STUDY ON THE INFLUENCE OF CUTTING PARAMETERS ON CONSUMPTION ENERGY AND SURFACE ROUGHNESS IN HIGH-SPEED FACE MILLING OF SKD11 STEEL AFTER HEAT TREATMENT USING ARTIFICIAL ECO-SYSTEM ALGORITHM

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ABSTRACT

This paper presents the assessment results of the cutting parameters influence on consumption energy (CE) and surface roughness (R_a) in high-speed face milling of SKD11 steel after heat treatment. Cutting parameters include spindle speed (n), feed rate (F) and depth of cut (t). The Box-Behnken experimental planning method is used to find the regression equation describing the relationship of three parameters with energy consumption and surface roughness with Design Expert software. The artificial ecosystem optimization (AEO) algorithm is used to optimize the objective function in terms of CE and R_a. From there, the influence of cutting parameters on each target is analyzed. Research results have important value in finding machining solutions that both save energy costs and improve surface quality in high-speed machining of SKD11 steel after heat treatment in particular and hard alloy steels in general.

Keywords: *High-speed milling, energy consumption, surface roughness, optimization, AEO.*

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1. INTRODUCTION

High-speed machining (HSM) is one of the modern technologies compared to traditional machining methods that allows to increase efficiency, accuracy and quality of parts [1]. Machining at high speeds on different types of workpiece materials is also performed in different cutting modes. This shows that for each type of material, machining is effective at a certain cutting speed range [2]. The quality of the surface in general and the surface roughness in particular plays a very important role in the machining performance because a good quality machined surface will definitely improve the fatigue strength, corrosion resistance. wear and increase tool life [3]. When studying the HSM of AISI 1045 steel in [4], it was found that the cutting speed is a significant parameter affecting the R_a and CE. Along the same line of research, Guna and Yucel in [5] analyzed optimally the cutting conditions for surface roughness when machining high-alloy chromium-nickel (Ni-Hard) white cast iron at two different levels of 50HRC and 60HRC. Ozel in [6] studied the cutting force combined with R_a during high-speed finishing for AISI H13 alloy steel (50 - 55HRC). Lawani's work [7] experimentally high-speed finishing of alloy steel MDN 250 (50HRC) showed that the feed rate greatly affects the R_a according to a 2nd order nonlinear model. Optimized cutting parameters when milling aeronautical alloy parts to improve surface quality are presented in [8]. Bhattacharya et al in [9] experimentally studied the influence of the machining parameters on R_a and power consumption during HSM of AISI 1045 alloy steel by Taguchi and ANOVA methods. Effect of milling parameters on machinability of SA508-3 steel in high-speed milling is described in [10]. Akhyar's study in [11] analyzed and optimized the cutting parameters when turning Ti-6Al-4V Titanium alloy steel with carbide-coated and uncoated cutting tools with HSM technology. Gunay and Yucel in [12] analyzed the influence and optimization of machining parameters and tool materials on R_a when machining high-alloy white cast iron (Ni-Hard) at two different hardness levels. Mafoudi in [13] studied tool wear and R_a during HSM of hard alloy AISI 4140 (50HRC) with PCBN coated tool. The feedrate is the factor that has the strongest influence on the R_a, which is the general conclusion when studying the relationship of cutting factors to the surface roughness after machining by the authors Aouici [14], Senthikumar [15], Padawe [16]. Another point of Aouici in [14] is the study of HSM of AISI H11 alloy steel (50HRC) with CBN coated cutting tools. Senthikumar in [15] experimented with R_a and tool wear when high turning machining Inconel 718 speed, while

Padawe [16] used Taguchi experimental method to study the influence of cutting parameters on cutting force and R_a during HSM of Inconel 718 alloy. Cui in [17] studied the chip formation process and R_a in face milling AISI H13 steel.

