Optimization of Cutting Parameters in Machining Polyoxymethylene Using RSM

M Aruna
Department of Mechanical Engineering, College of Engineering and computing, Al Ghurair University, Dubai, UAE

E-mail: maruna9@gmail.com

Abstract. Polyoxymethylene (POM) is an extensively used engineering thermoplastic polymer. Owing to its superior properties and potential applications in numerous turfs of structural machineries, it is essential to probe the machining of POM. The economy of machining operations plays an imperative role in increasing productivity and effectiveness. The persistence of optimal cutting parameters, such as cutting speed, feed and depth of cut, which are valid for given cutting tools, is one of the dynamic segments in process planning of metal parts. This research work concerns an experimental study dealing with cutting parameters and its effects on surface roughness (Ra) and material removal rate (MRR) during the turning of POM. The approach is based on Response Surface Technology (RSM). Experiments are designed using central composite design and second-order quadratic models are developed to define the optimal machining parameters. These optimized parameters are validated experimentally.

1. Introduction
Polymeric materials have been extensively used to replace traditional metallic materials owing to their high elastic properties. However, polymeric materials can be manufactured as near net shapes, machining is still essential to create the assembly of the products. Due to high ductility and low melting point, the selection of cutting tool and machining conditions plays an important role in machining [1]. In this work, the machining behaviour of high performance engineering polymer, such as ultra-high-molecular-weight polyoxymethylene has been investigated using central composite design. Polyoxymethylene (POM), also branded as Acetal, is an engineering thermoplastic, commonly used in construction machinery, vehicles, technology, transport and cargo handling, electrical, precision technology, domestic, food industry and medical appliances, where very high accuracy is needed in these machined parts [2]. The foremost raw materials are acetal copolymer and homopolymer. POM combines high stiffness with mechanical strength, besides revealing good elastic properties, high toughness, dimensional stability, excellent sliding friction characteristics and high hardness. Furthermore, POM has good fatigue properties and machinability. The beneficial assets of POM comprises Rockwell hardness of 122 (6 % more than nylon), Thermal expansion coefficient 0.000047 in /°F (14 % less than nylon), moisture absorption of 0.9% (87 % less than nylon).

Numerous problems associated with the precision and efficiency in cutting composites has become an essential topic in the manufacturing industry. Authors have reported several investigations on the machining mechanisms and production cost, such as tool wear, selection of machining parameters and control of surface finishing. A significant amount of research activities have also focused on the machinability of a wide variety of reinforced polymeric materials. Some authors [3–5] have compared the machining behaviour of pristine and reinforced polymers based on the characteristics of the matrix
phase, which is presented in both materials. However, only a limited amount of article is available to discuss the machining parameters of engineering polymers and their effect on the surface finishing. Investigators examined mainly the machining of phenolic composites [6]. The existence of a critical machining speed was recognized based on the specific cutting pressure and machining temperatures, which directly affect the tool wear. Machinability of polyether-ether-ketone (PEEK) reinforced with glass fibre using polycrystalline diamond (PCD) and cemented carbide (K20) tools are investigated by few researchers [7]. A better surface finishing was achieved when high cutting speed, low feed rate and PCD tool were set.

Orthogonal experiment is conducted to examine the cutting of polyamide (PA6) with and without reinforcing phase (30% glass fibre) using cemented carbide cutting tools. The consequence of glass fibres on the friction angle, shear plane angle, normal and shear stresses and chip deformation in several cutting conditions were assessed. The outcomes directed that the accumulation of glass fibres led to higher cutting force, friction angle and normal stress values [4]. In contrast, the polyamide without reinforcing attained greater shear stress and chip deformation values. Critical thrust forces are predicted and proved the consequence of different types of drills, such as twist drill, saw drill, candlestick drill, core drill and step drill, on the delamination physiognomies [8]. The thermal properties of engineering plastics significantly affected the surface roughness of drilled holes. The investigations on the machinability and hole dimensional accuracy in the drilling process of engineering plastics are left pending. The drilling forces and indemnities in the work piece material were much affected by the drill geometry factor. The viscoelastic properties of engineering plastics affected the cutting force and the surface roughness of machined parts [5]. The polyacetal or polyoxymethylene (POM) and polyetherimide (PEI) materials were drilled using 1 mm diameter drill. The hole accuracy (radius error) befits worse when the drill feed rate is lower and the spindle speed is higher [9].

