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RESEARCH

Multi-Objective Optimization of Sustainable Steel AISI 1045 Turning Energy Parameters Under MQL Condition

Branislav Sredanovic[a,*], Djordje Cica[a], Stevo Borojevic[a], Sasa Tesic[a], Davorin Kramar[b]

[a]*University of Banjaluka, Faculty of Mechanical Engineering, Stepe Stepanovića 75, Banja Luka, Bosnia and Herzegovina,*
[b]*University of Ljubljana, Faculty of Mechanical Engineering, Aškerčeva 6, 1000 Ljubljana, Slovenia.*

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* Corresponding author:

Branislav Sredanović
E-mail:
branislav.sredanovic@mf.unibl.org

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A B S T R A C T

Sustainable production requires reducing of production waste, energy consumption, and more efficient machining processes. However, in machining must be introduced advanced techniques for cooling and lubrication of cutting zone. An advanced techniques is minimum quantity lubrication (MQL), can be considered as a step towards sustainable machining. However, it is important to analyze cutting processes regard to energy consumption indicators, especially when machining materials that have a wide range of applications, such AISI 1045. In this study, the influence of process parameters on turning energy performance during turning of mentioned steel under MQL lubrication conditions were investigated. Full experiment plan was used, ANOVA was used for effect analyze, and RSM was used for modelling. Multi-objective optimization of process parameters, based on minimizing energy indicators, was performed. Procedure was defined cutting speed of 210 m/min, depth of cut of 1.5 mm, and feed rate of 0.224 mm/rev as optimal parameters. These parameters and MQL conditions can be used to get minimum energy indicators in AISI 1045 turning, especially in large-scale production.

1. INTRODUCTION

Traditionally, cutting cooling and lubrication fluids (CFL) are applied to increase the efficiency and performance of the machining processes. In other hand, it causes environmental problems due to chemical contents. In manufacturing, costs relating to using this fluids are about 7-17% of the total costs in machining process [1]. In order to eliminate the negative effects of CFL, the machining industries are continually seeking for new and improved current cooling and lubricating techniques by taking into account the environmental and financial issues. In the past years, a tremendous effort has been made to minimize or even completely avoid usage of cutting fluids. Minimum quantity of lubrication (MQL) have been proposed as a good alternative between completely dry and fully wet machining. MQL is one of the most adequate replacements for current flooding techniques in order to reduce the amount of lubricant due better economic,

environmental and process performance [2]. The use of MQL can reduce the wastages of cutting fluid by several times as compared with flood cooling [3]. Its application in turning process has been investigated by many researchers. In a general, machining using MQL offers several advantages over dry and wet machining, such as improved tool life [4, 5], low cutting temperature [6], improve dimensional accuracy [7], reduced cutting forces [8, 9], improved surface quality [10], and material machinability [11]. In addition, the MQL improve the surface topography [12].

Different studies have focused on employing different techniques to optimize MQL assisted turning. Anamalai et al. [13] performed multi-objective optimization during turning of SUS 304 stainless steel with bio-inspired nanofluid based MQL. Minimum cutting temperature and maximum heat transfer were selected as the optimization criteria. Revuru et al. [14] optimized turning titanium alloy under dry and MQL conditions using Taguchi analysis, based on the effects of machining parameters on cutting force, tool wear and surface quality. Suneesh and Sivapragash [15] optimize surface quality, cutting force, specific power consumption and cutting temperature in turning of a magnesium-alumina composite under dry and MQL cutting conditions. Mia et al. [16] studied the surface quality in MQL assisted turning of high hardness steel, with developing the predictive and optimization model. Tamang et al. [17] investigated the effect of cutting parameters on tool wear, surface quality and cutting power in dry and MQL machining conditions. Sarıkaya and Güllü [18] analyzed the effect of the machining parameters such as cutting speed, feed rate and depth of cut on surface roughness when turning of AISI 1050 steel under dry, wet, and MQL condition. Optimal level of process parameters was determined using the S/N ratio and desirability function analysis. Sohrabpoor et al. [19] applied grey relational analysis for optimizing machining conditions in MQL assisted turning by multiple performance characteristics. Thakur et al. [20] utilized Taguchi method to determine the best combination of the process parameters in MQL assisted high speed turning of superalloy Inconel 718. Comparison of different modeling methods were analyzed by Bustillo et al. [21]. They conducted experiments under dry, MQL, and flooding condition. They concluded that machine-learning techniques can be used for cutting process modeling. Pimenov et al. [22], were studied optimum condition in milling AISI 1045, based on minimization of energy consumption and tool wear, and maximization of productivity. For it, they are employed grey relational analysis. MQL with nanoparticle, regard turning sustainability, was analyzed by Abbas et al. [23]. There are concluded benefits of using nanoparticle. Influence of nanoparticle in MQL on surface roughness, in case of highest cutting speed was analyzed by Şafak and Kaçal [24]. In [25], Abbas et al. used artificial neural network with Edgeworth-Pareto method for obtaining of optimal parameters in face milling. Kuntoğlu et al. [26] used improved nature-inspired method H-ABC, and compared it with standard methods of optimization. In this study, productivity and cutting forces was base for optimal parameters obtaining.

