2005) showed that the various grinding parameters affected the geometric error generated during the surface grinding by using the Taguchi method and also the geometric error could be predicted by means of the response surface method. Of the different ways to deal with this problem, this paper is concerned with the construction of simpler approximation models to predict the system performance and develop a relationship between the system inputs and outputs. When properly constructed, these approximation models mimic the behaviour of the simulation accurately while being computationally cheaper to evaluate (Dirk et al., 2010).

Different approximation methods exist, each with their relative merits. This work concentrates on the use of data-driven, global approximations using compact surrogate models (also known as metamodels, replacement models, or response surface models). Examples include: rational functions, Kriging models, Artificial Neural Networks (ANN), splines, and Support Vector Machines (SVM). Once such a global approximation is available it is of great use for gaining insight into the behaviour of the underlying system. The surrogate may be easily queried, optimized, visualized, and seamlessly integrated into CAD/CAE software packages (Dirk et al., 2010).

Partial swarm optimisation (PSO)

PSO algorithm is similar to that of the evolutionary computation techniques in which a population of potential solutions to the optimal problem under consideration is used to probe the search space. Each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, correspond to individuals. Each particle in PSO flies in the D -dimensional problem space with a velocity dynamically adjusted according to the flying experiences of its individuals and their colleagues. The location of the i th particle is represented as:

$$X_i = [x_{i1}, x_{i2} \dots x_{iD}],$$

Where $x_{id} \in [l_d, u_d]$, $d \in [1, D]$, l_d , u are the lower and

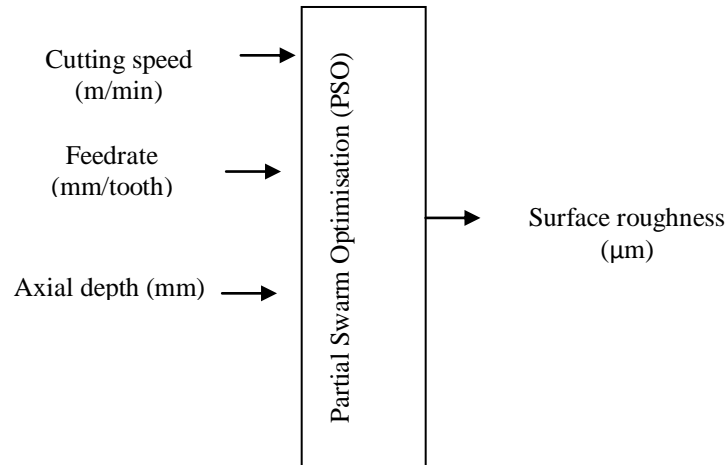


Figure 1. PSO for paddle cantilever.

upper bounds for the d^{th} dimension, respectively. The best previous position (which gives the best fitness value) of the i^{th} particle is recorded and represented as $P_i = [p_{i1}, p_{i2} \dots p_{iD}]$, which is also called P_{best} . The index of the best particle among all the particles in the population is represented by the symbol g . The location P_g is also denoted by g_{best} . The velocity of the i^{th} particle is represented by $V_i = [v_{i1}, v_{i2} \dots v_{iD}]$ and is clamped to a maximum velocity $V_{\text{max}} = [v_{\text{max}1}, v_{\text{max}2} \dots v_{\text{max}D}]$, which is specified by the user. The particle swarm optimization concept consists of, at each time step, regulating the velocity and location of each particle toward its P_{best} and g_{best} locations according to the Equations 1 and 2, respectively (Yijian and Xiongxiang, 2005):

$$v_{id}^{n+1} = wv_{id}^n + c_1r_1^n(p_{id}^n - x_{id}^n) + c_2r_2^n(p_{gd}^n - x_{id}^n) \quad (1)$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \quad (2)$$

The PSO outputs have been termed as one output node representing the state variable (heat affected zone) as shown in Figure 1. The experimental results are used for the optimisation of the tool life model using the PSO. The codes for the PSO are written in Matlab 7.0 which follows the logic of the pseudocode. According to Jialin Zhou et al. (2005) particle swarm optimization (PSO) technique perform than back propagation (BP) algorithms when predict the diameter error in a boring machining. To overcome the stagnation in searching a globally optimal solution, a PSO method with nonlinear time-varying evolution (PSO-NTVE) is proposed to approach the optimal solution closely. When determining the parameters in the proposed method, matrix experiments with an orthogonal array are utilized, in which a minimal number of experiments would have an effect that

approximates the full factorial experiments (Chia-Nan et al., 2007). Ying-Pin and Chia-Nan (2008) proposed a method with nonlinear time-varying evolution based on neural network (PSO-NTVENN) to design large-scale passive harmonic filters (PHF) under abundant harmonic current sources. The goal is to minimize the cost of the filters, the filters loss, and the total harmonic distortion of currents and voltages at each bus, simultaneously. The performance of PSO for function optimization in noisy environment is investigated, and an effective hybrid PSO approach named PSOOHT is proposed by Hui Pan et al. (2006).

