



## OPTIMIZATION OF MILLING PROCESS PARAMETERS FOR ENERGY SAVING AND SURFACE ROUGHNESS

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**Abstract.** Improving the technical parameters of the machining process is an effective solution to save manufacturing costs. The purpose of this work is to decrease energy consumption (*EC*) and average surface roughness (*ASR*) for the milling process of AISI H13 steel. The spindle speed (*S*), depth of cut (*a*), and feed rate (*f*) were the processing inputs. The milling runs were performed using the experimental plan generated by the Box-Behnken method approach. The relationships between inputs and outputs were established using the response surface models (RSM). The desirability approach (DA) was used to observe the optimal values. The results showed that the reductions of *EC* and *ASR* are approximately 33.75% and 40.58%, respectively, as compared to the initial parameter setting. In addition, a hybrid approach using RSM and DA can be considered as a powerful solution to model the milling process and obtain a reliable optimal solution.

**Keywords:** milling, energy, surface roughness, parameter, desirability approach, optimization.

## 1. INTRODUCTION

Diminishing energy consumed and improving the quality products are the important tasks of machining processes. Improving machine tool and machining technologies, such as intelligent controls and high value-added devices are effective solutions. The second approach pays attention to optimize machining conditions using optimization techniques in order to satisfy the technical targets. Apparently, the first branch based on hardware technologies requires huge investments to replace or renew existing devices. The optimizing machining process is inexpensive and has better sustainable development, compared to drastic improvements.

Increasing energy saving potentials and machined part quality using optimal parameters has been considered by many researchers. Bhardwaj *et al.* examined the impacts of machining parameters on the surface roughness for the end milling of AISI 1019 steel [1] and EN 353 material [2]. A predictive model was proposed to forecast the surface quality of the end milling of stainless steel [3]. Montevecchi *et al.* investigated the cutting force behavior in the laser deposition and wire-arc additive manufacturing [4]. Gok *et al.* developed a simulation model to analyze the effects of the rake angle and approach angle on the cutting forces for the milling of AISI 1040 steel [5]. Prado *et al.* proposed the effective methods to measure the tool wear for the milling of AISI H13 steel [6, 7]. Narayanan *et al.* used the genetic algorithm to improve the metal removal rate (MRR) and decrease the surface roughness for the turning process [8]. Rocha *et al.* optimized the processing factors to improve the technological parameters, such as the tool life, the surface roughness as well as the ratio between material removal rate and cutting force of the hard turning [9, 10]. Zhang *et al.* proposed a finite element simulation model to examine the effects of cutting speed and feed rate on the cutting force and cutting temperature [11]. Kuram optimized the nose radius and cutting speed effects for the milling of AISI 304 material [12]. As a result, the selection of optimal machining conditions to simultaneously decrease energy consumed and surface roughness for the milling of H13 steel has not performed in the works published.

To fulfil the mentioned research gaps, a multi-objective optimization for the milling of AISIH13 steel has considered for decreasing energy consumed and surface roughness. The predictive models of two responses are developed with the aid of RSM. The desirability approach (DA) is used to identify the optimal solution. This work is expected as a significant contribution to make the milling process becomes greener and more efficient.

## 2. RESEARCH METHODOLOGY

In the current work, energy consumption (*EC*) and average surface roughness (*ASR*) are considered as the machining responses. The total energy consumed in the machine tool can be devised into four primary components, including the energy of start-up, the air-cutting energy, the energy of cutting stage, and the energy of tool change, as shown in Fig. 1. In this work,

energy consumption in the cutting stage is considered as an objective. The value of  $EC$  is calculated using Eq. 1:

$$EC = PC \times t_c \tag{1}$$

where  $PC$  and  $t_c$  denote the power consumption and cutting time, respectively.

The average surface roughness ( $ASR$ ) indicates the arithmetic average of the absolute values of the roughness profile.  $ASR$  is one of the most effective surface roughness measures, which commonly uses in general engineering practice. It gives a good general description of the height variations in the surface.