From previous studies it was found MQL has a significant role in order to towards sustainable machining. In this present paper, higher value of cutting speeds and feed rates were used, due to increase productivity in turning of steel AISI 1045 under MQL conditions. Main target is investigation of energy indicators for this higher values, and finding sustainable condition. The influence of process parameters, as most easily managed parameters, on energy performance characteristics as machining force, cutting power and cutting pressure were studied. Afterwards, the simultaneous optimization of process parameters based on minimizing energy performance was performed.

2. EXPERIMENTAL SETUP

In this research, process parameters, cutting speed (v), depth of cut (a) and feed rate (f), were considered as controlling factors, and changed on three level each. Full experimental plan as L27 orthogonal array with three columns for controlled factors, and twenty-seven rows for their combinations, was used in the present analysis. This full plan of experiment was chosen due to obtaining more precise cutting process energy indicators models. More precise models are a better basis for optimization and installation in control systems. Table 1 shows the cutting parameters and their levels for the experiments. The levels of cutting parameters where chosen according to the cutting tool and machine tool specifications.

Table 1. The process parameter and their levels.

Code	Control factors	Unit	Level		
			1	2	3
A	Cutting speed	m/min	210	320	400
B	Depth of cut	mm	1.5	2.0	2.5
C	Feed rate	mm/rev	0.224	0.280	0.355

Turning experiments were performed in MQL conditions using a universal lathe Boehringer with 8 kW spindle power. During turning trials, MQL flow rate were and air pressure of MQL system were 30 ml/h and 0.3 MPa, respectively. The mixture of pressurized air and cutting fluid were supplied to the cutting zone through the nozzle. Nozzle was located 30 mm away from tool tip, at an angle of 90° of the cutting edge, and at angle of 30° from clearance face. In this way, needed lubricating is provided.

The chosen coated carbide insert was SNMG 120408. The cutting insert is square shaped with 0.8 mm nose radius and with simple chip breaker. Rake angle of tool was γ = 10°, clearance angle was α = 10° defined by tool holder. Tool holder is codified as PSDN R 2525 M12, which forming entering angle of κ = 45°. The experimental setup on machine tool, work material, cutting tool, and MQL system, dynamometer is displayed in Fig. 1.

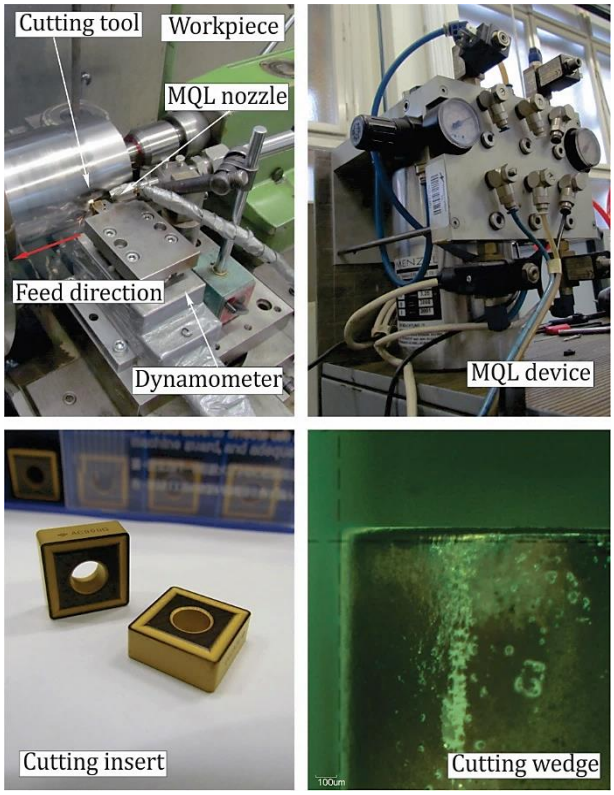

Fig. 1. Experimental setup.