EXPERIMENTAL SETUP

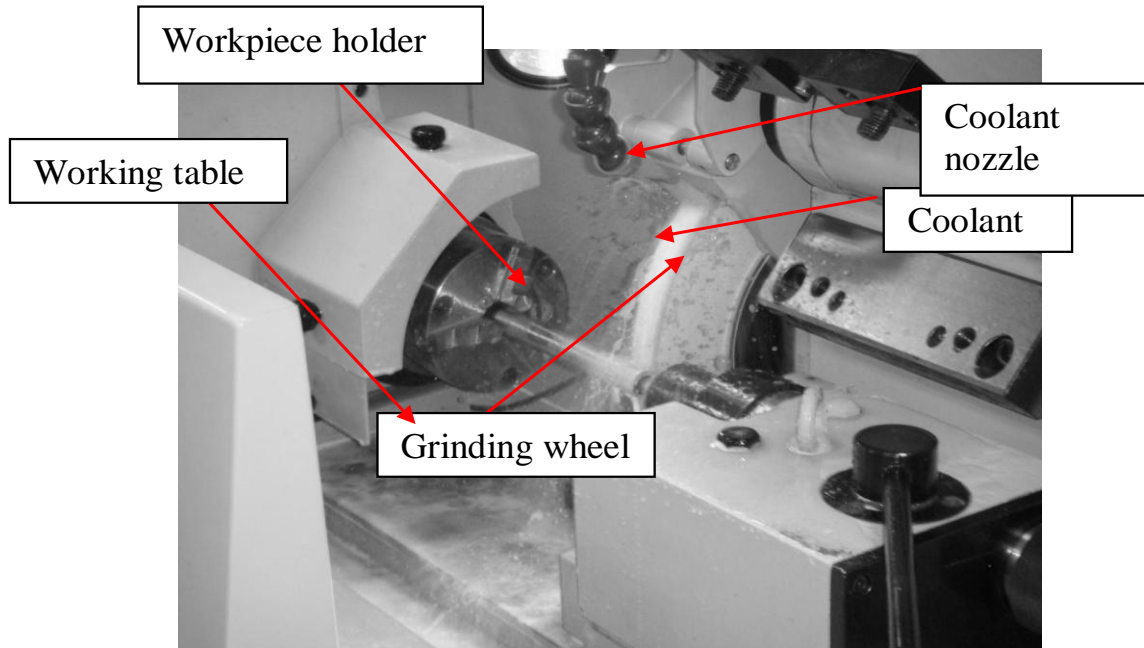
The experiments were conducted using Okumoto CNC surface grinder and the grinding wheel used for the experimentation was a medium grade alumina wheel with a grain size number of 60. The wheel has an outer diameter of 350 mm and width of 40 mm. The surface roughness's were measured using a perthometer. Three measurement traces parallel and perpendicular to the grinding direction were measured. The average of the three arithmetic average surface roughness (Ra) measurements along and across the grinding direction was used to represent the roughness of a ground surface. The workpiece used was carbon steel (AISI 1042) with a cylindrical cross-section and dimensions 150 mm length and 25 mm diameter. The experimental set-up details are shown in Table 1 and Figure 2. Chemical properties of workpiece are shown in Table 2. After the preliminary investigation, the suitable levels of the factors are used in the statistical software to deduce the design parameters for carbon steel as shown in Table 3. The lower and higher speed values selected are 40 rpm and 120 rpm, respectively. For diameter workpiece, the lower value is 18 mm and the higher value is 22 mm. For the depth of cut, the higher value is 20 μm and the lower value is 5 μm .

Design of experiment (DOE)

This is a method for obtaining an approximate function using results

Table 1. Experimental set-up detail.

