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Modelling and Optimization of Surface Roughness and Specific Tool Wear in Milling Process

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Abstract: The present study has been carried out to optimize three machining parameters in the milling process to achieve minimum surface roughness and tool wear along with the maximum material removal rate. A specific tool wear factor has been defined to evaluate both tool wear and material removal rate parameters simultaneously and the surface roughness was considered as the second output parameter. A set of experiments was designed using a DOE technique and conducted on a milling machine. The experimental data then was applied to develop different mathematical models and the best model was chosen based on analysis of variance (ANOVA). Three proposed methods of optimization with different natures were used to determine optimal output parameters based on selected models. The comparison between these methods showed that Regression-response optimization was superior to Simulated Annealing (SA) algorithm and Goal-attainment method. The Simulated Annealing (SA) algorithm also represented less error function compared to goal-attainment methods. The results of optimization revealed that optimum values for cutting speed and feed rate were ranged from 312 to 314 m/min and 0.085 to 0.12 mm/rev·tooth, respectively, while all optimization methods reached the same value of 1.0 mm for depth of cut parameter.

Keywords: goal-attainment method; machining parameters; regression-response optimization; simulated annealing algorithm; specific tool wear; surface roughness

1 INTRODUCTION

During the past few decades, there has been extensive research on improvement in the capability of the cutting tools. Tool wear leading to tool substitution is one of the most important economic aspects of machining. Generally, a decrease in tool wear criterion leads to a drop in material removal rate, directly aiming at the process productivity. On the other hand, surface roughness as a quality characteristic of the machined surface need to be considered as well. There are different methods of optimization to solve such an engineering problem.

Savkovic et al. [1] presented reliable intelligent models for selected output characteristics of the milling process, depending on the input parameters of the process: depth of cut, cutting speed and feed to the tooth. Khawaja et al. [2] applied response surface methodology for the development of mathematical models and selected the best combination of process parameters to optimized responses, i.e. surface roughness, material removal rate, and strength.

Yildiz et al. [3] applied a hybrid optimization method combining the Nelder-Mead local search algorithm with the Harris hawks optimization algorithm for the optimization of process parameters in machining operations. Then, they showed the efficiency of the method with comparison of their outputs with other results presented in the literature. In another work, they used Harris hawks optimization algorithm, the grasshopper optimization algorithm, and the multi-verse optimization algorithm to optimize processing parameters for different manufacturing processes [4].

Previously, many research papers have been reported in literature focusing on tool wear and surface roughness using modeling techniques; nevertheless, most of them have been developed for turning, whereas, there is little for the milling processes. Furthermore, they usually have applied one specific approach of optimization to achieve their goal without any comparison to other optimization methods. Kaye et al. [5] used a response surface methodology to develop a mathematical model to predict tool flank wear in turning by varying the spindle speed. Chien and Tsai [6] tried to develop a model for prediction of the tool flank wear and then optimize the model using a genetic algorithm for determining the optimum cutting conditions in turning of 17-4PH stainless steel. Sahoo and Pradhan [7] investigated machining characteristics in terms of surface roughness and flank wear in turning of Al/SiCp metal matrix composite using Taguchi methodology. Their analysis of tool wear showed that the most dominated wear mechanisms are abrasion and adhesion. Mia et al. [8] carried out MQL-assisted hard turning to study the surface roughness and tool wear parameters using a coated cemented carbide tool. They applied signal-to-noise ratio-based optimization and Taguchi orthogonal array-based design of experiment. It was concluded the surface roughness was significantly affected by cutting speed while the depth of cut had a predominant effect on the tool wear and feed rate significantly impacted the material removal rate. Amouzgar et al. [9] simulated a turning operation using finite element method and then applied evolutionary algorithms to minimize the interface temperature and tool wear depth. They found that the metamodel-based method reduced the computational time by 70%. Mia et al. [10] investigated the optimization of hard-turning parameters using two methods: teaching-learning-based optimization and bacterial foraging optimization. They achieved optimum cutting speed, feed rate, and depth of cut for the lowest surface roughness parameters and cutting temperature. Tsao [11] applied Taguchi method to improve parameters of the milling process. The proposed method decreased flank wear by 62%. Their experimental results indicated that the optimal process parameters can be determined effectively in milling A6061P-T651 aluminum alloy. Tamiloli et al. [12] carried out a grey fuzzy approach to obtain the optimal end milling process parameters by considering multiple performance characteristics. Recently, Savković et al. [13] investigated the influence of the cutting parameters on the surface roughness and the cutting forces during the face milling of aluminum alloy 7075. They showed that a minimum level for all input parameters was the optimal combination for the cutting force. To achieve the average arithmetic roughness, the minimum values for cutting speed and feed per tooth, and a median level for depth of cut were the optimal options.