According to the 2014, CO_2 emissions report of the US energy agency [18], 90% of energy consumption is in industrial production. Therefore, industries in general and the field of mechanical manufacturing in particular need to be responsible for minimizing energy consumption. Many studies show that if the technological process can be optimized in the production stages, it is possible to reduce CE from 6% to 40% compared to the present [19]. In fact, the wasted energy is mainly in the roughing step, the balance between machining productivity and CE needs to be considered. Draganescu in [20] has conducted statistical experiments on the CE of machining machines. The result obtained from this statistical model is the evaluation value of the efficiency of the machining process. Aggarwal in [21] studies the influence between cutting parameters and cutting environmental conditions on the power consumption of the processing machine in turning AISI P20 alloy steel. Bhattacharya [22] evaluated effect of cutting parameters on R_a and CE in machining AISI 1045 alloy steel based on Taguchi and ANOVA methods. The experimental study of He in [23] has also evaluated the CE of the whole machining process under the influence of cutting parameters. Bhushan in [24] carried out research to determine the cutting parameters in minimizing CE and increasing tool life in machining Al and SiC alloys. With the same content, Diaz in [25] also studied the power consumption level between different types of processing materials. Calvanese [26] and Ampara [27] studied the CE in milling low hardness alloys. With the research object being hard alloy steel materials, Sealy in [28] performed machining to study CE. Franco [29] analyzes a parametric model of CE in machining micro-drills.

Basically, the researches on CE in the cutting process mentioned above have the processing object of low hardness materials with conventional turning, milling and drilling. Most of these studies also do not deal with HSM. Research issues on CE in the HSM domain have not been mentioned much, especially in HSM of high-hardness materials. As can be seen, the parameters of the machining process such as cutting speed, feedrate and depth of cut affect production costs and product quality. Therefore, it is important to use an optimization engineering approach to determine the optimal values of these parameters in order to reduce production costs and at the same time achieve the desired product quality.

This paper presents the results of establishing two regression models to predict CE and R_a value in high-speed face milling of SKD11 steel with high hardness (55HRC) based on 17 specific experiments. The AEO optimization algorithm is used to find reasonable cutting parameters to ensure the minimum value of CE and R_a through these regression equations. The results of assessment the influence of the cutting parameters on the objective functions are also presented in detail.

2. MATERIALS AND METHODS

2.1. Experimental system

The material of the workpiece is alloy steel SKD11. The chemical composition in percent by mass of the workpiece is shown in Table 1.

Table 1. Chemical composition of SKD11 alloy steel workpiece

Ingredient	C (%)	Si (%)	Mn (%)	Cr (%)	Mo (%)	V (%)	P (%)
SKD11	1.4 - 1.6	≤ 0.6	≤ 0.6	11 - 13	0.7 - 1.2	≤ 1.1	≤ 0.03

The workpiece is rectangular in shape, with dimensions (Length x Width x Height) are 300mm x 250mm x 25mm (Fig. 1). The workpiece is heat treated with the Turbo-IPSEN/Germany equipment (Fig. 2) and the hardness is measured on the FR-1E/Hard Machine (Fig. 3). Hardness measurement results with the average value of SKD11 alloy steel workpiece after heat treatment reached 55 HRC according to the standard process supplied with the equipment. The cutting tool is a special high-speed milling tool YG SGN09080H (Fig. 4). The experiments were carried out on the dedicated high-speed milling machining center LEADWELL V-50L (Fig. 5). The machining strategy is face-milling. Machining power is determined based on measuring the effective voltage value and effective amperage of the CNC machine.

Fig. 1. SKD11 alloy steel workpiece after heat treatment

Fig. 2. Turbo-IPSEN heat treatment equipment

Fig. 3. Hardness Tester FR-1E Machine

Fig. 4. YG high speed milling tool SGN09080H

Fig. 5. LEADWELL V-50L machining Center

Therefore, to measure CE using the UNI-T UT136 voltage measuring devices, the effective amperage is measured with the Extech meter (Fig. 6). Using the roughness measuring device of Mitutoyo SJ-201 (Fig. 7).