Grinder	Okumoto CNC surface grinder
Grinding wheel	Al ₂ O ₃ wheel
Workpiece	Carbon steel (AISI 1042)
Workpiece dimension	Length 125 mm, diameter 25 mm
Coolant	Ethylene Glycol 0.252 (W/mK)
Surface roughness	Perthometer S2 (ISO 3274) RS232 used for electronic data collection

**Figure 2.** Experimental setup.**Table 2.** Chemical properties of AISI 1042 carbon steel.

Component	C	Mn	P	S	Fe
Wt %	0.40 -0.47	0.60-0.90	Max 0.04	Max 0.05	~98

Table 3. Levels of independent variables.

Variables	Low	Medium	High
Work Speed (rpm)	40	80	120
Diameter w/p (mm)	18	20	22
Depth of cut (μm)	5	12.5	20

of several numerical calculations to increase calculation efficiency and thereby implement design optimization. In the response surface method, design parameters are changed to formulate an approximate equation by the design of experiment method. An

approximate sensitivity calculation of a multicrestedness problem can be performed using a convex continuous function and applied to optimization. The Box-Behnken Design is normally used when performing non-sequential experiments. That is, performing the

Table 4. Regression estimation for variables for 1st order.

Term	Coefficient	T	Probability
Constant	0.66595	46.923	0
speed	-0.16147	-9.011	0
Diameter	0.08889	5.12	0
Depth of cut	-0.05703	-3.091	0.005
$R^2 = 83.99\%$			

experiment only once. These designs allow efficient estimation of the first and second-order coefficients. Because Box-Behnken designs have fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box-Behnken designs do not have axial points, thus we can be sure that all design points fall within the safe operating zone. Box-Behnken designs also ensure that all factors are never set at their high levels simultaneously (Box and Behnken, 1960); and Box and Draper 1986). The proposed linear model correlating the responses and independent variables can be represented by the following expression:

$$y = C + m\text{Work speed} + n\text{Diameter} + p\text{depth of cut} \quad (3)$$

Where y is the response; C , m , n and p are the constants Equation (1) can be written in the Equation (2):

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (4)$$

Where y is the response, $x_0 = 1$ (dummy variable), x_1 = cutting speed, x_2 = feedrate, and x_3 = axial depth. $\beta_0 = C$ and β_1 , β_2 , and β_3 , are the model parameters. The second-order model can be expressed as shown in Equation (3):

$$y'' = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{11} x_1 x_2 + \beta_{12} x_1 x_3 + \beta_{14} x_2 x_3 \quad (5)$$

RESULTS AND DISCUSSION

After conducting the first pass of the 27 grinding experiments, the surface roughness (R_a) readings are used to find the parameters appearing in the postulated first order model (Equation 3). In order to calculate these parameters, the least square method is used with the aid of Minitab. The first-order linear equation used to predict the surface roughness is expressed as:

$$Ra' = 0.178611 - 0.003847s + 0.044444d - 0.007151x \quad (6)$$

Where Ra is surface roughness; s is work speed; d is diameter; x is depth of cut.

Generally, increase of diameter of workpiece slightly increase the roughness meanwhile reduce working speed and depth of cut cause rough surface. This finding is supported by Hwang et al. (1999). According to the author, this phenomenon happens due to falling off of the

grain of the grinding wheel. The work speed is the most dominant factors on the R_a , followed by the diameter of workpiece and depth of cut respectively. Hence, a fine surface roughness is obtained with the combination of high speed, high depth of cut and low diameter. Kwak (2005) found the same trend and supports the findings. The relationship between the work speed, diameter and depth of cut and the R_a is statistically significant compare with other variables as shown in Table 4 whereas the probability values for lack of fit more than 0.05 as shown in Table 5. Normal plot as shown in Figure 3 observed that experimental values closely near to the normal line. Probability line is shown in Figure 4 that explains almost 80% of surface roughness values fall below $0.9 \mu\text{m}$. Due to the data points roughly follow the straight line, the p -value is over 0.05, and the AD statistic is low, it can conclude that the data are from a normally distributed population. Therefore, it can be used to fit line to estimate percentiles. The mean surface roughness is 0.67 and the standard deviation is 0.17. The second-order quadratic equation used to predict the surface roughness is expressed as:

$$Ra'' = -8.06 + 0.0062s + 0.83d + 0.0016x + 0.0000043s^2 - 0.018d^2 + 0.000048x^2 - 0.00053sd - 0.0000304sx - 0.0004xd$$