The spindle speed, feed rate, and depth of cut are listed as the key process parameters. The ranges of the factors are shown in Table 1. These values are determined with the support of the recommendations of the cutting tool manufacturer. Consequently, the optimizing problem can be defined as follows:

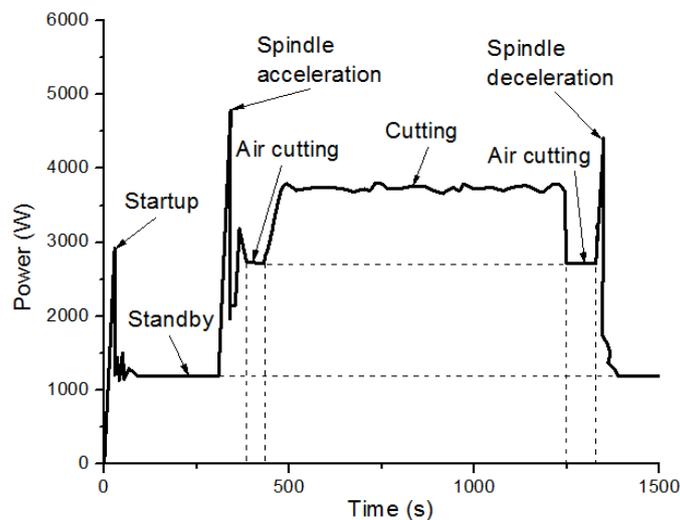
Find  $X = [S, a, f]$

Minimize energy consumption  $EC$  and surface roughness  $ASR$ .

Constraints:  $1500 \leq S \leq 4500$  (RPM),  $0.04 \leq f \leq 0.10$  (mm/ tooth),  $0.4 \leq a \leq 1.0$  (mm).

**Table 1.** Processing conditions.

Symbol	Parameters	Ranges
$S$	Spindle speed (RPM)	1500-4500
$f$	Feed per tooth (mm/tooth)	0.04-0.10
$a$	Depth of cut (mm)	0.4-1.0



**Figure 1.** Diagram of power consumption.

The optimizing procedure having a multi-objective optimization method is shown in Fig. 2. The sequential steps are listed as bellows:

Step 1: The machining runs are conducted according to the experimental matrix generated by the Box-Behnken method, which contains three central points [13].

Step 2: The *EC* and *ASR* models are then developed with respect to process parameters using the RSM approach. The detail of the RSM method can be found in the work of [14].

Step 3: Determining the optimal parameters using the DA.

The DA is applied to transform the response  $y_i(x)$  into an individual desirability function  $d_i$  ( $0 \leq d_i \leq 1$ ) for achieving the desired value. The value of  $d_i$  lies between 0 and 1, when  $d_i = '1'$ ; It indicates that the ideal response is achieved. The optimal results of the response are adjusted with different weight values. The targets are combined into the desirability function ( $D$ ) for multi-objective and processing factors. The optimal factors are determined based on the maximum value of the  $D$  [15].

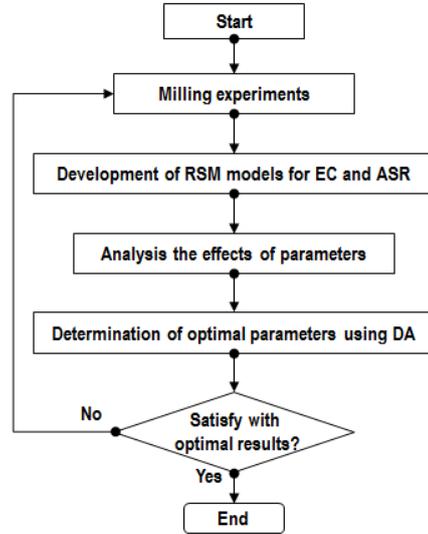


Figure 2. Optimization approach.

The  $d_i$  is calculated with respect to the maximizing goal:

$$d_i = \begin{cases} 0, Y_i \leq L_i \\ \left(\frac{Y_i - L_i}{H_i - L_i}\right)^w, L_i < Y_i < H_i \\ 1, Y_i \geq H_i \end{cases} \quad (2)$$

The  $d_i$  is calculated with respect to the minimizing goal:

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The  $d_i$  is calculated with respect to the target:

$$d_i = \begin{cases} \left(\frac{Y_i - L_i}{T_i - L_i}\right)^{w1}, L_i < Y_i < T_i \\ \left(\frac{Y_i - H_i}{T_i - H_i}\right)^{w2}, T_i < Y_i < H_i \\ 0, otherwise \end{cases} \quad (4)$$

The  $d_i$  is calculated with respect to the range:

$$d_i = \begin{cases} 1, & L_i < Y_i < H_i \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where  $L_i$ ,  $H_i$ ,  $T_i$ , and  $w_i$  are the low, high, target, and weight values of the  $i_{th}$  response, respectively.