Plastic parts are produced widely by injection moulding. Precise plastic components can be obtained by machining of plastics [10]. The surface quality of machined plastic components is greatly affected by feed rate and speed. While machining plastics, speed and feed has to be considered as significant factors for attaining dimensional accuracy and good surface finish [11]. Optimal cutting conditions has to be determined to accomplish superior machining performance in machining of polymers [12]. Optimum cutting parameters namely speed, feed rate depth of cut for plastic machining could be identified using regressions analysis and optimum cutting conditions offer better surface finish [13]. Experiments are designed using Taguchi method. This technique includes response table, response graph, normal probability plot, ANOVA. The result shows the rubberized fly ash geopolymer has potential to be machined and can be used for many engineering applications [13]. Response surface methodology is to express the output parameters. Experiments can be designed using Box behnken design plan as they have fewer design points making it less expensive to run than central composite design. Surface models developed for surface shows the effect of each input parameters and its effect with other parameters, depicting the trends of response [14]. Experiments and analysis could be conducted using design of experiments and optimum cutting parameters for machining of POM can be determined by measuring the surface roughness for each treatment combination and main effects and interaction effect can be studied by ANOVA [15].

Abundant research has focused on the material and tribological properties of POM. Determining the optimal process parameters is found to be the major issue in machining Polyoxymethylene. However, only a limited number of investigations about the effects of the turning and drilling parameters and the machining behaviour of such materials have been reported. The objective of this work is to optimize the process parameters namely cutting speed, feed rate and depth of cut while turning operations is performed on POM. Taguchi’s techniques have been used commonly in engineering design, and can be pragmatic to several facets such as optimization, experimental design, sensitivity analysis, parameter estimation, model prediction, etc. Taguchi based optimization technique has produced an exceptional and dominant optimization discipline that varies from traditional practices. Taguchi method practices a distinct highly fractionated factorial designs and other categories of fractional designs achieved from orthogonal arrays (OAs). It is to study the complete experimental region of interest for experimenter with a lesser number of experiments. This diminishes
the time and costs of experiments, and furthermore permits for an optimization of the process to be completed. The columns of an OA represent the experimental parameters to be optimized and the rows represent the individual trials (combinations of levels).

Previous research works are limited to ANOVA. In this research work, RSM technique is focussed principally to develop Response surface model. The cutting parameter combinations are designed by Taguchi’s Design of experiments (DOE). The surface roughness values and Material removal rate for various parameters are measured and Response surface methodology is used to analyze and validate the results of experimental measurements.

2. Methodology
Response surface methodology is an advanced tool nowadays which involves three factorial designs giving number of input (independent) factors and their corresponding relationship between one or more measured dependent responses. It is advantageous over conventional methods available and it includes less experiment numbers, its suitability for multiple factor experiments and search for common relationship between various factors towards finding the most suitable production conditions and forecast responses. RSM is a collection of mathematical and statistical techniques that are useful for modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [16]. The version 7 of Design Expert software is used to develop the experimental plan for RSM. The same software is also used to analyze the data collected.

The cutting parameters are to be designed using a response surface design. Experiments are conducted using different levels of cutting parameters. Once the experiments are carried out, the surface finish is measured using surface roughness tester and material removal rate is calculated. In the realistic application of RSM, it is necessary to extend an approximating model for the true response surface. The approximating model is based on the observed data from the process or system and is an empirical model. Surface roughness is presumed to be a task of prime variables cutting speed, feed rate and depth of cut. Multiple regression as a collection of statistical techniques is useful for building the types of empirical models requisite in RSM. The central composite design is used, since it gives a comparatively accurate prediction of all response variable averages. Central Composite Design (CCD) is nearly rotatable second-order design based on three-level incomplete factorial designs. In this design, the treatment combinations are at the midpoints of edges of the process space and at the centre.