All the second order variables (s^2 , d^2 , x^2 , sd , sx and xd) and interaction are insignificant as shown in Table 6. Speed, diameter and depth of cut still significant since probability values less than 0.05. It is observed that increase of speed and depth of cut produce fine surface roughness whereas this finding against with first order. This is maybe due to the effect of other independent variables such as s^2 , d^2 , x^2 , sd , sx and xd . Even though other independent variables is insignificant but the second order model is fit since probability value for lack of fit higher than 0.05 as shown in Table 7. As seen from Figure 4, the predicted R_a using the first order and second order RSM model is closely match with the experimental results. Second order exhibits the better agreement. Contour plots and surface plots are shown in Figures 5 and 6 in terms of relationship with each variable. It discovered that combination of low cutting speed and high depth of cut produce high surface roughness. Meanwhile combination of high cutting speed and high depth produce fine surface. On the other hand, diameter of work piece which range from 19.5 to 21 mm

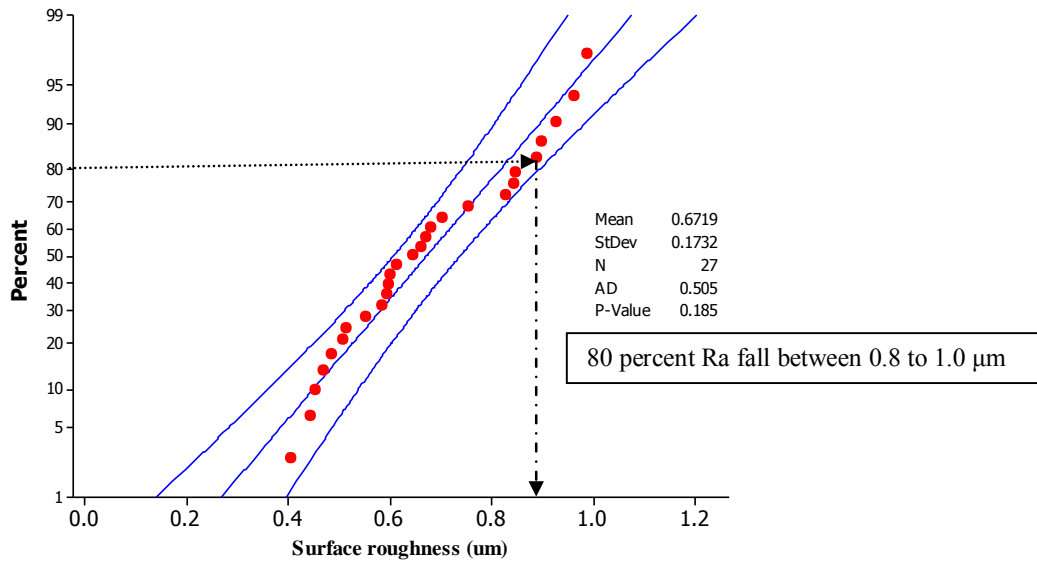


Figure 3. Probability distribution of surface roughness.