The workpiece material was carbon steel AISI 1045, cold drawn, which chemical composition is given in Table 2. Workpiece material had tensile strength of 820 N/mm^2, and converted hardness 42 HRc. The workpiece geometry was cylindrical, with diameter of 220 mm and overhang length 350 mm. I was fixed in standard lathe jaws, and bolstered by lathe spike, on other end.

Table 2. Steel AISI 1045 chemical composition.

Element	C	Si	Mn	Cr	Mo	Ni
%	0.46	0.40	0.65	0.40	0.10	0.40

The three components of the cutting forces, mutually perpendicular, and defined as main cutting force (F_c), feed force (F_f) and passive force (F_p), were recorded using a three-component Kistler 9259A dynamometer. The measurement chain also involves the charge amplifier (Kistler 5001), spectrum analyser (HP3567A) and personal computer for data acquisition and analysis. The standard piezo-effect dynamometer was rigidly mounted on the lathe using a custom designed adapter. The cutting force components was coincided with the lathe and workpiece axes. Main cutting forces was measured in direction of cutting speed vector, feed force was measured in direction of feed rate velocity, and passive force in normal direction on workpiece z-axis. Experimental runs were repeated two or three time, and the mean value was recorded. Every run is performed on 30 seconds of machining time, which gave enough time for the signal stabilisation. The machining force (F_R), cutting power (P_c) and cutting pressure (K_s) are defined in form of the following equations [27]:

$$F_R = \sqrt{F_c^2 + F_f^2 + F_p^2} \tag{1}$$

$$P_c = F_c \cdot v \tag{2}$$

$$K_s = \frac{F_c}{a \cdot f} \tag{3}$$

Cutting power describes converted energy per time, which used in chip separation process, and there is formulated as depending on velocity of main movement and force in direction of main movement. It is analysed as the very important part of tool machine total energy consumption, which can be measured by special electric devices. Cutting pressure is mechanical pressure on cutting tool edge area, and can be connected with stress in cutting tool material.

3. RESULTS AND DISCUSSION

In Table 3 results of cutting force component measuring are shown. Values of machining force, cutting power, and cutting pressure are calculated. Analysis of variance (ANOVA), as common statistical method, was employed for analysis of experimental results. In it, machining force, the cutting power, and the cutting pressure models were made based on least square method, and analysing the influence of cutting speed (v), depth of cut (a) and feed rate (f) on the results. Tables 4-6 show statistics for F_R, P_c and K_s, respectively. ANOVA was carried out for a 5% significance level, i.e., for a 95% confidence. This is to be noted that the tables include only those model coefficients whose effects on the results are statistically significant (P-value < 0.05).

Table 3. Experimental results.

Rn	*a* (mm)	*v* (m/min)	*f* (mm/rev)	F_c (N)	F_f (N)	F_p (N)
1	2.5	210	0.224	1203	551	400
2	2.5	210	0.280	1404	592	446
3	2.5	210	0.355	1800	696	551
4	2.5	320	0.224	1195	544	403
5	2.5	320	0.280	1388	582	453
6	2.5	320	0.355	1755	657	543
7	2.5	400	0.224	1205	576	441
8	2.5	400	0.280	1384	601	482
9	2.5	400	0.355	1752	664	578
10	2.0	210	0.224	995	477	358
11	2.0	210	0.280	1156	511	398
12	2.0	210	0.355	1469	568	475
13	2.0	320	0.224	964	359	286
14	2.0	320	0.280	1145	489	394
15	2.0	320	0.355	1446	535	467
16	2.0	400	0.224	972	427	342
17	2.0	400	0.280	1130	460	382
18	2.0	400	0.355	1422	500	451
19	1.5	210	0.224	825	417	339
20	1.5	210	0.280	939	442	362
21	1.5	210	0.355	1187	477	420
22	1.5	320	0.224	785	391	325
23	1.5	320	0.280	907	410	351
24	1.5	320	0.355	1136	445	412
25	1.5	400	0.224	735	318	283
26	1.5	400	0.280	849	343	316
27	1.5	400	0.355	1085	379	370