RSM designs also assist in quantifying the relationship amongst one or more measured responses and the vital input factors. In order to decide the relationship between the factors and the response variables investigated, the data collected must be investigated in a statistically sound mode by means of regression. Regression is performed in order to describe the data collected whereby an observed, empirical variable (response) is approximated based on a functional relationship between the estimated variable, yest and one or more regressor or input variable x1, x2,…,x4. In the case where there exist a non-linear relationship between a particular response and three input variables, a quadratic equation (1),

\[
\text{Surface roughness} = -1.94909 + 0.013162\text{Cutting speed} + 45.00778 \text{Feed} + 2.68761 \text{Depth of cut}\ldots
\]

\[
y_{est} = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_1 x_2 + b_5 x_1 x_3 + b_6 x_2 x_3 + b_7 x_2 + b_8 x_2^2 + b_9 x_1^2 + \text{error}
\]

Equation (2) may be used to describe the functional relationship between the estimated variable, yest and the input variables x1, x2 and x3. The least square technique is being used to fit a model equation containing the said regressors or input variables by minimising the residual error measured by the sum of square deviations between the actual and the estimated responses. This involves the calculation of estimates for the regression coefficients.

The present work mainly demonstrates the optimisation process of multiple responses i.e. MRR and Surface roughness using RSM technique. This multi-objective optimization is applied to obtain minimum surface roughness and maximum material removal rate.
2.1. Cutting conditions
In this examination three factors are being studied and their low and high levels are given below.

| Parameter          | Low Level | High Level |
|--------------------|-----------|------------|
| Cutting speed (m/min) | 200       | 260        |
| Feed (mm/rev)     | 0.1       | 0.4        |
| Depth of cut (mm) | 0.5       | 2.5        |

2.2. Experimental work
The primary experiments were conducted on the universal lathe machine. The material used for cutting was unreinforced Polyoxymethylene. Polyoxymethylene and other thermoplastics can be turned on a lathe with tools ground for plastics, at speed up to 550 m/min. In the present study, three cutting parameters, namely, cutting speed (Vc), feed rate (f) and depth of cut (ap) were considered. The cutting parameter ranges were selected based on machining guidelines provided by workpiece and tool manufacturer’s recommendations and previous researches. Three levels for cutting speed, feed rate and depth of cut were considered. The POM rods are machined at different levels of speed, feed and depth of cut, as per the experimental design. MRR is the volume of material removed per minute. The higher you’re cutting parameters, the higher the MRR. Surface roughness often reduced to roughness, is a component of surface texture. It is computed by the deviations in the direction of the normal vector of a real surface from its ideal form. If these eccentricities are huge, the surface is rough; if they are small, the surface is smooth. In surface metrology, roughness is normally measured to be the high-frequency, short-wavelength component of a measured surface. However, in practice it is often essential to know both the amplitude and frequency to ensure that a surface is fit for a purpose. There are many different roughness parameters in use, but is by far the most common, though this is often for old reasons and not for particular merit Ra, as the early roughness meters could only measure. Other common parameters include Rq, Rt, and Rz. The surface roughness is measured for the different combinations, using Mitutoyo SJ-410 portable surface roughness tester. It is measured at three different locations and the averages reported. The trials are performed in a random fashion. From the surface roughness value, a regression model is developed. The fit of the model and the significance of the different factors is checked using ANOVA.