This study defines a new output parameter named the specific tool wear where both tool wear and material removal rate have been evaluated. Surface roughness is considered as the second target output. Three methods of optimization with different natures have been proposed and compared to present a theoretical and systematic framework based on experimental results to achieve lower tool wear, surface roughness, and higher material removal rate in milling of steel AISI 1045 alloy.

2 MATERIALS AND METHODS

In this research, blocks of steel AISI 1045 alloy (sample size: 150 × 80 × 60 mm) were used as the workpiece. This steel is characterized by low strain hardenability and medium tensile strength between 570 and 700 MPa. This normalized and tempered alloy has a hardness ranging from 170 to 210 HRC and is widely used in the fabrication of axles, belts, pins, pumps, gears, and shafts in various industries. Experiments were conducted using an FP4MD universal milling machine. This machine has a positioning accuracy of ±0.005 mm with spindle speed ranging from 50 to 2500 rpm and desk feed rate of 0 to 900 mm/min. A 4-flute face milling cutter with 80 mm diameter was used in the machining process. The cutting tool consisted of a cemented carbide insert coated with TiN (ISO R245-12 T3 M-PM 4020). PVD coating material and thermal shock resistance of the substrate makes this insert suitable for both semi-dry and dry machining processes. The utilized inserts in the experiments had an inscribed circle diameter of 13.4 mm with an effective cutting-edge length of 10 mm and a corner radius of 1.5 mm. Fig. 1 shows a schematic diagram of the experimental setup. The surface quality was also measured by a roughness meter made by Taylor Habson company. The BX60 optical microscope manufactured by OLYMPUS company with the magnification of 50× to 1000× was utilized as well.

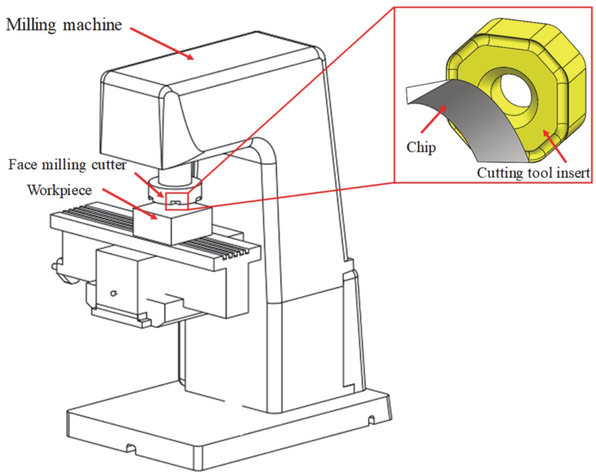


Figure 1 Schematic diagram of the experimental setup

2.1 Design of the Experiment

Design of experiment (DOE) has been one of the best tools to design and analyze complicated industrial problems. It is a useful method to investigate the level of effectiveness of the input variables on the output parameters. This approach is widely applied to systematically determine the optimal process parameters with fewer testing trials. This means lower cost whereas there are little errors compared with the full factorial trials. A comparison of different methods of DOE reveals that the Taguchi method is a powerful approach to optimize designs for performance [14, 15]. Three variables: cutting speed, feed rate, and depth of cut, each at three levels, were considered in the present study. As shown in Tab. 1, levels of these machining parameters were selected based on recommended cutting range of the insert by handbooks, and the limitation of the milling machine. In this research, instead of using 27 tests (full factorial), due to the time-consuming processes and high costs, 9 treatment combinations, each with three replications, were carried out in a random order thanks to Taguchi method (L_9).

Table 1 Independent variables and their levels

No.	Factor	Notation	Level −	Level 0	Level +
1	Cutting speed / m/min	v	126	201	314
2	Feed rate / mm/rev·tooth	f	0.06	0.12	0.18
3	Depth of cut / mm	a	1	1.5	2

Surface roughness R was measured in which the average arithmetical deviation of the area was calculated. Flank wear as a dependent variable appearing in the form of so-called wear land was measured by the width of flank wear (mm) (Fig. 2).