Table 4 presents the ANOVA data of machining force. The model F-value of 788.14 implied that the model is significant. Additional important coefficient in ANOVA analysis is determination coefficient (R^2), which represent the ratio of the explained variation to the total variation and is a measure of the degree of fit. When this coefficient approaches unity, the better the response model fits the actual data. The R^2 value for machining force model is 0.9966, indicating that the model represents 99.66% of the variability of machining force. Moreover, the value of adequate precision (AP) is also frequently used to test the adequacy of developed models. Adequate precision measures the signal to noise (S/N) ratio and value of ratio greater than 4 is desirable. Ratio of 94.621 indicates an adequate signal for developed model. The table suggests that the significant model terms can be arranged in the following order of decreasing significance of their effects: a, f, $a\times f$, v, $v\times a$, f^2 and a^2. However, the effect of depth of cut is the most significant factor associated with machining force.

Table 4. The ANOVA table for machining force.

Source	Sum of squares	DF	*F* value	*P* value
Model	$2.581\cdot10^6$	7	788.14	<0.0001
v	20002.55	1	42.76	<0.0001
a	$9.691\cdot10^5$	1	2071.71	<0.0001
f	$2.011\cdot10^5$	1	429.89	<0.0001
v×a	11160.33	1	23.86	0.0001
a×f	40095.12	1	85.71	<0.0001
a^2	2904	1	6.21	0.0221
f^2	8632.89	1	18.45	0.0004
Residual	8888.23	19		
Total	$2.59\cdot10^6$	26		

Table 5 presents the details of ANOVA applied on the cutting power data. The model F-value of 2562.1 implies the model is significant. The values were obtained as follows: R^2 = 0.9989 and AP = 191.926, which demonstrate that the developed model is reliable and could be used effectively for predicting the cutting power within the domain of the turning parameters. It suggests that the three influential interactions and one significant quadratic term can be arranged in the following order of descending significance: v, a, f, $v\times a$, $v\times f$, $a\times f$, and f^2. Cutting speed followed by the depth of cut are two dominant contributors to the cutting power.

Table 6 presents the details of ANOVA applied on the cutting pressure data. The model F-value of 83.71 implies the model is significant because there is less than 0.01% chance that this model F-value occurred due to noise. The R2 value is very high (R^2 = 0.9617), which is desirable. Also, the value of adequate precision (AP = 31.846) is

satisfactory. The table suggests that the predictors, one significant interactions and two significant quadratic term can be arranged in the following order of decreasing significance of their effects: a, f^2, v, $v\times a$, f and a^2. It can be noted that the depth of cut is the most important factor affecting cutting pressure.

Table 5. The ANOVA table for cutting power.

Source	Sum of squares	DF	*F* value	*P* value
Model	121.22	7	2562.1	<0.0001
v	37.86	1	5602.08	<0.0001
a	21.5	1	3181.21	<0.0001
f	5	1	739.96	<0.0001
v×a	3.02	1	446.62	<0.0001
v×f	1.36	1	201.25	<0.0001
a×f	0.9	1	133.31	<0.0001
f^2	0.25	1	36.88	<0.0001
Residual	0.13	19		
Total	121.34	26		

Table 6. The ANOVA table for cutting pressure.

Source	Sum of squares	DF	*F* value	*P* value
Model	$3.508\cdot10^5$	6	83.71	<0.0001
v	46749.67	1	66.93	<0.0001
a	$1.183\cdot10^5$	1	169.37	<0.0001
f	8561.01	1	12.26	0.0023
v×a	28254.55	1	40.45	<0.0001
a^2	7116.23	1	10.19	0.0046
f^2	49349.76	1	70.65	<0.0001
Residual	13969.47	20		
Total	$3.648\cdot10^5$	26		

3.1 Effects of turning parameters on the response factors

Based on the experimental result and after determining the significant terms, the second order (quadratic) response surface methodology (RSM) models were formulated. Mathematical models for the response variables, machining force, cutting energy and cutting pressure in terms of cutting speed, depth of cut and feed rate are given by Eq. (4), Eq. (5) and Eq. (6), respectively.