The value of the desirability function ( $D$ ) of the response is calculated as:

$$D = \left( \frac{N}{\prod_{i=1}^r d_i^{r_i}} \right)^{1/\sum r_i} \quad (6)$$

where  $N$  is the number of the responses measured.

**Table 2. Experimental results.**

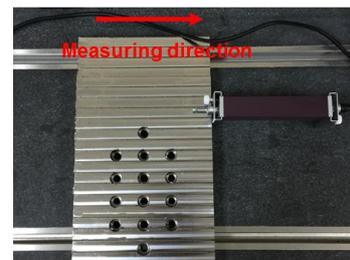
No.	$S$ (RPM)	$a$ (mm)	$f$ (mm/tooth)	$EC$ (kJ)	$ASR$ ( $\mu\text{m}$ )
1	1500.00	0.70	0.04	100.56	0.75
2	3000.00	0.70	0.07	35.82	0.68
3	1500.00	0.70	0.10	50.49	1.02
4	3000.00	0.40	0.10	26.24	0.79
5	3000.00	0.70	0.07	35.76	0.69
6	4500.00	1.00	0.07	30.51	0.72
7	4500.00	0.70	0.10	22.52	0.74
8	1500.00	0.40	0.07	54.49	0.81
9	3000.00	0.70	0.07	35.60	0.67
10	4500.00	0.70	0.04	44.74	0.42
11	1500.00	1.00	0.07	71.03	1.05
12	3000.00	1.00	0.04	63.85	0.82
13	4500.00	0.40	0.07	25.43	0.41
14	3000.00	1.00	0.10	32.31	1.08
15	3000.00	0.40	0.04	48.62	0.44



(a) Milling setting



(b) Measuring power



(c) Measuring roughness

**Figure 3. Experiment and measurement.**

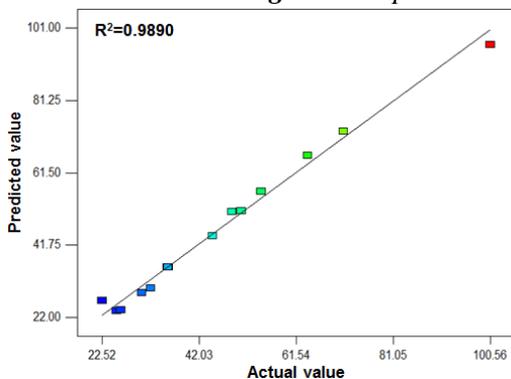
### 3. EXPERIMENTS AND MEASUREMENTS

The milling machine, namely Spinner U620 is used to perform the experimental trials. The dimensions of machining specimens were 350 mm×150 mm×25 mm. The precision vise is employed to clamp the workpiece, as shown in Fig. 3a. Power Meter KEW6305 is used to obtain the power used in the milling process. The measured data is visualized using the KEW6305 software, as shown in Fig. 3b. The cutting tool having a diameter of 12 mm and two wiper insert is used to conduct the cutting runs. A tester Mitutoyo SJ-301 is used to measure the roughness values in the machining direction, as shown in Fig. 3c.

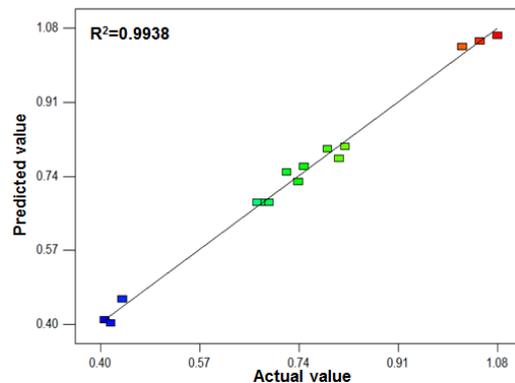


(a) Power measured at the experimental No. 11. (b) Power measured at the experimental No. 13.