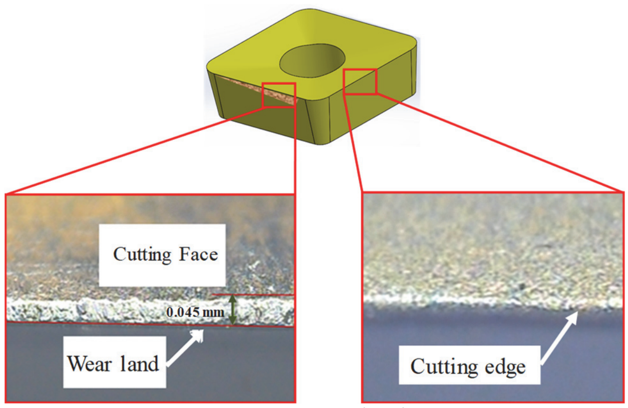


Figure 2 Measuring the width of the flank wear land

The specific tool wear VBs was then calculated from the measured flank wear and material removal rate as

$$VBs = \frac{VB}{MRR} \tag{1}$$

MRR is the material removal rate (cm^3/s) and calculated by the following equations:

$$MRR = \frac{L \times w \times a \times 10^{-3}}{t \times 60}, \quad t = \frac{L \times r \times \pi \times 2 \times 10^{-3}}{f \times v \times tooth} \tag{2}$$

where L is cutting length (mm), w is cut width (mm), t is machining time (min) and r is milling cutter radius.

2.2 Mathematical Model Development

The aim of mathematical modeling is establishing an inputs-outputs relationship to help understand how the typical value of the dependent variable changes when any of the independent variables is varied. Moreover, that is the first step to facilitate optimization of the process, optimal machining parameters to get minimum surface roughness, and specific tool wear. Based on Taguchi L_9 matrix, the results of nine tests are presented in Tab. 2.

Table 2 Experimental results of responses according to Taguchi L_9 orthogonal array

No.	Cutting Speed / m/min	Feed Rate / mm/rev·tooth	Depth of Cut / mm	Surface Finish / mm	Specific tool wear / cm/(cm^3/s)
1	126	0.06	1	1.67	0.0250
2	126	0.12	1.5	2.14	0.0106
3	126	0.18	2	2.22	0.0057
4	201	0.06	1.5	1.47	0.0139
5	201	0.12	2	2.04	0.0058
6	201	0.18	1	1.71	0.0075
7	314	0.06	2	1.75	0.0088
8	314	0.12	1	1.5	0.0077
9	314	0.18	1.5	1.94	0.0037

As detailed, the first three columns are the independent machining parameters and the fourth and fifth ones are dependent output objectives including surface roughness and specific tool wear respectively.

The statistical regression analysis had been applied to mathematically model the relationship between input and output parameters based on the data collected as per test. The coefficients values of developed regression functions such as linear, curvilinear, and logarithmic were calculated. It should be mentioned that these models were modified by an elimination process called stepwise technique which removes the inconsiderable terms to adjust the fitted model.

The most fitted function is the best model for the experimental data that accurately predict the actual output in the machining process. The next is the evaluation of the proposed models using ANOVA technique based on three factors, correlation factor R^2 (Tab. 3), probability value (p-value), and normality of residuals.

Table 3 Correlation factor values

Processed models	Output	R^2
Linear models	R	83.5
	VBs	89.3
Curvilinear models	R	77.3
	VBs	82.08
Logarithmic models	R	80.6
	VBs	99.6

Evaluation of different models reveals that the linear model for surface roughness and logarithmic model for specific tool wear are superior to others. These proposed models are presented below:

$$R = 1.23 - 0.00138v + 2.7f + 0.38a \tag{3}$$

$$VBs = 0.05012 \cdot v^{-0.656} \cdot f^{-0.892} \cdot a^{-0.777} \tag{4}$$

the probability plots of the above models are shown in Fig. 3. These plots were constructed for a confidence interval (CI) of 95%.