2.3. ANOVA analysis
F test analysis of variance (ANOVA) is executed and presented in Table 1 and 2, to check the statistical significance of the model. An ANOVA table is commonly used to summarize the tests performed. The analysis of variance (ANOVA) is applied to test adequacy of the developed models. The purpose of the ANOVA is to investigate which parameters significantly affect the response characteristics. The test for significance of the regression model and the test for significance on individual model coefficients are performed. Examination of the fit summary output reveals that the linear model is statistically significant for surface roughness. Table 1 shows the ANOVA table for response surface linear model for surface roughness. It is obvious from the results of ANOVA that the speed rate is the dominant factor affecting surface finish. The contribution of the feed and depth of cut is 9.35 and 1.48 respectively. The Model F-value of 3.62 infers the developed model is significant. P-values <0.0500 specify model relations are significant. Values larger than 0.1000 specify the model terms are not significant. Mathematical model is established using multiple regression method, Ra model correlation $R^2$ is 93.50%. The Lack of Fit F-value of 0.63 infers the Lack of Fit is not significant comparative to the pure error. There is a 75.42% chance that a Lack of Fit F-value will exist. This large value occurs due to noise. The Predicted $R^2$ of 0.0935 is in reasonable agreement with the Adjusted $R^2$ of 0.2929.

| Source     | Sum of Squares | df | Mean Square | F-value | p-value | significant |
|------------|----------------|----|-------------|---------|---------|-------------|
| Model      | 723.23         | 3  | 241.08      | 3.62    | 0.0361  | significant |
| A-Cutting Speed | 2.13         | 1  | 2.13        | 0.0320  | 0.8603  |             |
The analysis of variance of the response, MRR is summarized in Table 2 and the significant 2 Factorial model is shown. The feed is the dominant factor affecting MRR. The Model F-value of 1.19 suggests the model is not significant relative to the noise. There is a 37.16% chance that huge F-value could arise due to noise. P-values < 0.0500 signpost model terms are significant. In this item there are no significant model terms. Values > 0.1000 specify the model terms are not significant. The Lack of Fit F-value of 1.67 denotes the Lack of Fit is not significant relative to the pure error. There is a 29.78% chance that a Lack of Fit F-value will occur. Non-significant lack of fit is good.

Table 2. ANOVA Table for Material Removal Rate.

| Source       | Sum of Squares | df | Mean Square | F-value | p-value | not significant |
|--------------|----------------|----|-------------|---------|---------|----------------|
| Model        | 21220.99       | 6  | 3536.83     | 1.19    | 0.3716  | not significant|
| A-Cutting Speed | 925.89       | 1  | 925.89      | 0.3106  | 0.5868  | not significant|
| B-Feed       | 4307.12        | 1  | 4307.12     | 1.44    | 0.2508  | not significant|
| C-Depth of cut | 8.35          | 1  | 8.35        | 0.0028  | 0.9586  | not significant|
| AB           | 11615.17       | 1  | 11615.17    | 3.90    | 0.0700  | not significant|
| AC           | 4352.91        | 1  | 4352.91     | 1.46    | 0.2484  | not significant|
| BC           | 11.54          | 1  | 11.54       | 0.0039  | 0.9513  | not significant|
| Residual     | 38750.36       | 13 | 2980.80     |         |         |                |
| Lack of Fit  | 28174.54       | 8  | 3521.82     | 1.67    | 0.2978  | not significant|
| Pure Error   | 10575.82       | 5  | 2115.16     |         |         |                |
| Cor Total    | 59971.35       | 19 |             |         |         |                |

2.4. Model validation
Linear model Residual and Leverage values for Surface Roughness are shown in Table 3. It clearly depicts the actual and predicted values. The aim of this step is to predict and verify the improvement of the response using the optimal levels of the turning process parameters. Adequate Precision measures the signal to noise ratio. A ratio larger than 4 is necessary. The experimental ratio of 6.225 specifies an acceptable signal. This model can be used to circumnavigate the design space.

Table 3. Residual and Leverage values for Surface Roughness.

| Run Order | Actual Value | Predicted Value | Residual | Leverage | Internally Studentized Residuals | Externally Studentized Residuals | Cook's Distance | Influence on Fitted Value DFFITS |
|-----------|--------------|-----------------|----------|----------|-------------------------------|---------------------------------|-----------------|----------------------------------|
| 1         | 32.00        | 16.36           | 15.64    | 0.050    | 1.967                         | 2.187                           | 0.051           | 0.502                            |
| 2         | 3.10         | 17.03           | -13.93   | 0.257    | -1.981                        | -2.207                          | 0.339           | -1.299                           |
| 3         | 13.50        | 16.36           | -2.86    | 0.050    | -0.360                        | -0.350                          | 0.002           | -0.080                           |
Two factorial model Residual and Leverage values for MRR are shown in Table 4. It clearly depicts the actual and predicted values in relation with Cook’s distance.