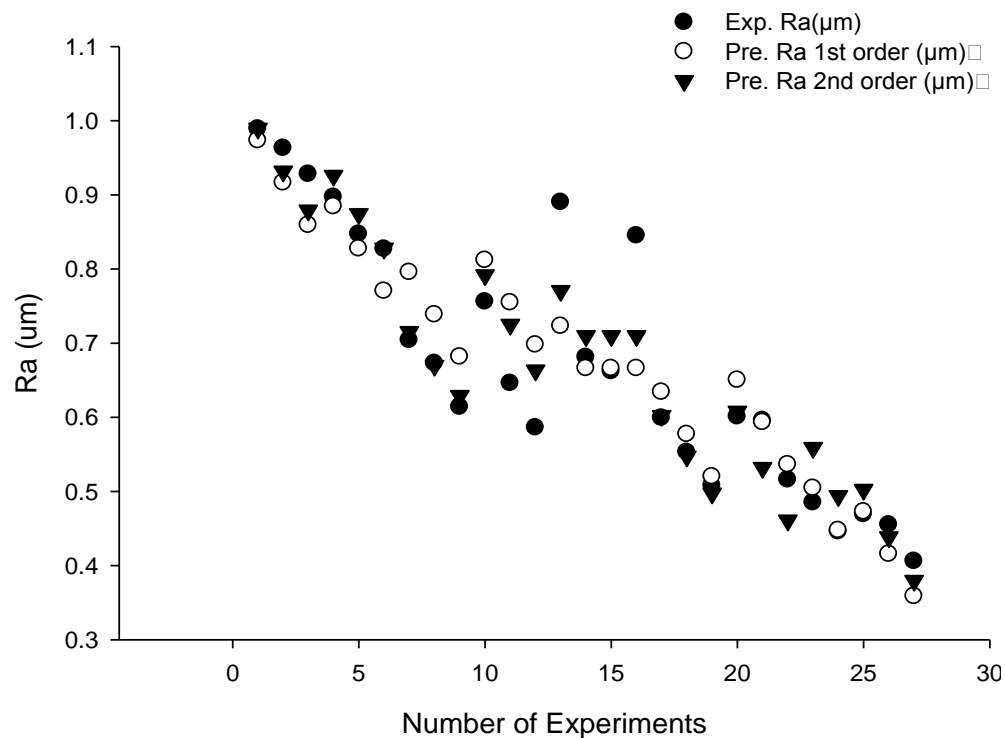


Figure 4. Comparison of two prediction models with experimental values.

combination with low depth produce high surface roughness. Higher surface roughness also produced with combination of low speed and high diameter of workpiece. The contour plot show the clear picture of relation between the variables and it is easy to be used by other unskilled machining operators.

The optimized surface roughness model is tested with experimental results. The predicted minimum surface roughness using optimised surface roughness model by PSO are compared with the measured surface roughness and these results are reported in Figure 7. The validation experiment is performed in the same machining