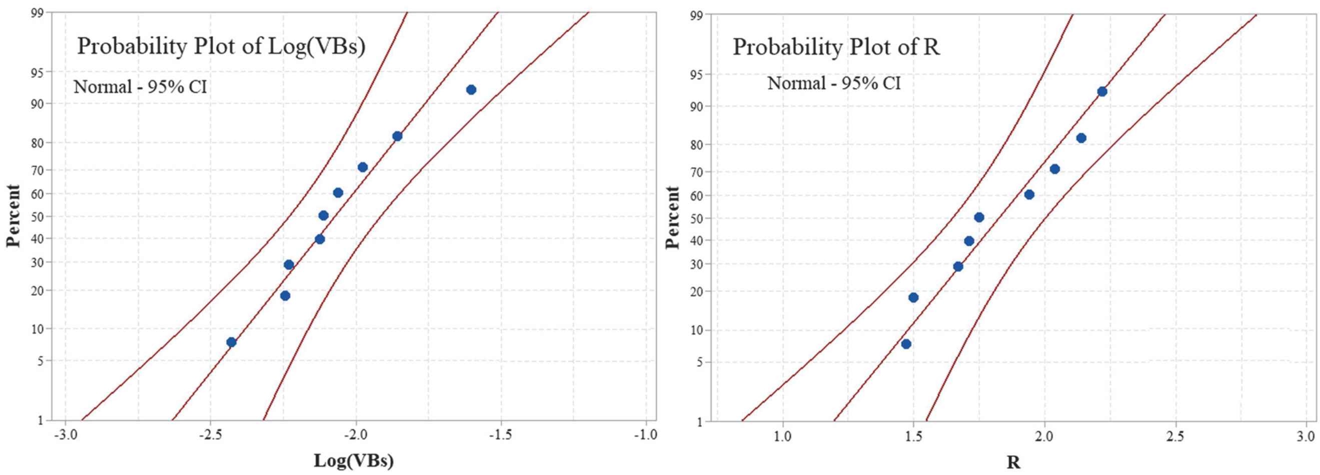


Figure 3 Probability plots for specific tool wear log(VBs) and surface roughness (R)

3 OPTIMIZATION PROCEDURE

In many real conditions, it is required to set the process parameters in such a way that the desired output is achieved. There is a multi-objective optimization problem containing two objectives (responses) that should be minimized simultaneously. In such problems, objectives usually act as opposed to each other; which means that one objective decreased while another is increased. So, a trade-off procedure is required to achieve a reasonable solution that relatively minimizes all of the objectives by satisfying the applied constraints. In the present paper, three methods are used to solve this multi-objective problem, namely the Simulated Annealing (SA) algorithm, Goal-attainment method, and Regression response optimization.

3.1 Simulated Annealing Algorithm

This is a problem of combination explosion where evolutionary algorithms have emerged as a powerful optimization procedure. The evolutionary algorithms are practical and effective optimization techniques widely applied to solve combinatorial engineering problems. Simulated Annealing (SA) is one of the novel algorithms, first proposed by Kirkpatrick et al. [16]. SA is a stochastic search algorithm applicable to a wide range of problems for which little prior knowledge is available. Inspired by nature, SA algorithm is adapted from the process of gradual cooling of metals. The annealing is a heat treatment where a solid is reheated to a high temperature known as the annealing point so that the molecules are able to move freely and then let it cool slowly until thermal mobility is lost. To reach the minimum energy, atoms try to arrange in perfect crystal structure which requires a proper cooling time. The solid is able to reach a certain thermal equilibrium status at temperature T. The Boltzmann distribution defines the probability of being at the energy level of E:

$$pr(E) = \frac{1}{Z(T)} \times \exp\left(-\frac{E}{K_B \cdot T}\right) \tag{5}$$

where K_B is the Boltzmann constant and $Z(T)$ is a normalization factor. The exponential term is named the Boltzmann coefficient. As temperature decreases, the Boltzmann distribution focuses on a state with the lowest energy and this will be the only possible state when the temperature comes close to zero. In this work, the employed SA code operates based on a neighborhood structure so that a small random change is made to one of the input variables at each step. The objective function value of the new solution (new input variables) is then compared with that of the current input variables. If this new solution demonstrates a lower objective function, the move will be accepted. Otherwise, there is a chance of escaping from local minima depending on the satisfaction of the following inequality:

$$\mathrm{e}^{-\frac{\Delta c}{T}} \geq Ran(0,1) \tag{6}$$

With a gradual decrease in temperature from a relatively high value to near zero as the search progresses, the probability of non-improving solutions becomes small as the difference in the costs (Δc) increases. As a result, at the beginning, even most worsening moves are accepted, but in the end, only improving ones are more likely to be accepted [17, 18].

It is required to define a proper function in the form of an error function to adopt SA technique for predicting the process parameters values. This function, based on a given R and VBs, would determine the goodness of any set of process variables regarding the resultant R and VBs. The multi-objective function in our problem is defined as a squared error function given below:

$$E_F = \frac{w_R (R_x - R)^2}{R_x} + \frac{w_{VB} (VBs_x - VBs)^2}{VBs_x} \tag{7}$$

In the above expression, R and VBs are what is gained from models and the desired surface roughness and specific tool wear values are specified by R_x and VBs_x as the target values. w_R and w_{VB} are weights for R and VBs respectively determining the importance of one objective compared to another one. Moreover, in some optimization techniques changing the value of weights can improve results. It is worth noting that changing weights in SA algorithm show no improvement in error function due to its nature of random, thus they are considered equal in SA algorithm. During the search, the algorithm tries to determine process parameters in such a way that error function E_F is minimized letting them approach their desired values.