**Figure 4.** Representative values of the power consumed.



(a) For energy consumption.



(b) For average surface roughness.

**Figure 5.** Assessment of the model adequacy.

## 4. RESULTS AND DISCUSSIONS

### 4.1. Development of predictive models

The milling results are given in Table 2. The values of the power consumed at the different inputs are depicted in Fig. 4.

The adequacy of the RSM models can be assessed by the value of the coefficient of determination  $R^2$ .  $R^2$  is a statistical indicator, which presents how close the data are to the fitted regression line. The  $R^2$  value of 1 reveals the perfect correlation. The  $R^2$ -values of the *EC* and *ASR* are 0.9890 and 0.9938, respectively, indicating the good agreements between experimental and predictive values. Additionally, it can be stated that the data evenly distribute on the straight lines. Therefore, the adequacy of the RSM models proposed for the responses is acceptable (Fig. 5).

Table 3 shows the ANOVA results for energy consumption. The factor having a p-value less than 0.05 are significance. As a result, the  $S$ ,  $a$ ,  $f$ ,  $Sf$ ,  $S^2$ , and  $f^2$  are significant terms. The  $S$  is the most effective factor with respect to the single term due to the highest contribution (48.35 %), followed by  $f$  (32.72 %), and  $s$  (3.78 %), respectively. The contributions of  $S^2$  and  $f^2$  are 6.99 % and 4.00 %, respectively.

**Table 3.** ANOVA results for energy consumption.

Source	Sum of squares	Mean square	F-value	p-value	Remark	Contribution (%)
<b>Model</b>	6054.27	672.70	49.84	0.0002	Significant	
$S$	2940.51	2940.51	217.87	< 0.0001	Significant	48.35
$a$	230.18	230.18	17.05	0.0091	Significant	3.78
$f$	1990.86	1990.86	147.51	< 0.0001	Significant	32.73
$Sa$	32.81	32.81	2.43	0.1797	In significant	0.54
$Sf$	193.94	193.94	14.37	0.0127	Significant	3.19
$af$	21.02	21.02	1.56	0.2673	In significant	0.35
$S^2$	425.16	425.16	31.50	0.0025	Significant	6.99
$a^2$	4.40	4.40	0.33	0.5929	In significant	0.07
$f^2$	243.40	243.40	18.03	0.0081	Significant	4.00
<b>Residual</b>	67.48	13.50				
<b>Total</b>	6121.76					

The ANOVA results of average surface roughness are shown in Table 4. The developed model is significant due to the p-value less than 0.0001. The significant terms are  $S$ ,  $a$ ,  $f$ ,  $a^2$ , and  $f^2$ . The  $S$  is the most effective factor with the contribution of 36.53 %, followed by  $a$  (30.28 %), and  $f$  (29.29 %). The contributions of  $a^2$  and  $f^2$  are 2.07 % and 1.15 %, respectively.

**Table 4.** ANOVA results for average surface roughness.

Source	Sum of squares	Mean square	F-value	p-value	Remark	Contribution (%)
<b>Model</b>	0.6128	0.0681	88.4334	< 0.0001	Significant	
$S$	0.2245	0.2245	291.4935	< 0.0001	Significant	36.53
$a$	0.1861	0.1861	241.6234	< 0.0001	Significant	30.28
$f$	0.1800	0.1800	233.7662	< 0.0001	Significant	29.29
$Sa$	0.0012	0.0012	1.5909	0.2628	In significant	0.20
$Sf$	0.0006	0.0006	0.8117	0.4089	In significant	0.10
$af$	0.0020	0.0020	2.6299	0.1658	In significant	0.33
$S^2$	0.0003	0.0003	0.3671	0.5710	In significant	0.05
$a^2$	0.0127	0.0127	16.5509	0.0097	Significant	2.07
$f^2$	0.0071	0.0071	9.1783	0.0291	Significant	1.15
<b>Residual</b>	0.0039	0.0008				
<b>Total</b>	0.6167					