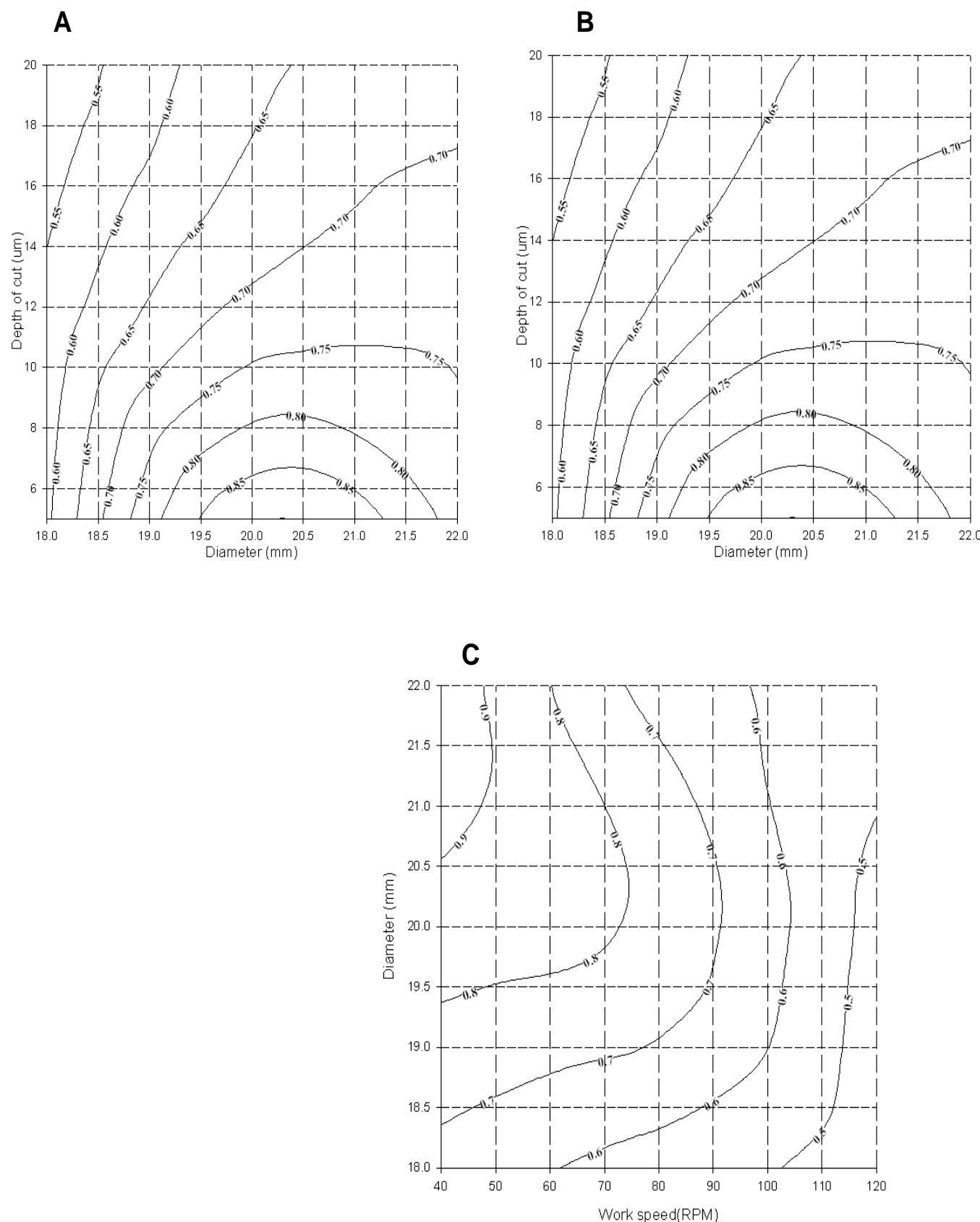


Figure 5. Contour plot of (a) Work speed-depth of cut; (b) Diameter-depth of cut; (c) Work speed-diameter.

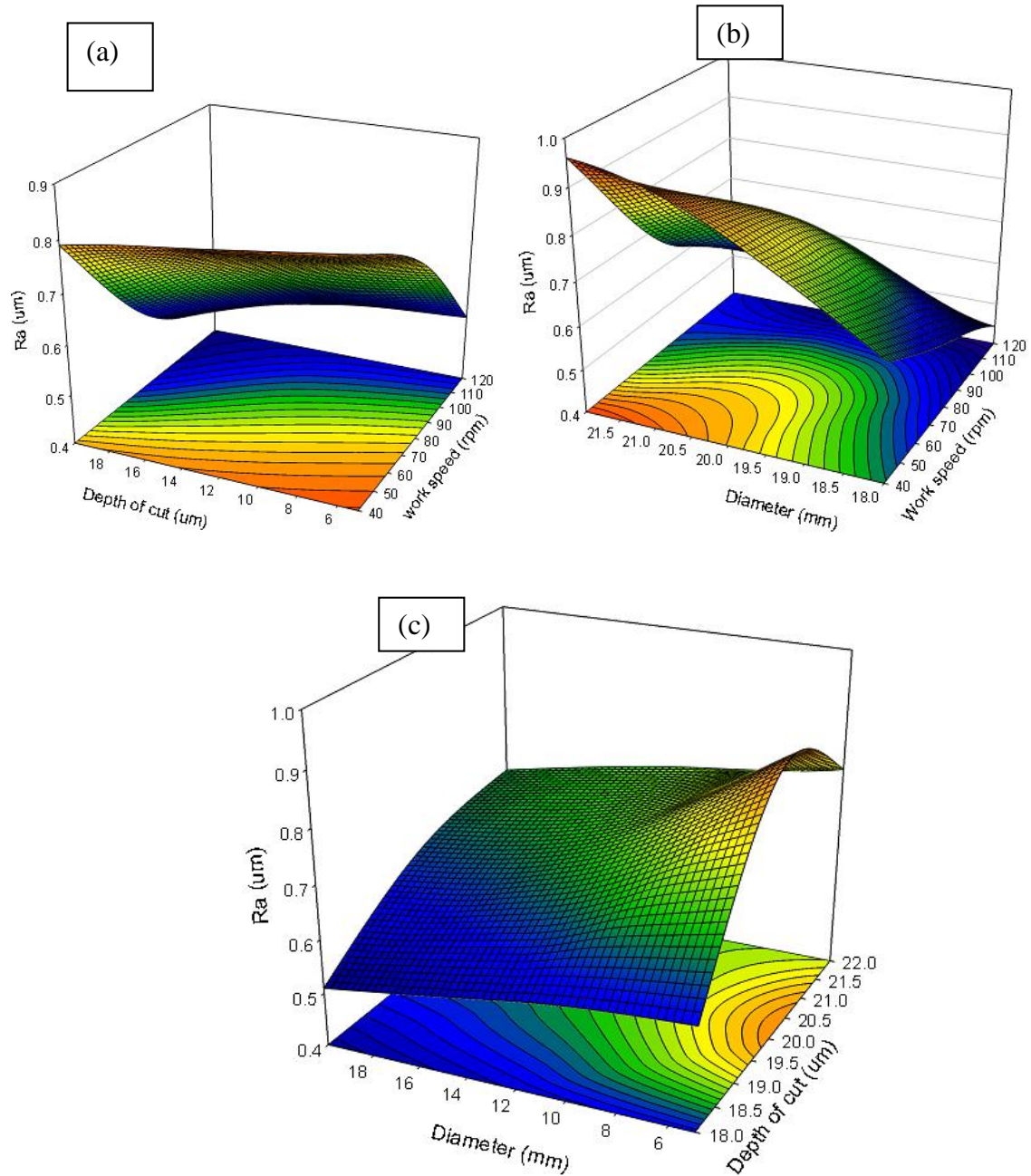


Figure 6. Surface plot of (a) Work speed-diameter; (b) Work speed-depth of cut; (c) Diameter-depth of cut.