3.2 Goal-attainment Method

The goal-attainment method is first proposed by Gembicki [19] to solve multi-objective problems. In this method, it is assumed that the optimization problem is constructed from a set of objectives $J_i(x)$ with $i = 1, 2, \dots, n$. It is also assumed that the approximate values of the final solutions are known for the set of objectives. These solutions are named as the design goals. Objectives should try to converge to these goals. So, a set of parameters are defined as design goals J_i^* for each objective in the optimization problem. It should be noted that the objectives may not achieve the goals (under-achievement). However, there is also possibility of achieving exactly the design goal, or even achieving and exceeding the goal to further minimize the objectives (over-achievement). The degree in which objectives achieve the design goals is controlled by the set of weights (factors) w_i. In order to find appropriate initial values for the design goals, several optimization problems must be solved in which different initial values of the design goals have been applied [20-22]. Even if the initial values for the design goals are not already available for a specific problem, the appropriate values can be obtained by conducting a parameter study or a simple try and error procedure. A general goal-attainment optimization problem can be defined as the minimization of γ such that Eq. (8) is satisfied for all objectives.

$$J_i(x) - w_i\gamma < J_i^* \ , \ i = 1, 2, \dots, n \tag{8}$$

In Eq. (8), $w_i\gamma$ is the amount of deviation that the ith objective J_i may have from the ith design goal J_i^*. In other words, the degree of the under- or over-achievement is controlled by this factor. w_i magnitude usually is ranged from zero to 1 and assigned to the ith objective to emphasize its importance in comparison to the other objectives. The algorithm tries to minimize γ so that the objectives achieve the design goals. For this purpose, it starts from a given initial point in the space searching for a special point that minimizes the objectives according to the input machining parameters. The minimization process by the goal-attainment method can be easily described in a two-dimensional space; which is the case in the present paper. A simple schematic illustration of such a problem is shown in Fig. 4. In this figure, the initial point is defined by $A = \left[J_1^0, J_2^0\right]$ in the two-dimensional space and the feasible objective region stated by $\Omega(\gamma)$, the algorithm starts to move from A towards the feasible region Ω in the search direction vector defined by γw with $w = [w_1, w_2]$. If it is assumed that this vector intersects region Ω in point $B = \left[J_1^s, J_2^s\right]$ and its corresponding value of γ is zero, a feasible solution is exactly achieved the design goal. If a negative value was obtained for γ, it indicates that the design goals are over-attained and a better solution (than that of design goal) is obtained for the problem. A positive value of γ represents the under-achievement condition in which the design goals are not attainable for the objectives. This procedure is similar to calculating the nearest point from the initial point A to the feasible objective region $\Omega(\gamma)$ in the direction defined by $A + \gamma w$. An optimization model is obtained by applying this method to calculate the optimum machining parameters that minimize the equations stated in Eq. (3) and Eq. (4) simultaneously. This model can be stated as minimizing γ such that

$$J_i\left(a, f, v\right) - w_i \gamma < J_i^*\quad,\ i = 1 \text{and} 2 \tag{9}$$

where a, f and v are machining parameters as already defined in Tab. 1 The configured model is a multi-objective optimization problem with inequality constraints. Objectives $J_1\left(a, f, v\right)$ and $J_2\left(a, f, v\right)$ are defined as R and VBs according to Eq. (3) and (4) respectively.

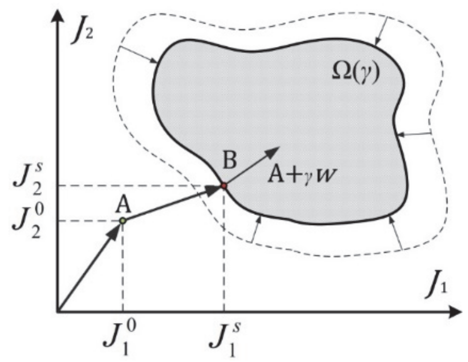


Figure 4 A schematic diagram of the optimization process using the goal-attainment method

3.3 Regression-response Optimization Method

Response optimization is a method that identifies the combination of variable settings and allows for compromise among the various responses [23]. The optimization is carried out by obtaining the individual desirability for each response (R and VBs) and combining those to obtain the composite desirability thereby maximizing or minimizing the composite desirability and achieving the optimal input variables [24].

4 RESULTS AND DISCUSSION

The proposed SA code was programmed in MATLAB 9.0® and executed on an AMD Ryzen 3 1300× Quad-Core with a 3.50 GHz processor. It is worth noting that controlling parameters of the algorithm were modified several times during the research to achieve the best SA algorithm structure for this case study. These parameters are as follows: cooling schedule function $c_{k+1} = \alpha c_k$ (α = 0.95); initial temperature (c_0) 20; neighborhood generation pairwise interchange; termination criterion ranging from 100 to 100000 iterations. Longer execution of the algorithm, with more iteration and higher initial temperatures, showed no more improvement. The code was run several times and its three optimization results are summarized in Tab. 4 As shown, the specific tool wear was less than 0.009, while the surface roughness was about 1.50 revealing that the proposed models can estimates the process properly. The presented data also can be used to calculate material removal rate and flank wear land by Eq. (1) and the following equation respectively:

$$VB = \frac{VBs \times w \times a \times f \times v}{3\pi \times r} \tag{10}$$

For instance, according to No. 1 run in Tab. 4 flank wear land and material removal rate will be 0.0462 mm and 0.5844 cm^3/s respectively.