Fig. 6. Total effective voltage and current measuring device

Fig. 7. Roughness measuring device

Based on the assessment of the machinability of the material SKD11 with a hardness of 55HRC, the machinability of the CNC machine and the range of cutting parameters recommended by the cutting tool manufacturer, the range of experimental cutting parameter values is selected as shown in Table 2.

Table 2. Limits of experimental cutting parameter values

Parameters	Unit	Low level (-1)	Basic level (0)	High level (+1)	Variables
t	mm	0.1	0.15	0.2	x_1
F	mm/min	500	600	700	x_2
n	rev/min	4000	5000	6000	x_3

The value of CE is measured right in the machining stage. The effective voltage and effective strength meters are installed in the electrical cabinet of the CNC milling machine. During the experiment, which recorded both devices at the same time, the measured values were taken at 20 different times of the experiment and averaged. Machining time is measured directly on the CNC machine from the moment the tool control command goes down to cut into the workpiece to the command to bring the tool back to safety. After each experiment, stop the machine temporarily to check the settings for the last time and prepare to time the machine for the next experiment. The R_a value on the machined test surface is measured at 3 different positions according to the standard length of the measuring device. The R_a value measurement results are taken as the average value of the measurements.

2.2. Data collection

Experimental results of measuring parameters U (V), I (A), machining time (seconds) and R_a value are shown in Tab. 3. Energy consumption E (J) is calculated according to the formula as follows E = U x I x t. Each objective function is built from 3 inputs with Box-Behnken model in RSM method. This model is quite common and effective with the least number of experiments.

Table 3. Experimental results

No.	n (rev/min)	F (mm/min)	t (mm)	U (V)	I (A)	t (second)	E (J)	R_a (μm)
1	4000	500	0.15	408	3.72	57	86512.32	0.39
2	6000	500	0.15	407	3.89	57	90244.11	0.50
3	6000	700	0.15	407	3.86	41	64411.82	0.33
4	4000	600	0.2	407	3.78	49	75384.54	1.14
5	4000	700	0.15	406	3.75	42	63945.0	1.04
6	5000	500	0.2	408	3.85	57	89535.6	0.44
7	5000	600	0.15	410	3.81	50	78105.0	0.41
8	6000	600	0.2	405	3.82	48	74260.8	0.66
9	5000	600	0.15	405	3.73	50	75532.5	0.38
10	5000	700	0.1	406	3.74	41	62256.04	0.42
11	5000	600	0.15	405	3.83	49	76006.35	0.56

12	6000	600	0.1	405	3.87	48	75232.8	0.98
13	5000	500	0.1	405	3.72	56	84369.6	0.46
14	5000	600	0.15	403	3.7	52	77537.2	0.56
15	5000	600	0.15	401	3.76	52	78403.52	0.76
16	4000	600	0.1	401	3.58	53	76085.74	0.70
17	5000	700	0.2	406	3.9	45	71253.0	0.46

2.3. Predictive model of CE and R_a values

Using DESIGN EXPERT 12 software to assist in building regression equations with Box-Behnken experimental model in response surface method (RSM) with 3 factors and 5 experiments in the center.

The regression equation predicts the CE is presented as follows:

$$\begin{aligned} E &= 77116{,}91 - 10099{,}04x_2 \\ &\quad + 3540{,}74x_3 - 3959{,}04x_1^2x_3 \text{ (J)} \end{aligned} \tag{1}$$

The regression equation for the R_a is shown belows:

$$\begin{aligned} R_a &= 0{,}534 - 0{,}2050x_1x_2 - 0{,}19x_1x_3 \\ &\quad + 0{,}228x_1^2 - 0{,}197x_2^2 \text{ (μm)} \end{aligned} \tag{2}$$