$$F_R = 1760.18 - 1.628\cdot v - 488.04\cdot a - 5105.3\cdot f + 0.64\cdot v\cdot a + 1758.8\cdot a\cdot f + 88\cdot a^2 + 9063\cdot f^2 \quad (4)$$

$$P_c = 9.77 - 0.0178\cdot v - 2.95\cdot a - 43.344\cdot f + 0.011\cdot v\cdot a + 0.054\cdot v\cdot f + 8.34\cdot a\cdot f + 48.7\cdot f^2 \quad (5)$$

$$K_s = 5858.36 - 2.57\cdot v - 1023.78\cdot a - 13790.8\cdot f + 1.02\cdot v\cdot a + 137.76\cdot a^2 + 21668.8\cdot f^2 \quad (6)$$

In this part of study, 3D plots for the models responses were plotted based on the developed RSM models (Eqs (4) to (6)) in order to examine the effect of turnng parameters on individual response. Fig. 2 illustrates the two-factor interaction effects of cutting parameters on machining force.

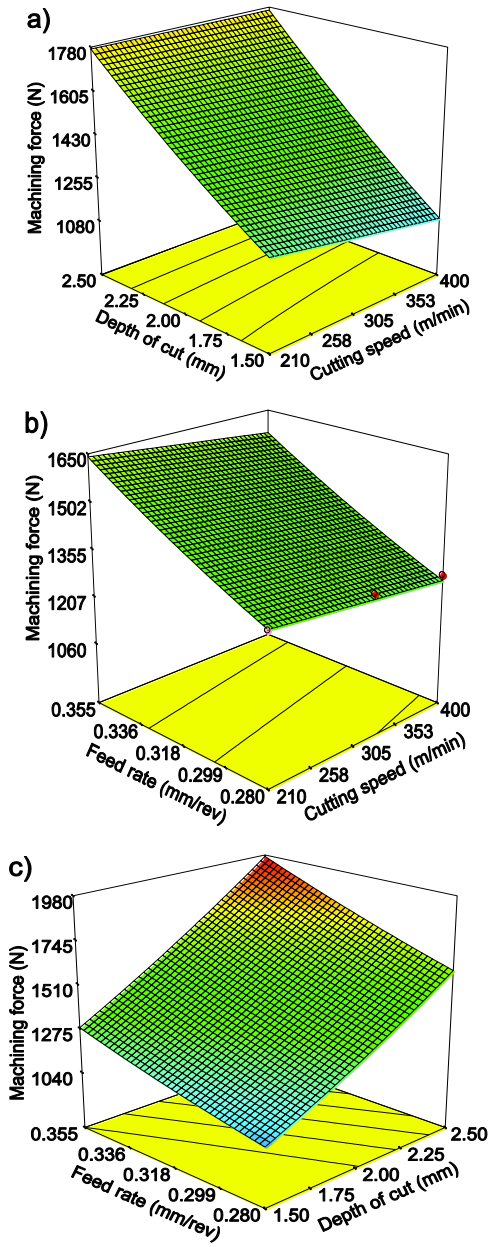

Fig. 2. Interaction effects of cutting parameters on machining force for: a) feed rate of 0.280 mm/rev, b) depth of cut 2 mm, c) cutting speed 210 m/min.

As seen from Fig. 2(a), the machining force is low when the depth of cut is at low level for all the values of cutting speed. Furthermore, for any given depth of cut, the machining force does not vary considerably with variations in cutting speed. The machining force is very sensitive to

feed rate variations at all values of cutting speed. As observed from Fig. 2(b), it can be seen that, the machining force is highly sensitive to feed rate variations as compared to cutting speed. Fig. 2(c) shows the effect of feed rate and depth of cut on machining force. It is clearly evidenced from these figure that the machining force is minimal at low values of both the feed rate and depth of cut. Further, the machining force is more sensitive to depth of cut variations compared to feed rate effect. According to the previous analysis, Table 3 indicates that the effect of depth of cut on machining force has a highest statistical importance. Hence, by combining the aforementioned interaction effects, it is evident that the selection of low values of depth of cut and feed rate are necessary for minimizing the machining force. Previously assertions is in accordance with the physics of the chip separation process. By increasing the depth of cut and the feed rate, a larger chip cross section is obtained, which leads to a higher load on the cutting tool, i.e. an increase in the cutting forces. The depth of the cut has a greater influence due to the direct connection with the separated chip width, and the chip shear plane width. Influence of depth of cut has linear functionality, and influence of feed rate has linear functionality almost. The increase of the machining cutting force caused by the increase of the cutting speed is a consequence of the absence of workpiece material built up edge on the cutting tool wedge, and the faster flow of separated chip over the rake surface of the tool. The decrease of machining force due to the increase in cutting speed is more pronounced for larger feed rates.