To evaluate the performance of the proposed SA algorithm, a convergence curve for a sample test run is shown in Fig. 5. This curve illustrates that most of the improvements achieved within the first 1000 iterations (40^s of search time) indicate the quick coverage of algorithm and the efficiency of proposed SA procedure.

Table 4 Optimization results of the proposed SA algorithm

No.	Process Parameters By SA			Predicted Value by SA	
	v / m/min	f / mm/rev·tooth	a / mm	R / mm	VBs / cm/(cm^3/s)
1	306	0.10	1.20	1.532	0.0079
2	312	0.12	1.00	1.503	0.0077
3	284	0.11	1.00	1.514	0.0088

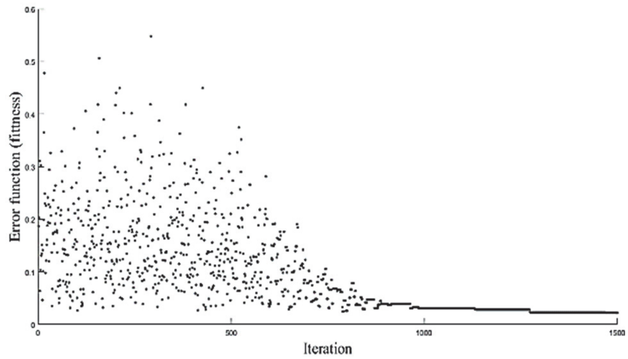
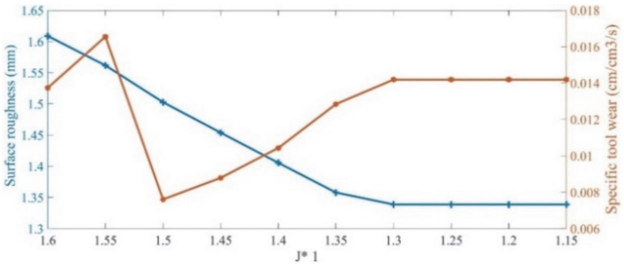
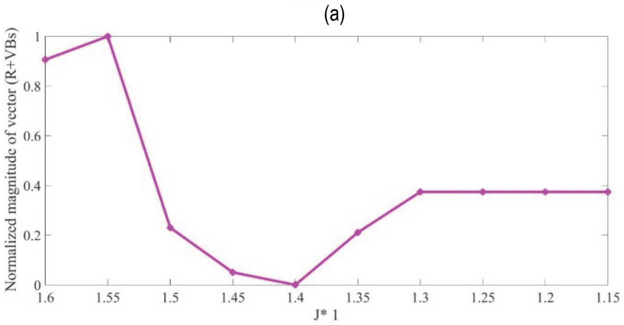


Figure 5 Convergence rates for SA algorithm

As for the goal-attainment optimization technique, the method was developed to solve the problem and obtain the optimum machining parameters that minimized the specific tool wear (VBs) and surface roughness (R) simultaneously. The mentioned model in section 4.2 was implemented in MATLAB software and solved using *fgoalattain* function. Design goals were determined by running the code several times and conducting a simple try and error process. The effect of the factors including weights, design goals, and the initial point was also investigated on the results. An optimization model depicted in Eq. (9) was constructed and solved using a developed MATLAB code. The initial point of the optimization problem was chosen as the midpoint between the upper and lower limits based on the boundaries of the machining parameters stated in Tab. 1. It is worth noting that different alternatives were utilized for the initial point; nevertheless, no sensible change was observed in the results. Appropriate selection of the design goal vector J_i^* can be considered as the main challenge in the goal attainment method. According to the results of the SA algorithm, $J^* = \left[J_1^*, J_2^*\right] = \left[1.5, 0.009\right]$ was applied as the first guess for the design goal; however, it was observed that a further decrease in the design goal improved the process of minimization of the objectives. The weight vector was assumed as w = [0.5, 0.5] means assigning the same importance level to the objectives J_1 and J_2. The results of several runs for optimization model revealed that the value of J_2^* had no significant effect on the output results. Therefore, the change of J_1^* in the design goal vector was taken into consideration and the optimization model was solved using the mentioned code. Fig. 6 shows changes in objectives (R and VBs) as J_1^* decreases from 1.6 to 1.15. As the variations in either J_1^* or J_2^* leads to the definition of a new design goal, the algorithm tries to achieve this new goal by changing both objectives simultaneously.