Table 4. Residual and Leverage values for MRR.

| Run Order | Actual Value | Predicted Value | Residual | Leverage | Internally Studentized Residuals | Externally Studentized Residuals | Cook's Distance | Influence on Fitted Value DFFITS |
|-----------|--------------|-----------------|----------|----------|---------------------------------|---------------------------------|-----------------|----------------------------------|
| 1         | 126.00       | 177.92          | -51.92   | 0.50     | -0.976                          | -0.974                          | 0.007           | -0.223                           |
| 2         | 257.00       | 191.77          | 65.23    | 0.257    | 1.386                           | 1.443                           | 0.095           | 0.849                            |
| 3         | 160.00       | 177.92          | -17.92   | 0.50     | -0.337                          | -0.325                          | 0.001           | -0.075                           |
| 4         | 155.00       | 179.23          | -24.23   | 0.257    | -0.515                          | -0.500                          | 0.013           | -0.294                           |
| 5         | 136.80       | 167.12          | -30.32   | 0.645    | -0.932                          | -0.927                          | 0.225           | -1.248                           |
| 6         | 148.40       | 177.92          | -29.52   | 0.50     | -0.555                          | -0.539                          | 0.002           | -0.124                           |
| 7         | 190.00       | 124.03          | 65.97    | 0.645    | 2.027                           | 2.355                           | 1.065⁽¹⁾        | 3.172⁽¹⁾                         |
| 8         | 250.20       | 220.67          | 29.53    | 0.645    | 0.907                           | 0.901                           | 0.213           | 1.213                            |
| 9         | 149.00       | 176.60          | -27.60   | 0.257    | -0.587                          | -0.571                          | 0.017           | -0.336                           |
| 10        | 123.00       | 207.79          | -84.79   | 0.257    | -1.802                          | -1.998                          | 0.160           | -1.176                           |
| 11        | 146.00       | 164.07          | -18.07   | 0.257    | -0.384                          | -0.371                          | 0.007           | -0.218                           |
| 12        | 255.50       | 263.36          | -7.86    | 0.645    | -0.241                          | -0.233                          | 0.015           | -0.313                           |
| 13        | 200.00       | 148.05          | 51.95    | 0.257    | 1.104                           | 1.114                           | 0.060           | 0.655                            |
| 14        | 210.00       | 177.92          | 32.08    | 0.050    | 0.603                           | 0.587                           | 0.003           | 0.135                            |
| 15        | 39.78        | 106.54          | -66.76   | 0.645    | -2.051                          | -2.397                          | 1.091⁽¹⁾        | -3.228⁽¹⁾                        |
| 16        | 220.00       | 212.94          | 7.06     | 0.645    | 0.217                           | 0.209                           | 0.012           | 0.281                            |
| 17        | 127.49       | 154.04          | -26.55   | 0.645    | -0.816                          | -0.805                          | 0.172           | -1.084                           |
| 18        | 224.60       | 177.92          | 46.68    | 0.050    | 0.877                           | 0.869                           | 0.006           | 0.199                            |
2.5. Results

The normal probability plots of the residuals and the plots of the residuals versus the predicted response for surface roughness and MRR are shown in Figure 1, 2, 5 and 6 respectively. The Figure 1, 5 revealed that the residuals fall on a straight line indicating that the errors are disseminated ordinarily. The Figure 2, 6 revealed that they have no obvious pattern and unusual structure. This implies that the models proposed are adequate and there is no reason to suspect any violation of the independence or constant variance assumption. The interaction effects between the three factors are shown in the Figure 3. From the figures, it can be inferred that the three factors speed, feed and depth of cut are relatively independent of each other, i.e. variation of one factor doesn’t significantly affect the effects of other factors on the response.

|   | 19  | 200.40 | 20  | 200.40 |
|---|-----|--------|-----|--------|
|   | 239.20 | 174.65 | 177.92 | 174.65 |
|   | 61.28 | 25.75 | 0.645 | 25.75 |
|   | 0.050 | 0.645 | 0.791 | 0.791 |
|   | 1.152 | 0.791 | 1.168 | 0.779 |
|   | 1.168 | 1.168 | 0.010 | 0.162 |
|   | 0.050 | 0.645 | 0.268 | 1.050 |

Figure 1. Normal probability plot of residuals for Ra data.