Fig. 3 shows the effects of two factor interactions on cutting power. Figure 3(a) exhibits the estimated response surface for cutting power in relation to the process parameters of depth of cut and cutting speed. It is obvious that the power is highly sensitive to depth of cut as well as cutting speed variations. Further, it is also observed that the cutting power is also highly sensitive to cutting speed (Fig. 3(b)) and depth of cut (Fig. 3(c)) variations for a specified feed rate. The minimum cutting power is required at low values of depth of cut, cutting speed and feed rate. Thus, the cutting power can be controlled by appropriately setting these cutting parameters. Compared to the machining force, the cutting power has a slightly different behaviour depending on the process parameters. It is clear from the definition of power, that an increase in speed significantly affects the increase in cutting power, due to the multiplication of machining force and cutting speed. The increase in the depth of cut, and especially the feed rate, have a slightly smaller effect than the cutting speed, because its influence is contained in the force. The influences of the process parameters have an almost linear dependence.

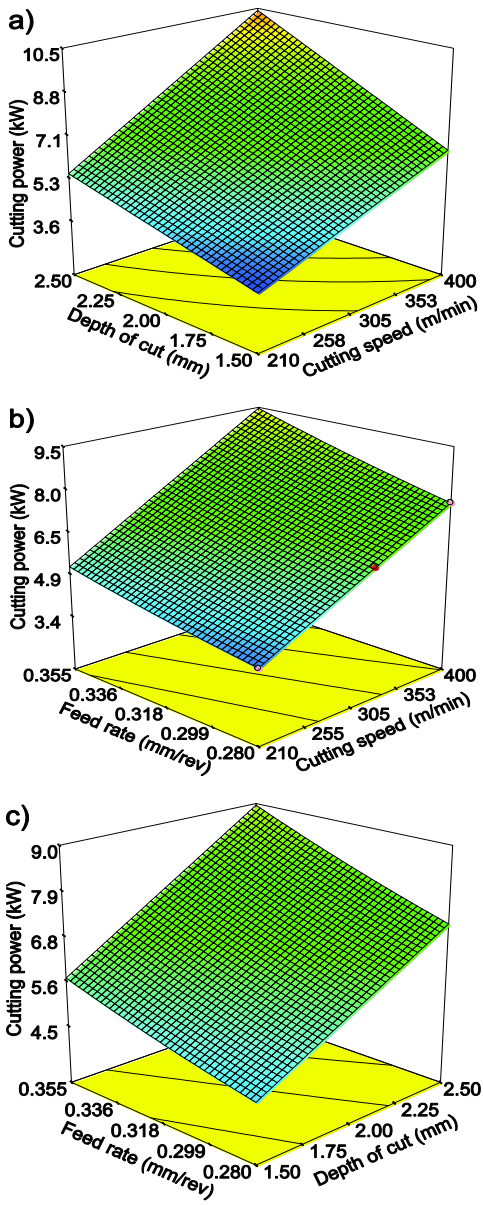

Fig. 3. Interaction effects of cutting parameters on cutting power for: a) feed rate of 0.280 mm/rev, b) depth of cut 2 mm, c) cutting speed 210 m/min.

The response surface plots showing the interaction effects of turning parameters on cutting pressure is shown in Fig. 4. As seen in Fig. 4(a), with high depth of cut and cutting speed, the cutting pressure can be reduced. It is evident from Fig. 4(b) that the cutting pressure will be

minimal at higher cutting speed for middle value of feed rate. The effects of feed rate and depth of cut on cutting pressure are shown in Fig. 4(c). It is obvious that depth of cut strongly influenced cutting pressure and that cutting pressure decreases with the increase in depth of cut.