The predictive models of energy consumption and average surface roughness are expressed as follows:

$$EC = 186.19666 - 0.04777S + 71.77919a - 2074.73516f - 0.00636Sa + 0.15474Sf - 254.7185af \quad (7)$$

$$-12.12490a^2 + 9021.34110f^2$$

$$ASR = 0.91972 - 0.00018S - 0.34722a - 0.88889f + 0.00028SF - 2.5af + 0.65278a^2 + 48.61111f^2 \quad (8)$$

#### 4.2. Parameter effects

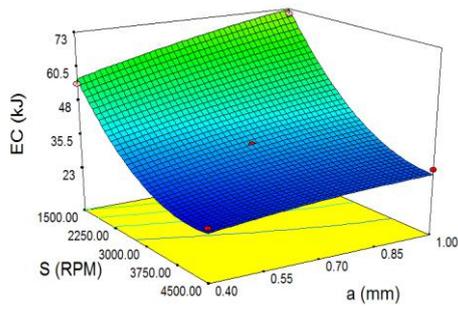
The effects of process parameters on energy consumption are depicted in Fig. 6. As a result, an increment in the feed rate and/or spindle speed leads to a reduction in energy consumption. Generally, a higher power of the motor is required to rotate the spindle at a higher value. Furthermore, an increased chip thickness generated by a higher feed rate also causes a higher power. Fortunately, an increased feed rate or spindle speed leads to a reduction in the cutting time, resulting in low energy consumed. A higher depth of cut causes larger plastic deformation, leading to greater resistance in the chip formation; hence, higher energy is consumed.

Fig. 7 depicted the impacts of the process parameters on the *ASR*. An increased cutting speed causes a high temperature of the cutting region, resulting in a decrease in the strength and hardness of the workpiece. Therefore, the chip is easily detached from the machined surface; hence, a smoother surface is obtained. A higher feed leads to an increment in the feed marks on the machined surface and the high roughness is observed. Furthermore, at a higher depth of cut, an increment in the milling forces and chattering is observed; hence, the surface quality is decreased.

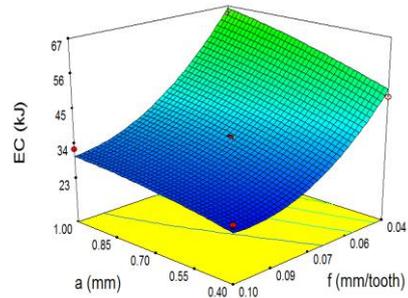
#### 4.3. Optimal results

Generally, the relationship between two objectives can be assessed by the weights of importance, which use to avoid the subjective judgment for the decision-making process and reflect the trade-off analysis among the responses considered. The common methods, such as the equal weight, the entropy weight, and analytical hierarchy process are used to select the weight values [16]. In this work, the equal weight method is applied to the optimization process. The weight value of 0.5 is used for each objective.

The mathematical formulas showing the relationship between inputs and outputs are used to find optimal parameters with the support of the desirability approach. A total of 8 optimal results are observed, in which the point with the *D* value close to 1 is the best solution. The optimal values of the inputs are shown in Fig. 8a. The values of the desirability are depicted in Fig. 8b. The desirability of 0.992 revealed that the optimal results observed are reliable and feasible. As revealed in Table 5, the reductions of the *EC* and *ASR* are about 33.75% and 40.58%, respectively.

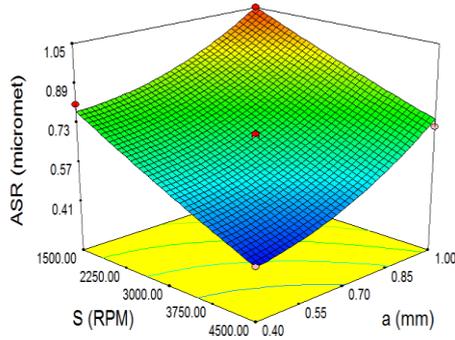


(a) EC versus a and S.