2.4. AEO algorithm

In this section, the optimization problem is considered to find the smallest value and the corresponding CP values through the algorithm. Three basic processes in nature are simulated in AEBO including production, consumption and decomposition. In each ecosystem, producers are the weakest, the best are decomposers, other organisms such as herbivores, omnivores, carnivores are consumers and follow the natural laws of survival in the food chain. The energy level of each individual species is the objective function value. The highest objective function value corresponds to producer, and vice versa, the lowest objective function value corresponds to the decomposer. For the finding the minimum value problem, the optimal solution is the lowest objective function value. Producers randomly generate individuals in the ecosystem, these individuals are constantly changing positions (corresponding to energy levels) and perform the consumption process in limited space to reach the state has the lowest energy level. Consuming individuals are continuously created at random to replace previous ones and direct other instances to search different areas [30]. Assume that population **X** consists of n individuals xi, $i = 1 \ldots n$. The biologically production process is described as follows $x_1(t+1) = (1-a)x_n(t) + ax_{rand}(t)$; $a = (1 - t/T)r_1$; $x_{rand} = \mathbf{r}(U - L) + L$. In which, n is the population size, T is the maximum iterations, L and U are the lower and upper bounds, respectively, r_1 is a random number in the interval [0, 1], **r** is a vector of individuals random in the range [0, 1], a is the linear weighting factor to move the individual linearly from the randomly generated position to the position of the best individual as the number of iterations increases and x_{rand} is the individual randomly generated in the search space.

Consumption process is carried out immediately after the producer has performed its task. Consumers may eat another random consumer with a lower energy level, or eat a producer, or eat both, provided the conditions for survival energy levels are met to meet nutritional needs own care. The movement to change the position of the consumers is done randomly and carries instinctive foraging behavior. The Levy Flight technique was developed based on the efficient foraging behavior of the species and is characterized by the consumption coefficient C with $C = \frac{1}{2}\frac{V_1}{|V_2|}; V_1, V_2 \sim N(0,1)$; In which, N(0, 1) is a normal distribution with a mean of 0 and a standard deviation of 1. The updated solution of the herbivore is made possible by the production process as $x_i(t+1) = x_i(t) + C[x_i(t) - x_1(t)]; i = 2 \ldots n$. The updated solution of the carnivore is made possible by the consumption process as:

$$\begin{aligned} &x_i(t+1) = x_i(t) + C[x_i(t) - x_j(t)]; \\ &i = 2..n; j = \text{randi}([2i-1]) \end{aligned} \tag{3}$$

The up-to-date solution of the omnivore is achieved by both processes including production and consumption:

$$\begin{aligned} &x_i(t+1) = x_i(t) + C[x_i(t) - x_1(t)]r_2 + (1-r_2)[x_i(t) - x_j(t)]; \\ &i = 3..n; j = \text{randi}([2i-1]) \end{aligned} \tag{4}$$

In which, r_2 is random value in interval [0, 1]. In the nature of an ecosystem, decomposition provides nutrients for production process. The mathematical model of the decomposition process is described as follows:

$$\begin{aligned} &x_i(t+1) = x_n(t) + D[e.x_n(t) - h.x_i(t)]; \\ &D = 3u; u \sim N(0,1); e = r_3.\text{randi}([1;2]) - 1; h = 2r_3 - 1 \end{aligned} \tag{5}$$

In which, D is the decomposition factor, factors ϵ and h are the weights.