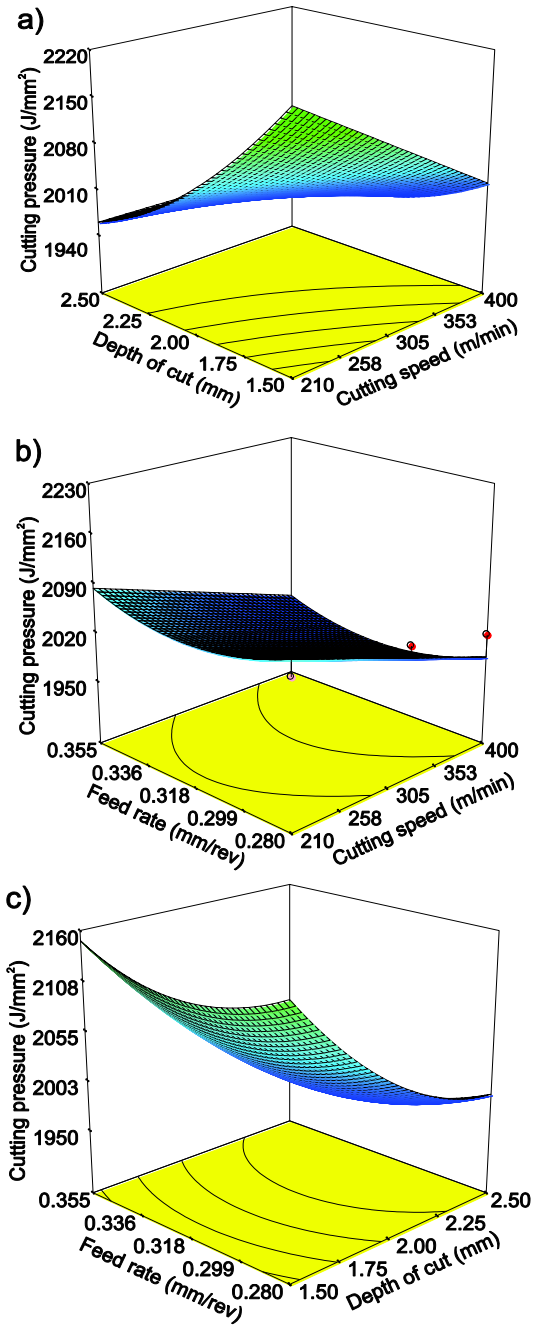

Fig. 4. Interaction effects of cutting parameters on cutting pressure for: a) feed rate of 0.280 mm/rev, b) depth of cut 2 mm, c) cutting speed 210 m/min.

The cutting pressure is directly related to the tool wear mechanism and tool life. The effects of pressure parameters are nonlinear. As the cutting speed increases, the cutting force decreases, and so does the cutting pressure. The influence of the cutting speed on the cutting pressure is identical to the influence on machining force, which is clear from the cutting pressure formulation. The influence of depth of cut and feed rate on cutting pressure is nonlinear. The nonlinearity is consequence of combined influence of feed rate and depth of cut on the force value with their combination in the counter of cutting pressure formulation. As the depth of cut and feed rate increase, the contact area of the workpiece material and the cutting tool wedge increases, leading to a lower pressure. In terms of values, the lowest pressure values are not strictly related to the minimum or maximum parameter values, leading to stronger optimization needs.

3.2 Turning process optimisation

In optimisation of machining processes, can be used a more different optimisation methods, as shown in the mentioned previous researches. In this research, the use of the genetic algorithm coupled with principal component analysis (PCA) for determining the optimal turning parameters is reported. This method was chosen because it throws out irrelevant predictors and conducts the process with transformed predictors and with fewer of them. In this way, PCAs are used to reduce predictor's dimensionality, their independence, and avoid their interpretability.

The optimal turning parameters can be derived in accordance to the preference towards the three objectives, namely, machining force, cutting energy and cutting pressure. In order to establish the optimization problem, the four above-mentioned second order regression Eqs. (4-6) are used to formulate the fitness function. In present study, the target of the optimization process is to estimate the optimal levels of turning parameters that contribute to the minimum value of machining force, cutting energy and cutting pressure.