environment as the training experiment. The errors of surface roughness obtained by optimised min surface roughness model are 2.15%. The optimum cutting parameters for minimum surface roughness are cutting speed 120 RPM; Diameter 18 mm and axial depth 20 μm .

Surface texture

Scanning electron micrographs of work surfaces ground

at speeds 120, 80 and 40 revolution per minute are shown in Figures 8a, b and c respectively. It appears from these figures that the steel specimens ground under low speed conditions (I) show distinct signs of plastic flow and surface fracturing, the degree depending upon the type and hardness of the steels. It indicates that sufficiently high temperatures developed in low speed grinding to affect the surfaces. This observation observed also by use of a medium speed (11) improved the surface condition to some extent by carrying away a certain

Table 5. Variance analysis for first order model (ANOVA) for 1st order.

Source	Degree of freedom	Sequence sum of square	F	Probability
Regression	3	0.65496	40.23	0
Linear	3	0.65496	40.23	0
Residual Error	23	0.12481		
Lack-of-Fit	21	0.10456	0.49	0.844
Pure Error	2	0.02025		
Total	26	0.77977		

Table 6. Regression estimation for variables for 2nd order.

Term	Coefficient	T	Probability
Constant	0.709668	25.464	0
Speed	-0.157738	-9.9	0
Diameter	0.088889	5.809	0
Depth of cut	-0.058267	-3.551	0.002
Speed*speed	0.006864	0.26	0.798
Diameter*diameter	-0.073589	-2.68	0.016
Depth of cut*depth of cut	0.002517	0.096	0.925
Speed*diameter	-0.042167	-2.25	0.038
Speed*depth of cut	-0.009144	-0.46	0.652
Diameter*depth of cut	-0.006	-0.32	0.753

$R^2 = 90.13\%$.

Table 7. Variance analysis for first order model (ANOVA) for 2nd order.

Source	Degree of freedom	Sequence sum of square	F	Probability
Regression	9	0.70813	18.67	0
Linear	3	0.65496	50.03	0
Square	3	0.03051	2.47	0.097
Interaction	3	0.02266	1.79	0.187
Residual error	17	0.07164		
Lack-of-Fit	15	0.05139	0.34	0.917
Pure error	2	0.02025		
Total	26	0.77977		

amount of heat. When grinding with high speed (111) the improvement was quite remarkable (Chattopadhyay et al., 2003).

Conclusion

This research illustrates the grinding of carbon steel (AISI 1042) with and predicting their subsequent surface roughness (Ra). There is becoming a need for investigating the grinding of various types of steel and their Ra which in turn can be useful in developing more

cost effective personalised products. The authors have shown the use of surrogate model to formulate an optimised minimum Ra prediction model for grinding of carbon steel (AISI 1042). This prediction model is tested on the validation experimental and the error analysis of the prediction result with the measured results is estimated at 2.15 % for minimum Ra which is small and shows the efficacy of the prediction model. Finally, the simulation results show that use of PSO combine with RSM can be very successively used for reduction of the effort and time required. This means that it can solve many problems that have mathematical and time