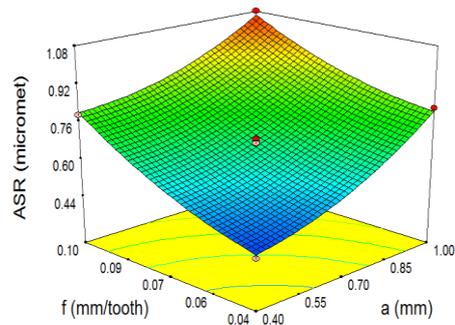


(b) EC versus a and f.

**Figure 6.** The effects of the factors on energy consumption.

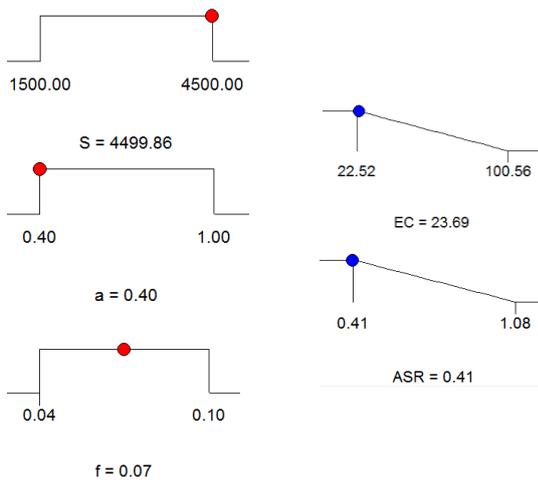


(a) ASR versus a and S

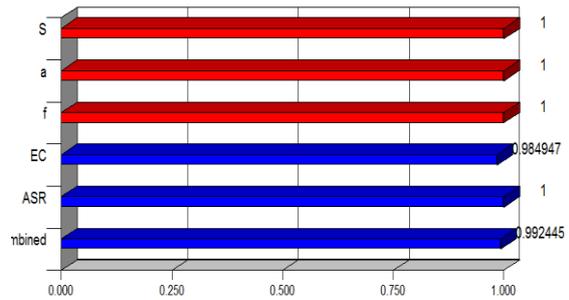


(b) ASR versus a and f

**Figure 7.** The effects of the factors on average surface roughness.



(a) Optimal values.



(b) Desirability graph.

**Figure 8.** Optimization results.

**Table 5.** Optimization results.

Method	Optimal factors			Responses	
	S (RPM)	a (mm)	f (mm/tooth)	EC (kJ)	ASR ( $\mu\text{m}$ )
<b>Optimal values</b>	4500	0.40	0.07	23.69	0.41
<b>Initial values</b>	3000	0.70	0.07	35.76	0.69
<b>Reduction (%)</b>				33.75	40.58

## 5. CONCLUSION

This paper presented a machining parameter-based optimization for the machining AISI H13 steel in order to decrease energy consumption and surface roughness. The RSM models for the *EC* and *ASR* having R<sup>2</sup>-values of 0.9890 and 0.9938; respectively, can be used for the milling process of AISI H13 steel to forecast the optimal parameters with sufficient accuracy. The highest levels of the spindle speed and/or feed rate can be used to save energy used, while the lowest values of feed and/or depth of cut lead to a smoother surface. The optimal values of the *S*, *a*, and *f*, are 4500 RPM, 0.04 mm, and 0.07 mm/tooth, respectively. The *EC* saves about 33.75% while the *ASR* decreases approximately 40.58% at the optimal solution.