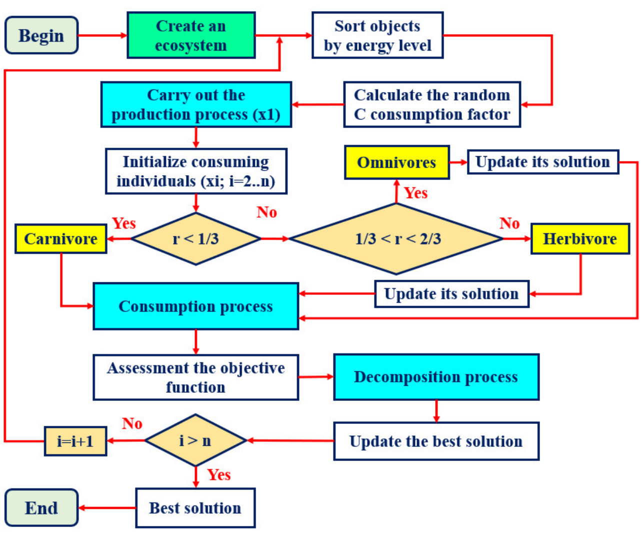

Fig. 8. AEO algorithm diagram

Individuals in a population continuously interact with each other simultaneously with the operation of three basic processes. The algorithm will stop with the criteria of the number of iterations. At this point, the best value lies with the individual with the minimum energy level. The working principle of production, consumption and decomposition is detailed in [30]. The algorithm diagram can be considered as Fig. 8.

2.5. Optimization results and discussion

2.5.1. Optimized CE and R_a values

The regression equations predicting CE and R_a are described in Eq. (2) and Eq. (3). The optimization goal is to find the optimal cutting parameters to ensure the minimum CE and R_a values in the CNC machining process with the conditions within the allowable limits corresponding to the machine's machinability and the working limit of the cutting tool. The algorithm is built on the basis of boundary conditions as follows: $-1 \le x_1, x_2, x_3 \le 1$, corresponding to the limit of cutting parameters including spindle speed in the range $4000 \le n \le 6000$ (rev/min); The feed rate is $500 \le F \le 700$ (mm/min) and the depth of cut is $0.1 \le t \le 0.2$ (mm). The AEO algorithm parameters were performed with an initial population size of 100. The number of iterations was 100. The influence factors related to the AEO algorithm were calculated as described above. The optimal calculation program is built on MATLAB software and gives the results as shown in Fig. 9 and Fig. 10.

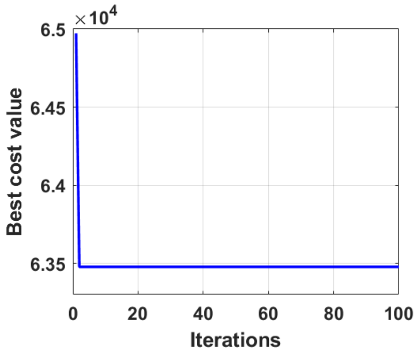

Fig. 9. Value of CE function

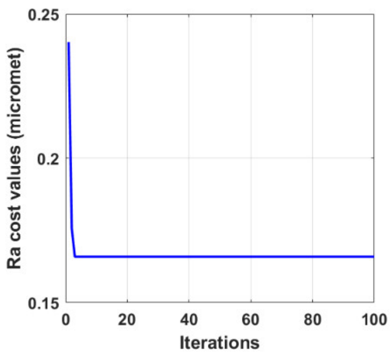

Fig. 10. R_a function value

The optimal CE value that can be achieved is E_{min} = 63477.13 (J) at $x_1 = 0$; $x_2 = 1$; $x_3 = -1$. These optimal values correspond to the cutting parameters: n = 5000 (rev/min), F = 700 (mm/min), t = 0.1 (mm). The minimum CE reaching 63477.13 (J) does not mean the smallest power consumption because this energy also depends on the machining time. If the machining time is small, the CE is also small. That explains the fact that to achieve low CE, the maximum feedrate F = 700 (mm/min), the smallest cutting depth t = 0.1 (mm) is also a factor that helps to reduce cutting force and reduce CE on machine axes. Here, the cutting power can be very large, but due to the small machining time, the total CE is minimal. The minimum R_a value that can be achieved is 0.166µm at $x_1 = 0.866$; $x_2 = 1$; $x_3 = 1$. These optimal values correspond to the cutting parameters: n = 5866.2 (rev/min), F = 700 (mm/min), t = 0.2 (mm).