Figure 2. Residuals Vs Run for Ra data.

Figure 3. Contour plot for Ra data.

Figure 4. 3D surface graph for Ra data.
A 2D contour plot was generated for the responses at any two independent variables while keeping the others at their 0 level. The contour for the response surface for surface roughness and MRR is shown in Figure 3 and 7. It is clear from the figure that at medium feed rate, the best surface finish is obtainable and when the cutting speed is somewhere at middle range experimented. It is also clear that the surface roughness rises with growing feed. The observation made for MRR is also an increasing trend. MRR escalates with the upsurge in cutting speed. It is clearly visible from Figure 7 as red portion. The MRR is dependent on the cutting speed which is a significant factor.

The RSM was used to study the three-dimensional response plots, which were generated from the effects of the three variables on surface roughness and material removal rate. The response values are now investigated, by building contour and 3D surface plots, to study the effects of the different factors on the response. Response optimization is performed using the derived regression model, and the optimal values are determined. Figure 4 and 8 shows the 3D graph of the effect of cutting speed and feed on the surface roughness and MRR. Both have curvilinear profile in accordance to the model fitted.
From the obtained regression model, the optimum values are determined. If the objective is to minimize surface roughness (Ra) only, MRR is not optimized. From the Figure 4, it can be inferred that cutting speed and feed have a linear relationship with surface roughness (Ra). When the objective is to maximize the material removal rate (MRR) only, Ra is not optimized. The optimization plot for the above condition is provided in the Figure 8. Material removal rate is linearly dependent on the three factors—speed, feed and depth of cut, which is verified from the graph. Also from the plot, Maximum MRR is obtained when all three cutting parameters are at maximum value.

The goal is to minimize surface roughness (Ra) and maximize material removal rate (MRR), Clearly, the optimum response is obtained at V = 260 m/min, f = 0.1935 mm/rev, d = 2.5 mm. The consequences of the experimental data are used for predicting the outcome of assorted input machining parameters such as cutting speed, feed and depth of cut on the surface roughness when machining POM. Cutting speed has the strongest effect on the surface roughness among the selected parameters; it is inversely proportional to the response. It is found that the roughness could be controlled in the design stage which is the most effective and inexpensive way.

2.6. Confirmation tests
In order to validate the adequacy of the model developed, confirmation run experiments are performed (Table 5). The predicted values and the associated prediction interval are centred on the model developed previously. The predicted model mean value and the actual experimental values are compared. Two sided with confidence level 95% and population 99% are considered. All these values are presented in Table 5.

| Response            | Predicted Mean | Predicted Median | Observed | Std. Dev. | SE Mean | 95% CI low for Mean | 95% CI high for Mean | 95% TI low for 99% Pop | 95% TI high for 99% Pop |
|---------------------|----------------|------------------|----------|-----------|---------|---------------------|----------------------|------------------------|------------------------|
| Surface Roughness   | 17.0257        | 17.0257          | 17.031   | 8.15728   | 4.1362  | 8.25733             | 25.794               | -19.9822               | 54.0336                |
| Material Removal    | 191.766        | 191.766          | 191.61   | 54.5967   | 27.6836 | 131.959             | 251.573              | -66.1549               | 449.687                |

3. Conclusion
In this paper a methodology based on RSM optimization, for identifying the optimal parameters for machining a work piece are presented. The advantageous properties of POM and its applications are studied. The experimental study is conducted and the effects of different factors named speed, feed and depth of cut, on surface roughness are reported. Response optimization is performed, to obtain minimum surface roughness and maximum material removal rate. The optimization results obtained in this work confirm that the proposed optimization method is a very useful tool for multi-objective optimization of machining parameters. The model generated by RSM design for surface roughness and material removal rate has been found suitable to predict the performance of the POM material. The deviation under the confidence level of 95% in the data values of experimentally collected and that generated from the RSM linear model assure the accuracy of the RSM model.