## ACKNOWLEDGMENT

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## REFERENCES

- [1] B.Bhardwaj, R.Kumar, P.K. Singh, Effect of machining parameters on surface roughness in end milling of AISI 1019 steel, Proc. Inst. Mech. Eng. B., 228 (2014) 704-714. <https://doi.org/10.1177/0954405413506417>
- [2] B.Bhardwaj, R.Kumar, P.K. Singh, An improved surface roughness prediction model using Box-Cox transformation with RSM in end milling of EN 353, J. Mech. Sci. Technol., 28 (2014) 5149-5157. DOI: [10.1007/s12206-014-0837-4](https://doi.org/10.1007/s12206-014-0837-4).
- [3] M.R. Policena, C. Devitte, G. Fronza, R.F. Garcia, A.J. Souza, Surface roughness analysis in finishing end-milling of duplex stainless steel UNS S32205, Int. J. Adv. Manuf. Technol., 98 (2018) 1617-1625. <https://doi.org/10.1007/s00170-018-2356-4>
- [4] F.Montevecchi, N.Grossi, H.Takagi, A.Scippa, H.Sasahara, G. Campatelli, Cutting Forces Analysis in Additive Manufactured AISI H13 Alloy, Procedia CIRP, 46 (2016) 476-479. <https://doi.org/10.1016/j.procir.2016.04.034>
- [5] K. Gok, H. Sari, A. Gok, S. Neseli, E. Turkes, S. Yaldiz, Three-dimensional finite element modeling of effect on the cutting forces of rake angle and approach angle in milling, Proc. Inst. Mech. Eng. E., 231 (2017) 83-88. <https://doi.org/10.1177/0954408915576698>
- [6] M.T.Prado, A.Pereira, J.A.Pérez, T.G.Mathia, Methodology for tool wear analysis by a simple procedure during milling of AISI H13 and its impact on surface morphology, Procedia Manuf., 13 (2017) 348- 355. <https://doi.org/10.1016/j.promfg.2017.09.090>
- [7] M.T.Prado, A.Pereira, J.A.Pérez, T.G.Mathia, Methodology for tool wear analysis by electrical measuring during milling of AISI H13 and its impact on surface morphology, Procedia Manuf., 13 (2017) 356-363. <https://doi.org/10.1016/j.promfg.2017.09.017>
- [8] N.S. Narayanan, N.Baskar, M.Ganesan, Multi Objective Optimization of machining parameters

for Hard Turning OHNS/AISI H13 material Using Genetic Algorithm, *Mater. Today Proc.*, 5 (2018) 6897-6905. <https://doi.org/10.1016/j.matpr.2017.11.351>.

[9] L. C. S. Rocha, A. P. de Paiva, P. R. Junior, P. P. Balestrassi, P. H. Campos, Robust multiple criteria decision making applied to optimization of AISI H13 hardened steel turning with PCBN wiper tool, *Int. J. Adv. Manuf. Technol.*, 89 (2017) 2251-2268. DOI: [10.1007/s00170-016-9250-8](https://doi.org/10.1007/s00170-016-9250-8).

[10] L. C. S. Rocha, A. P. de Paiva, P. R. Junior, P. P. Balestrassi, P. H. Campos, Robust weighting applied to optimization of AISI H13 hardened steel turning process with ceramic wiper tool: A diversity-based approach, *Precis. Eng.*, 50 (2017) 235-247. <https://doi.org/10.1016/j.precisioneng.2017.05.011>

[11] Q. Zhang, S. Zhang, L. Jianfeng, Three Dimensional Finite Element Simulation of Cutting Forces and Cutting Temperature in Hard Milling of AISI H13 Steel, *Procedia Manuf.*, 10 (2017) 37-47. <https://doi.org/10.1016/j.promfg.2017.07.018>

[12] E. Kuram, Nose radius and cutting speed effects during milling of AISI 304 material, *Mater. Manuf. Process*, 32 (2017) 185-192. <https://doi.org/10.1080/10426914.2016.1198019>

[13] H. S. Park, T.T.Nguyen, X.P. Dang, Multi-objective optimization of turning process of hardened material for energy efficiency, *Int. J. Pr. Eng. Man.*, 17 (2016) 1623-1631. DOI: [10.1007/s12541-016-0188-4](https://doi.org/10.1007/s12541-016-0188-4).

[14] A. Mehrvar, A. Basti, A. Jamali, Optimization of electrochemical machining process parameters: Combining response surface methodology and differential evolution algorithm, *Proc. Inst. Mech. Eng. E.*, 231 (2017) 1114-1126. <https://doi.org/10.1177/0954408916656387>

[15] M. M. Liman, K. Hossein, Modeling and multi response optimization of cutting parameters in SPDT of a rigid contact lens polymer using RSM and desirability function, *Int. J. Adv. Manuf. Technol.*, 102 (2019) 1443-1465. <https://doi.org/10.1007/s00170-018-3169-1>

[16] R. Kumar, P. S. Bilga, S. Singh, Multi objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation, *J. Clean. Prod.*, 164 (2017) 45-57. <https://doi.org/10.1016/j.jclepro.2017.06.077>.