2.5.2. Effect of cutting parameters on CE

This section focuses on evaluating the influence of cutting parameters pairs on CE. The influence of the depth of cut (t) and feedrate (F) is considered when the spindle speed reaches $x_1 = 0$ or n = 5000 (rev/min). Fig. 11 clearly shows the influence of this pair of parameters. Accordingly, the greater the CE, the greater the depth of cut and the smaller the feedrate. Conversely, the smaller the depth of cut and the larger the feedrate, the smaller the CE. When the spindle speed is fixed, the feedrate affects the CE more than the depth of cut. With the same machined surface area, the lower the feedrate, the longer the machining time on the machine. Each surface area to be machined consists of multiple horizontal and vertical toolpaths, the total toolpath length being the same. Basically, the longer the machining time, the greater the CE, on the other hand, the increased cutting depth also increases the cutting force, resulting in a greater CE.

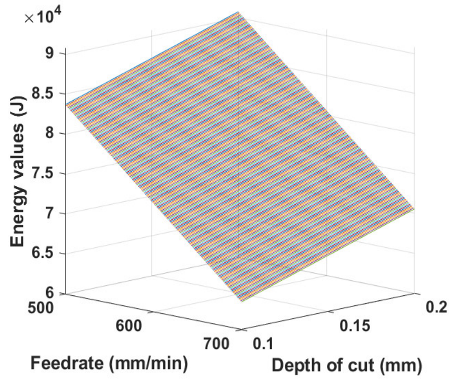

Fig. 11. Effect of depth of cut and feedrate

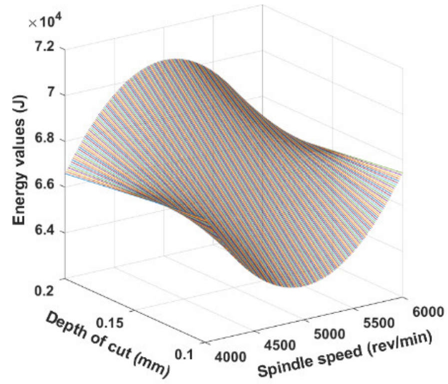

Fig. 12. Effect of depth of cut and cutting speed

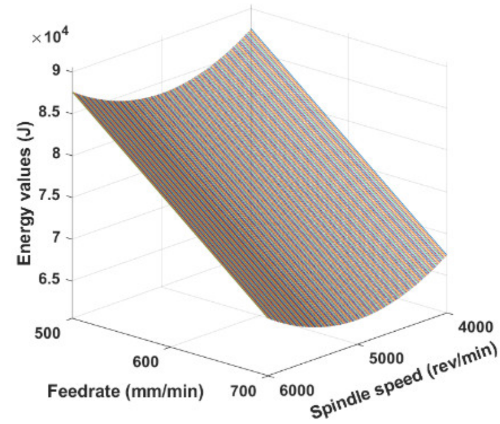

Fig. 13. Effect of spindle and feedrate

Corresponding to the optimal value $x_2 = 1$ or F = 700 (mm/min), the influence of depth of cut (t) and spindle speed (n) is shown in Fig. 12. The CE of machining is highest or lowest at spindle speed n = 5000 (rev/min), the greater the depth of cut, the greater the energy dissipated. Closer to the two edges of the spindle speed values, the change in depth of cut has little effect on CE value. Finally, the effect of spindle speed (n) and feedrate (F) is determined when $x_3 = -1$ or t = 0.1(mm). Fig. 13 shows the influence of the cutting parameters pair (n, F) on CE. When the spindle speed is fixed, the CE value decreases as the feedrate increases. On the other hand, when the feedrate is fixed, the CE decreases to the lowest at the midpoint (level 0 in the experiment). Thus, the CE is minimal when the feedrate is highest and the spindle speed is average (n = 5000 (rev/min)). For HSM, the spindle speed is often very large, so the trend in machining programming to reduce CE will be to try to increase the value of the feedrate.

2.5.3. Effect of cutting parameters on R_a value

Corresponding to the optimal value of spindle speed $x_1 = 0.866$ or n = 5866.2 (rev) /min), evaluation of the effect of depth of cut (t) and feedrate (F) on R_a is depicted in Fig. 14.