(a)



(b)

Figure 6 Results of the optimization conducted using the goal attainment method (a) diagram of surface roughness (R) and specific tool wear (VBs) regarding the first design goal (J_1^*); (b) diagram of the normalized magnitude of vector R + VBs regarding the first design goal (J_1^*) (assumptions: J_2^* = 0.005, w = [0.5, 0.5] and A = [220, 0.12, 1.5])

As J_1^* decreases from 1.6 to 1.3, the optimized surface roughness (R) decreases from about 1.61 to 1.34 and stays constant for further decline in the design goal (Fig. 6a). In contrast to R, the value of the specific tool wear first fluctuates between 0.017 and 0.008, then starts to increase gradually in goal value of 1.5. Once VBs reaches 0.014 it stabilizes at this value (Fig. 6a). From these graphs it can be seen that there is a threshold value for the design goal as crossing that to further minimize the objectives, no change can be obtained for the results. Determination of a specific result that minimizes simultaneously both of the objectives seems to be impossible since objectives act as opposed to each other in some intervals of the first design goal. For example, in the interval [1.55-1.3], the first objective (R) had a totally descending trend while the second (VBs) had a descending then ascending behavior. To choose an optimal solution that relatively minimizes both of the objectives, data illustrated in both diagrams were first normalized in the interval [0-1]. The magnitude of the normalized resultant vector (R + VBs) was then calculated and presented in Fig. 6b. As shown in the graph when J_1^* is 1.4, a trade-off point can be obtained that relatively minimizes both of the objectives. By substituting J_1^* = 1.4, the optimized values of R and VBs were obtained as 1.405 mm and 0.010 cm/(cm^3/s) respectively. The corresponding machining parameters for these optimized values were v = 314 m/min, f = 0.085 mm/rev·tooth and a = 1 mm. These results were achieved by assigning the same weights to the objectives. In some cases, as already mentioned, the minimization of an objective is more important than the others, hence the designer may sacrifice other objectives to achieve an appropriate possible solution to the first one by increasing its weight high enough.

Regarding the regression-response optimization technique, as the goal is to minimize R and VBs responses, the target and upper boundary values had been set based on the minimum and maximum values in experimental data. In this technique, the weight of every response determines how the desirability is distributed on the interval between the lower (or upper) bound and the target shaping the desirability function. In order to consider the best weight percentage for two responses based on error function criterion, the weight for VBs objective was changed from almost zero to 1 and accordingly, the weight for the second objective was changed. Eq. (7) was applied to evaluate the best weight for every response. As shown in Fig. 7, generally, decreasing weight factor for VBs has a profound effect on decreasing error function. These results indicate that the best weights for VBs and R are 0.4 and 0.6 respectively.

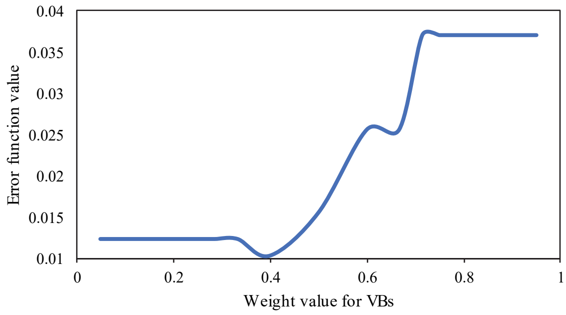


Figure 7 Weight value evaluation based on the error function

Fig. 8 details how well a combination of variables satisfies the goals defined for the responses where d and D are the individuals and composite desirability values respectively. Individual desirability evaluates the manner in which the settings optimize a single response, while composite desirability evaluates how the settings optimize a set of responses overall. There is a range of zero to one as desirability where one indicates the ideal case and zero represents that one or more responses are outside their acceptable limits.

The optimization plot (Fig. 8) shows the effect of each variable on the surface roughness and specific tool wear (composite desirability). The numbers displayed at the top of a column present the level of the current parameter settings (in red) corresponded to the red lines on the plot. The horizontal lines and numbers in blue show the responses for the current input parameters level. As highlighted in figure, increasing cutting speed improves both surface roughness and specific tool wear; but, by contrast, feed rate and depth of cut move in the opposite direction to improve both responses. The results of regression-response optimization show that optimum values for machining parameters are v = 314 m/min, f = 0.117 mm/rev·tooth and a = 1 mm. Based on these input parameter, surface roughness and specific tool wear can reach 1.49 mm and 0.0078 cm/(cm^3/s) respectively.