4. References
[1] Juan C Campos Rubio, Tulio H Panzera and Fabrizio Scarpa 2014 Machining behaviour of three high-performance engineering plastics Proc., of the Inst. of Mech. Engrs, Part B: J. of Engg. Manufacture 1–10
[2] Endo H and Marui E 2006 Small-hole drilling in engineering plastics sheet and its accuracy estimation Int. J. Mach. Tool Manufacture 46(6) 575–579
[3] Fetecau C, Stan F, Munteanu A and Popa1 V 2008 Machining and surface integrity of polymeric materials Int. J. Mater. Form 1(1) 515–518
[4] Davim JP and Mata FJ 2007 A Comparative evaluation of the turning of reinforced and unreinforced polyamide Int. J. Adv. Manuf. Technology 33 (9–10) 911–914
[5] Campos Rubio JC, Panzera TH, Abrao AM, Paulo E. Faria and Paulo Davim 2011 Effects of high speed in the drilling of glass whisker reinforced polyamide composites (PA66 GF30): statistical analysis of the roughness parameters J. Compos. Materials 45(13) 1395–1402
[6] Sreejith PS, Krishnamurthy R, Malhotra SK, Narayanasamy K and Malhotra SK 2000 Evaluation of PCD tool performance during machining of carbon/phenolic ablative composites J. Mater. Prod. Technology 104(1) 53–58
[7] Davim JP and Reis P 2004 Machinability study on composite (polyether-ether-ketone reinforced with 30% glass fibre– PEEK GF 30) using polycrystalline diamond (PCD) and cemented carbide (K20) tools Int. J. Adv. Manuf. Technology 23(5–6) 412–418
[8] Hocheng H and Tsao CC 2006 Effects of special drill bits on drilling-induced delamination of composite materials Int. J. Mach. Tool Manufacture 46(12–13) 1403–1416
[9] Endo H and Marui E 2005 Effect of the specimen geometry on wear – combination of polyacetal (POM) and carbon steel for machine structures Wear 258(10) 1525–1530
[10] Akira Kobayashi and Kenji Hirakawa 2006 Ultraprecision Machining of Plastics Part 1 Polymethyl Methacrylate Polymer-Plastic Tech. Engineering 22(1)1984 15-25
[11] Jagtap K and Pawade R 2014 Experimental investigation on the influence of cutting parameters on surface quality obtained in SPDTS of PMMA Intr. J. of Adv. Design and Manuf. Technology 7(2) 53- 58
[12] Mehdi Moghri, Milos Madic, Mostafa Omidi and Masoud Farahnakian 2014 Surface roughness optimization of polyamide-6/Nanoclay Nanocomposites using artificial neural network: genetic algorithm approach The Scientific World Journal 2014 1-7
[13] Paizun AA, Fathullah M, Abdullah MMA, Shayfull Z and Faheem Tahir 2019 Surface roughness optimization on rubberized fly ash geopolymer in lathe operation using Taguchi method AIP Conference Proceedings vol 2129 p 02018
[14] Manohar M, Jomy Joseph, Selvaraj T and Sivakumar D 2013 Application of Box Behnken Design to optimize the parameters for turning Inconel 718 using coated carbide tools Int. J. of Scient. & Engg. Research 4(4) 620
[15] Arifin N, Yusoff H, Sudin I, Kadir AZA, Ali R, Yacob S, Arshad A and Ismail SA 2016 Study the effect of CNC milling parameters on surface roughness of POM material ARPN J. Engg. and Applied Sciences 11(10) 6611-6614
[16] Montgomery D C 1997 Design and Analysis of Experiment (New York : Wiley)