Fig. 14 shows, the smaller the R_a value, the higher the surface quality. As the feedrate and depth of cut increase, the R_a value decreases which means that the surface quality increases. As the feedrate increases gradually, the R_a value decreases along the 2nd order line, when the depth of cut increases, the R_a value decreases along a linear 1st order line. The influence of depth of cut (t) and spindle speed (n) is shown in Fig. 15 with the optimal value $x_2 = 1$ or F = 700 (mm/min). From that, when fixing the depth of cut, the R_a value is influenced by the spindle speed along the 2nd line and has a minimum point. As the depth of cut changes, the minimum position also changes, with the lowest minimum at the depth of cut and the highest spindle speed. The influence of spindle speed (n) and feedrate (F) is considered in Fig. 16 corresponding to the optimal value $x_3 = 1$ or t = 0.2 (mm). The change in feedrate and spindle speed affects the R_a value quite complexly. When the feedrate is fixed, the R_a value distributed over the spindle speed is a function of 2nd order, at the lowest feedrate the lowest Ra value is in the middle. As the feedrate increases, the minimum R_a value moves towards the point with the highest spindle speed.

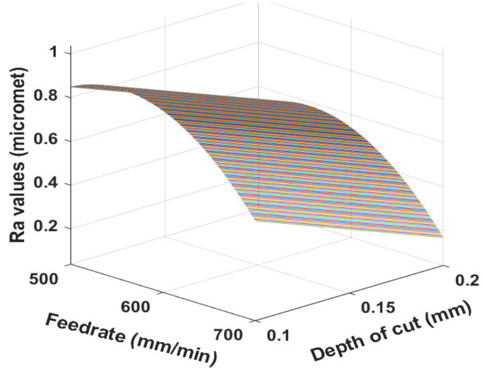

Fig. 14. Effect of depth of cut and feedrate

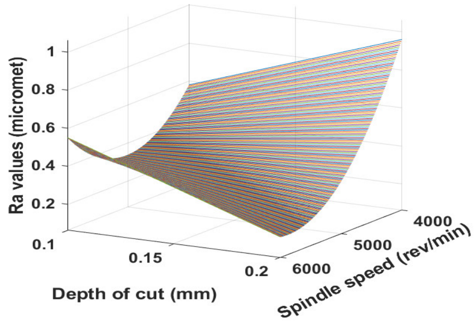

Fig. 15. Effect of depth of cut and spindle speed

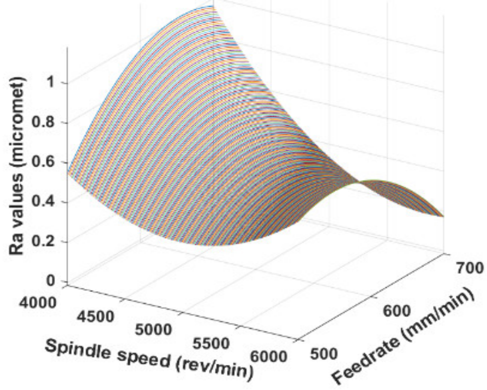

Fig. 16. Effect of spindle speed and feedrate

3. CONCLUSIONS

In summary, this paper presents the establishing results of two predictive models of CE and R_a values when high-speed face milling of SKD11 steel with high hardness. Predictive models are used to optimize CE and Ra values based on the AEO algorithm. Accordingly, the influence of cutting parameters on these two objective functions is also analyzed. Some of the main results can be described as follows

- Feedrate affects CE more than depth of cut and spindle speed;
- Spindle speed affects CE more than depth of cut;
- The feedrate has the most influence on the R_a value, then the spindle speed and finally the depth of cut;

• The surface quality decreases sharply when simultaneously increasing the feedrate and spindle speed values;

• Increased spindle speed and fixed value of feed rate and depth of cut can improve surface quality.

These results have important value in improving surface quality and reducing energy costs. In essence, this can be considered as a multi-objective problem that needs to be mentioned. This issue will be considered in the near future.

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