For multi-objective optimization of the MQL turning process, where noted F_{Rmin} as the minimum value of F_R, P_{cmin} as the minimum value of P_c and K_{smin} as the maximum value of K_s, the following objective function is created:

$$Min(X) = w_1 \frac{Y_u(F_R)}{F_{R\min}} + w_2 \frac{Y_u(P_c)}{P_{c\min}} + w_3 \frac{Y_u(K_s)}{K_{s\min}} \quad (7)$$

These minimum and maximum values of the responses are obtained from the experimental results. The values of the weights w_1, w_2 and w_3 assigned to F_R, P_c and K_s, respectively. Can be provided that $w_1 + w_2 + w_3 = 1$. Here, the weighting values of each performance characteristics are determined using principal component analysis. Experimental results were used to evaluate the correlation coefficient matrix and determine the corresponding eigenvalues. The mentioned eigenvalues are shown in Table 7.

Table 7. The eigenvalues and explained variation for principal components.

Principal component	Eigenvalue	Explained variation (%)
First	2.3526	78.4
Second	0.4467	14.9
Third	0.2007	6.7

In Table 8 are listed the eigenvector corresponding to respective eigenvalue. The variance contribution for the first principal component characterizing the four objectives is as high as 78.4%. The contribution of the corresponding objective to the principal component is represented by its square. Thereby, the squares of its corresponding eigenvectors were chosen as the weighting factors of the related objective. Coefficients w_1, w_2 and w_3 in Eq. (7) are thereby set as 0.2988, 0.3330 and 0.3682 respectively.

Table 8. The eigenvectors for principal components.

Quality characteristic	Eigenvector		
	First principal compon.	Second principal compon.	Third principal compon.
Machining force (F_R)	0.5466	-0.7974	0.2557
Cutting power (P_c)	0.5771	0.5779	0.5751
Cutting pressure (K_s)	-0.6068	-0.1688	0.7771

The minimization of the fitness function value of Eq. (7) is subjected to the boundaries of the cutting parameters. The range of values of experimental conditions in Table 1 were considered in this study. Once the optimization problem was formulated, it was then solved using genetic algorithm (GA). The parameters of genetic algorithm were set as follows: the number of generations was 1880, the population size was 90, the mutation probability was 0.025 and the crossover probability was 0.8. The results of it, show that the best combination turning parameters values for simultaneously optimizing performance characteristics of the MQL assisted turning using proposed fitness functions is: 210 m/min, 1.5 mm, and 0.224 mm/rev for cutting speed, depth of cut and feed rate, respectively. With purpose to verify the optimum cutting conditions a confirmation experiment at the optimum settings was performed, indicating the optimal machining force is 981 N, the cutting power is 2.87 kW and cutting pressure is 2437.5 MPa.

4. CONCLUSIONS

In this research, turning of AISI 1045 steel under MQL condition was investigated. Standard L27 orthogonal array based on the full plan design of experiments was employed. Cutting speed, depth of cut and feed rate at three levels each were considered as controlling factors, while machining force, cutting power and cutting pressure were considered as responses.

The reduced second order models developed using response surface methodology confirmed to be a powerful tool for modelling machining force, cutting power and cutting pressure in MQL turning. The relative error of developed models is very low, under 8%. All models have high regression coefficient over 0.9. The machining force is highly sensitive to depth of cut and feed rate variations at all values of cutting speed. The minimum machining force is required at low values of both depth of cut and feed rate. According to the presented results, the cutting power is highly sensitive to cutting speed and depth of cut variations as compared to feed rate. However, the combination of low cutting speed, depth of cut and feed rate is necessary for minimizing the cutting power. The cutting pressure is significantly affected by depth of cut as compared to cutting speed and feed rate. Higher values of depth of cut and feed rates are necessary to minimize the cutting pressure. A genetic algorithm multiple objective optimization technique has proved very useful for determining optimal cutting parameters within the showed turning conditions.

The conducted and presented experimental, statistic and optimization approaches provide reliable methodologies to improve turning process of AISI 1045 steel under MQL condition. Turning process was carried out with higher values of cutting speed, which gives more significant productivity in MQL condition. These procedures can lead to finding the optimal values of depth of cut, feed rate and speed, as the most easily variable input turning parameters. As a result, it is clear that the optimal energy situation of the turning process can be achieved. In industry, presented explicit mathematical models and optimization procedures can be integrated in expert systems for sustainable process planning, and serve to establishment of smart machining.

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