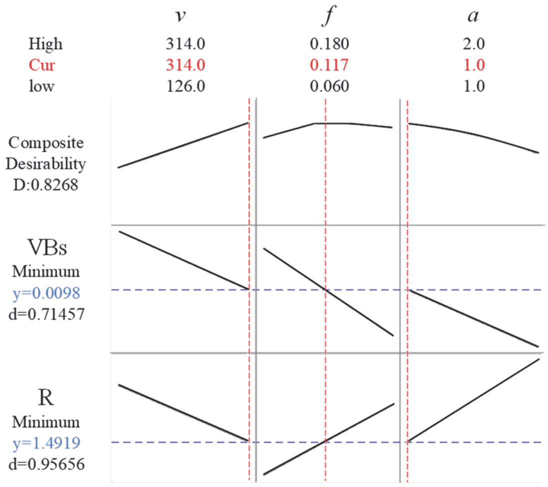


Figure 8 The variables effects on the predicted responses

Tab. 5 compares the results for different compositions of input parameters obtained from three optimization methods. It is worth reminding that unlike SA which generates different compositions and results in every run of the algorithm, the goal-attainment and regression-response optimization methods produce only one specific result. So, the compositions presented in this table were the best results in several runs of the SA program. Computational results show that the regression-response optimization method has less error function compared to the proposed SA algorithm and goal-attainment method indicating it can determine parameters for the minimum surface roughness and specific tool wear in the milling process with higher efficiency.

The percentage influence of three machining parameters on surface roughness and specific tool wear are also evaluated in Fig. 9. Based on the Analysis of Variance (ANOVA), it is found that feed rate is the most significant variable on specific tool wear. It is nearly twice more effective than the depth of cut and cutting speed. In comparison, depth of cut is the variable that has the most influence on surface roughness followed by feed rate and cutting speed.

Table 5 Results comparison of three optimization methods

Methods	Process Parameters By SA			Predicted Value by SA		Error function
	v / m/min	f / mm/rev·tooth	a / mm	R / mm	VBs / cm/(cm^3/s)	Error function
SA Algorithm	312	0.120	1.00	1.503	0.0077	0.0148
Goal-attainment	314	0.085	1.00	1.405	0.0104	0.0183
Response	314	0.117	1.00	1.492	0.0078	0.0138

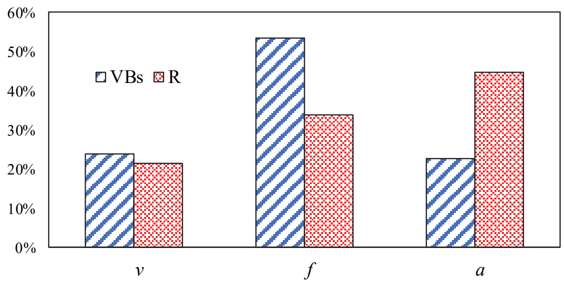


Figure 9 The percentage of effect of machining parameters on specific tool wear and surface roughness

5 CONCLUSIONS

In this paper, a procedure to formulate and model the relationship between three determining factors in the milling process was introduced. Three independent variables including cutting speed, feed rate, and depth of cut and two output parameters including surface roughness and specific tool wear had been selected. After developing and checking the adequacies of mathematical models with regard to ANOVA, it was found that the fittest models for R and VBs were linear and logarithmic respectively. These models were then used to optimize two target parameters using different optimization methods. Three different methods of optimization with different natures were applied to determine optimal output parameters in the process including SA algorithm (an evolutionary algorithm), goal-attainment method and regression-response optimization techniques. Utilizing these optimization methods, mathematical models were optimized to obtain a group of optimal process parameters, which minimizes surface roughness and specific tool wear values. The comparison of results obtained through these optimization methods based on error function, indicates that although all techniques demonstrate acceptable outputs, regression-response optimization presents the best combination of parameters. The Simulated Annealing (SA) algorithm also reveals less error function compared to goal-attainment methods. The results of optimization revealed that optimum values for cutting speed and feed rate were ranged from 312 to 314 m/min and 0.085 to 0.12 mm/rev·tooth, respectively, while all optimization methods reached the same value of 1.0 mm for the depth of cut parameter. Besides, Analysis of Variance (ANOVA) showed that feed rate is the most significant variable on specific tool wear, and depth of cut is the variable that has the most influence on surface roughness followed by feed rate and cutting speed. It should be noted that the presented results are based on experimental data of the milling process and can be a different case by case depending on its answer space. Applying these optimization techniques to the different manufacturing processes is proposed as future work.

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