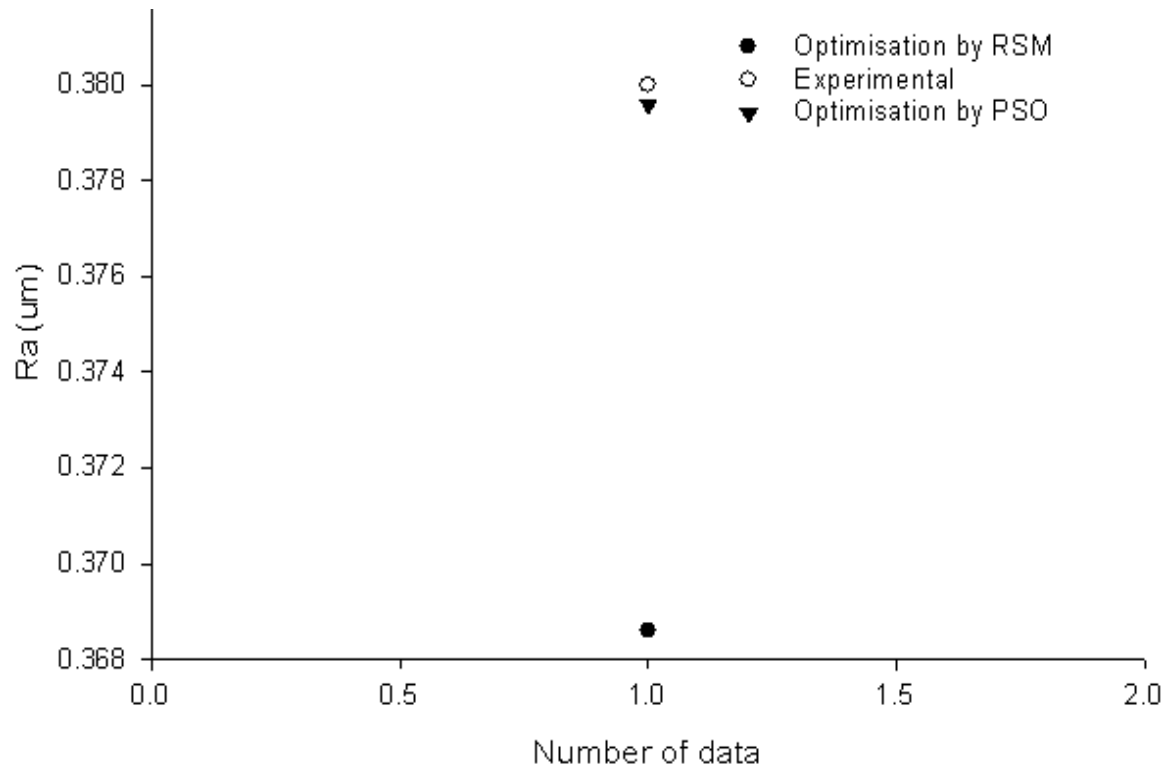


Figure 7. Optimization values comparison.

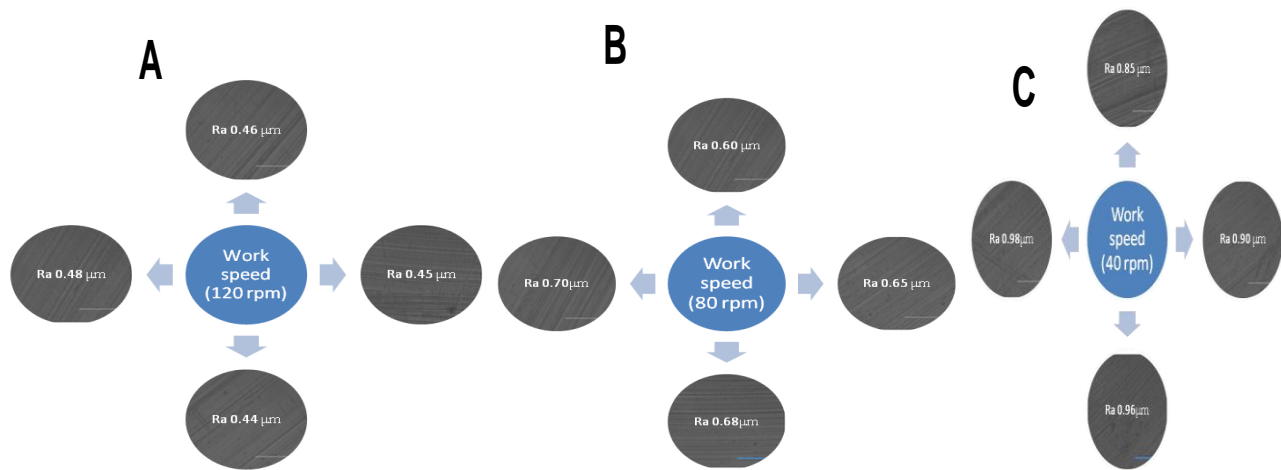


Figure 8. A); Surface texture at speed 120 rpm, B) Surface texture at speed 80 rpm, C) Surface texture at speed 40 rpm.

difficulties.

ACKNOWLEDGEMENTS

The authors would like to express their deep gratitude to Universiti Malaysia Pahang (UMP) for providing the

laboratory facilities and financial support under grant number RDU 090274.

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