Investigations of surface quality and energy consumption associated with costs and material removal rate during face milling of AISI 1045 steel

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Abstract
Machining of AISI 1045 steel is prominent in several industries due to their good machining characteristics. In this study, the optimum conditions of fly (face) milling of parts made of AISI 1045 steel was analyzed. The generated surface quality, the cost of the cutting tool components, the energy consumption, the wearing of the cutting tool, and material removal rate are the main parameters in this study. Several cutting experiments over different cutting lengths have been conducted and analyzed statistically to determine the optimum targeted cutting conditions. A multilayer regression analysis was conducted on obtained experimental results and inducing non-linear mathematical equations with high coefficient of determination \( R^2 = 0.98 \). The influence of feed per tooth \( f_z \), cutting speed \( v_c \), flank wear \( V_B \) to surface roughness \( R_z \), cutting power \( P_c \), material removal rate (MRR), sliding distance \( l_s \), and the tool life \( T \) has been considered. The overall results, estimated through Grey relational analysis (GRA), revealed that the optimum fly milling performance for a fast manufacturing (case 1) are obtained for feed per tooth \( f_z = 0.25 \) mm/tooth, cutting speed \( v_c = 392.6 \) m/min, and machined length \( l = 5 \) mm. While the optimum parameters for resource (tools) conservation (case 2) are feed per tooth \( f_z = 0.125 \) mm/tooth, cutting speed \( v_c = 392.6 \) m/min, and machined length \( l = 5 \) mm.

Keywords Face milling · Fly milling · Cost saving · Power consumption · