INVESTIGATION AND ANALYSIS OF ELECTROCHEMICAL MACHINING OF 321-STAINLESS STEEL BASED ON RESPONSE SURFACE METHODOLOGY

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Abstract: *Electrochemical machining (ECM) is prevalent and competitive manufacturing process which uses for machining of hard and tough materials in high tech industries. Hence, experimental investigations on ECM of different materials play essential role to effectively utilize this process. This paper demonstrates a systematic approach for achieving comprehensive mathematical models in order to investigate the effect of machining parameters on the process responses of 321-Stainless-Steel and analysis of machining performance based on the response surface methodology (RSM). Machining voltage, tool feed rate, electrolyte flow rate and concentration of* $NaNO_3$ *solution were considered as the machining parameters while material removal rate (MRR) and surface roughness (*R_a*) were considered as the process responses. Experimental plan was performed by a central composite design (CCD), and the proposed mathematical models statistically have been evaluated by analysis of variance (ANOVA). Analysis shows that the RSM method has been appointed properly as the design of experiments (DOE) method for resolving curvature in ECM process responses. Also, the results show that the machining performance is greatly influenced by machining parameters. Especially the voltage and electrolyte concentration are the most important parameters.*

Keywords: electrochemical machining, modeling, material removal rate, surface roughness, response surface methodology

1. Introduction

ECM is a modern and non-traditional machining which contributes significantly in various industries from consumer product to more sophisticated, high-tech applications and to produce micro to macro scale products. Moreover, ECM gives advantages over other conventional and non-conventional machining processes. As a case in point, conductive materials regardless of their hardness and toughness can be machined with a tool which is not harder than workpiece and there is especially no tool wear. In view of the fact that in this cold process there is no contact between cathode and anode, products without any residual stress and heat affected zone (HAZ) can be machined [1].

Even though traditional methods for conducting experiments such as trial-and-error, best-guest approach and one variable at a time (OVAT) still common [2], these methods are time consuming and incapable of detecting the interactions between variables [3]. Thus, implementation of design-of-experiments (DOE) method has increased in various manufacturing processes [4]. Response surface methodology, RMS, is capable of resolving curvature in the output associated with each input, detecting interactions effects and establishing mathematical models with suitable sets of experiments [5].

However, the ECM process involves several physical and chemical phenomena and a number of process parameters that make it difficult to model the process [6]. Consequently, experimental investigations, DOE, statistical and optimization approaches play a vital part in selection of proper selection of parameters setting which influence the machining performance considerably [7, 8].

There are researches that had been investigated this process experimentally and offer some excellent results and approaches for modeling and predicting machining conditions; still, much more experimental studies must be conducted to cover wide range of materials and methods for optimization and improving machining performance [9].

The purpose of this research is investigating the effect of ECM process parameters, i.e. machining voltage (x_1), tool feed rate (x_2), electrolyte flow rate (x_3) and electrolyte concentration (x_4) on machining criteria, i.e. MRR and R_a of 321stainless steel. This kind of steel contains titanium which making it an excellent choice for prolonged high temperature applications such as aircraft exhaust stacks, manifolds, welded equipment, jet engine parts and so on. Response surface methodology (RSM) is also used for correlating and analyzing the various machining parameters on the response; therefore, mathematical models develop through RSM. In addition, the adequacy of the developed mathematical models has also been tested by the analysis of variance (ANOVA).

2. Experimental Procedure and Details

Set-up and machine:

The experiments were carried out on home-developed machine. This machine was set up in this investigation shows in Fig. 1 consists of four well-designed units, i.e. machine, electrolyte, control and power supply unit. The tool feeds forwards and backwards using the AC servo motor through a ground precision ballscrew with pitch of 2.5 mm and precision linear guides. Machining place was built by Plexiglas with a door provided more convenience for changing the workpiece. All used connectors, valves and hose made of 316 stainless steel, PVC and polyethylene; thus, the electrolyte composition does not change moving through these parts. Two PVC tanks have duty for supplying and storing electrolyte. Main pump with 3-ph AC motor and inverter provide setting electrolyte flow rate with help of ultrasonic flowmeter. Another magnetic pump used for draining electrolyte form storing tank to main supplying tank through filters. Output of power supply is 30 volt and 100 ampere.

Fig. 1 *The ECM machine.*

Materials and measurements:

Fig. 2 displays workpiece and tool with their fixtures in the machining chamber. Thirty-one 321stainless steel bars 8 mm in diameter specimens were used as workpiece for runs. Commercial cylindrical copper with the same diameter as workpiece were also employed as tool. As long as experiments conducted in stable conditions and with uniform initial gap distance, workpiece and tool were grinded and deburred to remove any possible surface irregularities to guarantee an even and parallel surfaces. The experiments were carried out in $NaNO_3$ solution electrolyte with various concentrations. The electrolyte flow system used in cross and planning method to ensure an effective flushing during machining. The weight of workpiece was measured before and after machining by a precision weighing machine (0.0001g) for calculating the material removal rate (MRR). The arithmetic mean roughness (R_a) was employed to evaluate surface roughness of specimens. This measurement was performed with the help of surface tester SJ-210-MITUTOYO. The cut-off length and measuring speed were set as 0.8 mm and 0.5mm/s respectively.

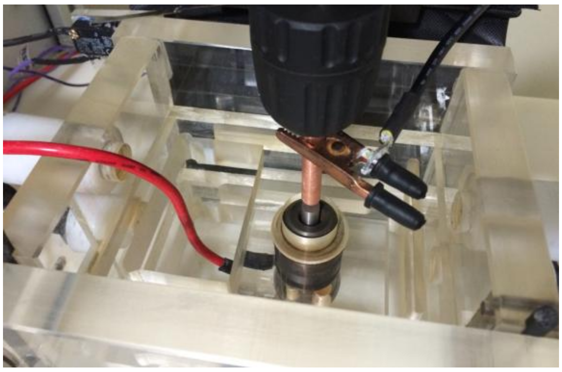

Fig. 2 *Machining chamber with workpiece and tool.*

3. Design of Experiments (DOE)

Experimental plan and conditions

The machining was carried out for a fixed time interval of 2 min and an initial gap distance was 0.6 mm. In the present study, the experimentation strategy was considered based on central composite second order rotatable design (CCD) for the purpose that the higher-order input parameters effects and their interactions on machining responses were determined. The values of four process inputs and their levels are shown in Table 1. Therefore, the design consists of 31 runs, in which 16 factorial points, 8 axial points, 7 center points for estimating the experimental error and the central composite parameter α was considered 2 to ensure a rotatable design. Table 3 presents the values of machining responses, i.e. MRR and Ra according to experimentation plan with various sets of machining parameters, i.e. voltage (x_1), tool feed rate (x_2), electrolyte flow rate (x_3) and electrolyte concentration (x_4). Fig. 3 shows the sample workpieces before and after machining.

Table 1: *The independent ECM process factors and their levels.*

Factors	Symbol	Unit	Levels				
			-2	-1	0	1	2
Voltage	x_1	V	10	15	20	25	30
Tool feed rate	x_2	mm/min	0.2	0.3	0.4	0.5	0.6
Electrolyte flow rate	x_3	l/min	5	6	7	8	9
Electrolyte concentration	x_4	g/l	50	100	150	200	250

Response Surface Methodology (RSM):

In this research, Response Surface Methodology (RSM) was applied, as one of DOE methods, for determining how the machining parameters influence machining responses. RSM is a powerful way for building the relationship between machining parameters and responses that are useful for the modeling and analysis of the problems; accordingly, the relationship mathematically and statistically could be developed by second-order polynomial as follows:

$$y = b_0 + \sum_i^k b_i x_i + \sum_i^k b_{ii} x^2 + \sum_i \sum_j b_{ij} x_i x_j + \varepsilon \qquad (1)$$

Fig. 3 *Workpiece after and before machining.*

Where y is the desired response, e.g. MRR and R_a in this paper, xi is the uncoded or coded levels of the independent variables, and ε is the fitting error. Also, the coefficient b0 is the constant value or intercept and the coefficients bi, bii and bij represent the linear, quadratic and interaction terms respectively [10].

Table 3: *Central composite design plan matrix and results.*

Exp. No.	Factors				Responses	
	x_1	x_2	x_3	x_4	MRR (g/min)	R_a(μm)
1	-1	-1	-1	-1	0.1253	0.76
2	1	-1	-1	-1	0.2134	1.08
3	-1	1	-1	-1	0.1547	0.89
4	1	1	-1	-1	0.2361	1.13
5	-1	-1	1	-1	0.1246	0.84
6	1	-1	1	-1	0.2107	1.16
7	-1	1	1	-1	0.1569	0.96
8	1	1	1	-1	0.2525	1.31
9	-1	-1	-1	1	0.1673	1.29
10	1	-1	-1	1	0.2921	1.94
11	-1	1	-1	1	0.1975	1.63
12	1	1	-1	1	0.3218	2.21
13	-1	-1	1	1	0.1779	1.47
14	1	-1	1	1	0.2979	2.15
15	-1	1	1	1	0.2019	1.78
16	1	1	1	1	0.3235	2.49
17	-2	0	0	0	0.1154	1.22
18	2	0	0	0	0.3379	2.17
19	0	-2	0	0	0.1989	1.12
20	0	2	0	0	0.2755	1.51
21	0	0	-2	0	0.1927	1.12
22	0	0	2	0	0.2194	1.35
23	0	0	0	-2	0.1365	0.72
24	0	0	0	2	0.2696	2.45
25	0	0	0	0	0.2351	1.00
26	0	0	0	0	0.2291	0.98
27	0	0	0	0	0.2250	1.02
28	0	0	0	0	0.2238	0.96
29	0	0	0	0	0.2220	1.04
30	0	0	0	0	0.2275	0.95
31	0	0	0	0	0.2232	1.02

4. Validation and Analysis of Models

Adequate and suitable measures, tests and analyses were examined the models, so the fitness of the models to the experimental data, significant and insignificant parameters and adequacy of models were analyzed; that is, the analysis of variance (ANOVA) and the F-ratio test have been executed to check the goodness of the mathematically modeled fittings. Moreover, the R-squared (R-Sq) and adjusted R-squared (R-Sq(adj)) is used for assessing the modeling goodness of fit, as more the R^2 approaches unity, the better the model fits the experimental data. Indeed, the best condition of analysis of effective models happens as the lack-of-fit is insignificant. Then, a student's t-test has also been performed for determining the significance of each parameter in the models. Accordingly, insignificant terms have been eliminated from the models, and ANOVA has been done again through the available significant terms.

Mathematical modeling of MRR:

According to the model explained by Eq. 1, Table 3 details the ANOVA and F-ratio test information about MRR response. On the grounds that the p-value of the quadratic model is greatly less than 0.05, the model is statistically significant in the 95% of confidence interval. Besides, the p-value of the lack-of-fit is more than 0.05, so this term is insignificant which is desired. Through the ANOVA result, the MRR model is developed with coded variables as follows:

$$\begin{aligned} MRR = &-0.3374 + 0.0055x_1 - 0.0496x_2 + 0.0755x_3 \\ &+ 0.00072x_4 - 1.4494E-05x_1^2 + 0.2275x_2^2 \\ &- 0.00551x_3^2 - 2.50494E-06x_4^2 + 0.00049x_1x_2 \\ &+ 5.875E-05x_1x_3 + 3.4875E-05x_1x_4 \\ &+ 0.0073x_2x_3 - 2.0875E-04x_2x_4 + 9.125E-06x_3x_4 \qquad (2) \end{aligned}$$

The R^2 (R-Sq) and adjusted R^2 (R-Sq(adj)) are respectively 99.48% and 99.03% for the above MRR model ensuring an excellent fitting for the model. A student's t-test has also been performed for the determination of significant terms in the MRR model. It is concluded that all the linear terms, quadratic terms of input factors x_2, x_3 and x_4, and interaction effect of factors x_1 and x4 are significant, and other terms are insignificant. The insignificant terms have been eliminated; the ANOVA have again been done to significant terms. As a result, the final reduced model of MRR based on significant parameters is developed as follows:

$$\begin{aligned} MRR = &- 0.35879 + 0.00549x_1 - 0.02305x_2 + 0.08043x_3 \\ &+ 0.00069x_4 + 0.23137x_2^2 - 0.00547x_3^3 - 2.48952E \\ &- 06x_4^4 + 3.48750E-05x_1x_4 \qquad (3) \end{aligned}$$

Table 3: *The ANOVA results for MRR response using the Minitab software.*

Source of variation	**DF**	**Sum of Squares**	**Mean Squares**	**F value**	**P value**
Regression	14	0.103873	0.007419	219.16	0.000
Linear	4	0.100478	0.025120	742.00	0.000
Square	4	0.002148	0.000537	15.85	0.000
Interaction	6	0.001216	0.000208	6.14	0.002
Residual Error	16	0.000542	0.000034		
Lack-of-Fit	10	0.000419	0.000042	2.06	0.195
Pure Error	6	0.000122	0.000020		
Total	30	0.104414			
R-Sq = 99.48%, R-Sq(adj) = 99.03%					

Mathematical modeling of R_a:

The same procedure is used to deal with the R_a and the ANOVA details of quadratic model are shown in Table 4. The results of the table points out that the model is significant and the lack-of-fit is insignificant according to the p-values. Based on the ANOVA result, the developed mathematical model for R_a with coded variables as follows:

$$\begin{aligned} Ra = &8.75714 - 0.29921x_1 - 7.01905x_2 - 0.91042x_3 - 0.0234x_4 + 0.0069x_1^2 \\ &+ 7.74256x_2^2 + 0.05743x_3^2 + 5.79702E-05x_4^2 - 0.01125x_1x_2 + 0.00338x_1x_3 \\ &+ 0.00035x_1x_4 + 0.08125x_2x_3 + 0.01013x_2x_4 + 0.00051x_3x_4 \qquad (4) \end{aligned}$$

The R^2 and adjusted-R^2 for the R_a trimmed model are respectively 99.82% and 99.67% revealing sufficient adequacy in model predictive capabilities. The student's t-test has also been done for determining the significance of each parameter. The results of this test indicate that all linear and quadratic terms of parameters and the interaction between x_1 (voltage) and x_3 (flow rate), x_1 and x_4 (concentration), x_2 (tool feed rate) and x_4, and x_3 and x_4 are significant. The other model terms can be regarded as insignificant terms. By removing these insignificant terms and applying the ANOVA, the proper quadratic model for R_a can be developed as follows:

$$\begin{aligned} Ra = &8.61964 - 0.303714x_1 - 6.6753x_2 - 0.87792x_3 - 0.0234x_4 + 0.0069x_1^2 + 7.74256x_2^2 \\ &+ 0.05743x_3^2 + 5.79702E-05x_4^2 + 0.00338x_1x_3 + 0.00035x_1x_4 + 0.01013x_2x_4 + 0.00051x_3x_4 \qquad (5) \end{aligned}$$

Table 4: *The ANOVA results for R_a response using the Minitab software.*

Source of variation	**DF**	**Sum of Squares**	**Mean Squares**	**F value**	**P value**
Regression	14	7.73831	0.55274	648.07	0.000
Linear	4	6.16678	1.54170	1807.59	0.000
Square	4	1.39314	0.34828	408.35	0.000
Interaction	6	0.17839	0.02973	34.86	0.000
Residual Error	16	0.01365	0.00085		
Lack-of-Fit	10	0.00688	0.00069	0.61	0.767
Pure Error	6	0.00677	0.00113		
Total	30	7.75195			
R-Sq = 99.82%, R-Sq(adj) = 99.67%					

5. Results and Discussion

Effect of machining parameters on MRR:

Fig. 4 displays the surface and contour plot of the MRR response versus the voltage (x_1) and concentration (x_4) factors, while the tool feed rate and electrolyte flow rate factors held at middle level (0.4 mm/min and 7 l/min). The result showed that an increase in voltage and concentration leads to increase in the MRR. This is supported by the fact that by increasing both of these factors results in a higher electrolyzing current in machining gap and causing faster dissolution.

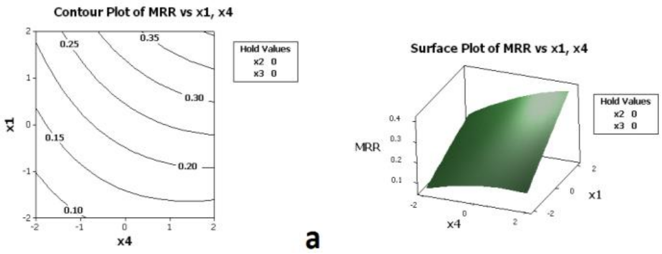

Fig. 4 *Surface and Contour Plot of MRR: MRR: Voltage (x_1) and Concentration (x_4).*

Moreover, Fig. 5 illustrates the surface and contour plot of the MRR response in term of voltage and flow rate of electrolyte at a constant level of sources tool feed rate and concentration kept at zero level (0.4 mm/min and 150/l). As it is shown in this Figure, high removal rate are achievable at high voltage along at low and high level of flow rate.

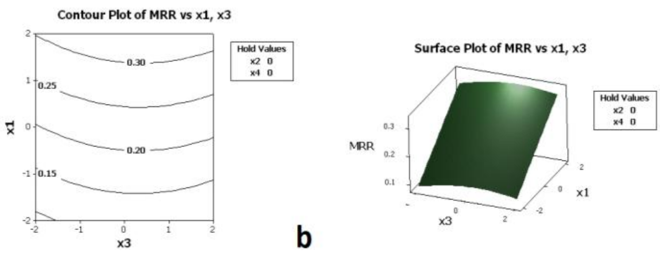

Fig. 5 *Surface and Contour Plot of MRR: MRR: Voltage (x_1) and Flow rate (x_3).*

Same trend can be deduced form Fig. 6. This Figure is the surface and contour plot of the MRR response versus concentration and flow rate of electrolyte at middle level of other factors. Increasing in voltage and concentration at low level of electrolyte flow rate causes steady flow of electrolyte and at high level of electrolyte flow rate causes better flushing in machining gap; thus, the conductivity and as a result the current density increase which causes high metal dissolution.

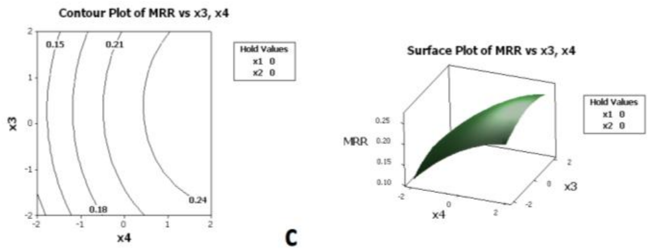

Fig. 6 Surface and Contour Plot of MRR: Flow rate (x_3) and Concentration (x_4).

Effect of machining parameters on R_a:

Fig. 7 displays the R_a response based on the voltage (x_1) and electrolyte flow rate (x_3) and the value of tool feed rate and electrolyte concentration were kept fixed at zero level. Analyzing the 3D surface plot, it concluded that high level of voltage and electrolyte flow rate deteriorate the surface finish. Also, by increasing the electrolyte flow and decreasing the voltage, the surfaces finish boots. As by increasing in voltage, the metal dissolution grows then faster flow of electrolyte helps the proper flushing of electrolyte in the IEG. From the contour plot, it is noted that for improving the better surface quality, choosing the voltage and flow rate of the electrolyte in middle to low level gives better selections.

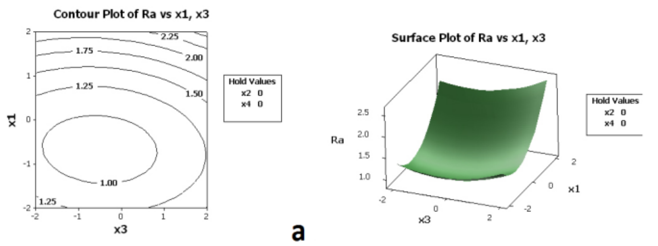

Fig. 7 Surface and Contour Plot of R_a: Voltage (x_1) and Flow rate (x_3).

Furthermore, the surface and contour plot of R_a response versus the voltage (x_1) and electrolyte concentration (x_4) at zero level of tool feed rate and electrolyte flow rate is shown in Fig. 8. It can be inferred that the surface finish gets better condition as the voltage and the electrolyte concentration decreasing. The electrolyte concentration in this study was considered in wide range from 50 g/l to 250 g/l. From the surface plot it can be concluded that at the high level of voltage and concentration lead the worst surface finish. Also, the contour plot shows that the concentration between 50 to 100 g/l and decreasing in the machining voltage from middle to low level provide the best selection for these inputs parameter on the R_a response.

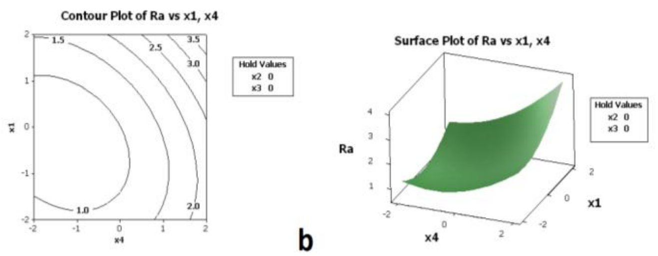

Fig. 8 Surface and Contour Plot of R_a: Voltage (x_1) and Concentration (x_4).

Fig. 9 shows the effect of the electrolyte flow rate (x_3) and the electrolyte concentration (x_4) parameters on the R_a response as 3D surface and contour plot while the other two parameters, voltage and tool feed rate, held at middle level. As can be seen from these Figures, the better surface finish is occurred at low level of concentration. Also, the low level of flow rate and high level of concentration worsen the surface finish greatly since at this condition, the poor flushing of electrolyte in the inter electrode gap (IEG) results in higher R_a.

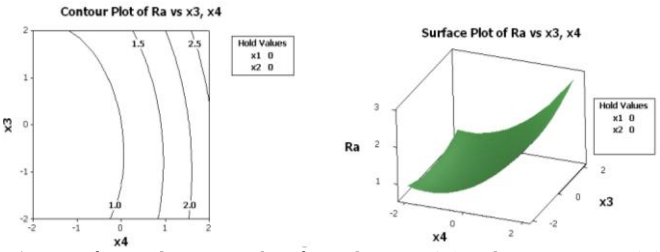

Fig. 9 Surface and Contour Plot of R_a: Flow rate (x_3) and Concentration (x_4)

6. Conclusions

This study highlights that the electrochemical machining of 321 stainless steel criteria, i.e. MRR and Ra are greatly influenced by the different machining parameters. To sum up, the followings can be acquired from this investigation as main findings:

- ❖ For gaining the model that covers all linear, quadratic and interaction terms, the RSM method has been appointed properly as the DOE method for resolving curvature in ECM process responses.
- ❖ Mathematical models have been developed through the RSM method for correlation the machining parameters, i.e. voltage, tool feed rate, electrolyte flow rate and concentration on the machining criteria, i.e. MRR and Ra, of 321 stainless steel.
- ❖ According to the ANOVA and student t-test, among the process parameters, the machining voltage and electrolyte concentration are the most effective factors on the machining criteria.
- ❖ Increasing voltage and electrolyte concentration lead to increase in the MRR. Also, the proper flushing of electrolyte improves MRR which can be regulated by the electrolyte flow rate.
- ❖ According to the wide range of voltage (10 – 30 v) and electrolyte concentration (50 – 250 g/l NaNO3 solution), the surface quality is improved by decreasing in voltage and decreasing in concentration.

REFERENCES

1. Rumyantsev, E. & Davydov, A. (1989). Electrochemical machining of metals, MIR Publishers, Moscow, Russia.
Int J Adv Manuf Technol, Vol. 69, pp. 563–581.
2. Neto, J.C.S., Silva, E.M. & Silva M.B. (2006). Intervening variables in electrochemical machining. J Mater Process Technol, Vol. 179, pp. 92–96.
3. Montgomery D.C. (2009). Design and analysis of experiments. New York: John Wiley.
4. Singh, G.K., Yadava, V. & Kumar, R. (2010). Multiresponse Optimization of Electro-Discharge Diamond Face Grinding Process Using Robust Design of Experiments. Mater Manuf Processes, Vol. 25(8), pp. 851-856.
5. Moradi, M., Ghoreishi, M., Frostevarg, J. & Kaplan, A.F.H. (2013). An investigation on stability of laser hybrid arc welding. Optics and Lasers in Engineering, Vol. 51, pp. 481–487.
6. Haridy, S., Gouda, S.A. & Wu, Z. (2011). An integrated framework of statistical process control and design of experiments for optimizing wire electrochemical turning process. Int J Adv Manuf Technol, Vol. 53, pp. 191–207.
7. Hwang Y. K. & Lee C. M., (2010). Surface roughness and cutting force prediction in MQL and wet turning process of AISI 1045 using design of experiments. J. Mech. Sci. Technol. Vol. 24, pp. 1669-1677.
8. Venkata Rao, R. & Kalyankar, V.D. (2014). Optimization of modern machining processes using advanced optimization techniques: a review. Int J Adv Manuf Technol, Vol. 73, pp. 1159-1188.
9. El-Taweel & T. A. (2008). Modelling and analysis of hybrid electrochemical turning-magnetic abrasive finishing of 6061 Al/Al2O3 composite. Int J Adv Manuf Technol, Vol. 37, pp. 705–714.
10. Myers, R.H. & Montgomery D.C. (1995). Response surface methodology: process and product optimization using designed experiments. New York: Wiley.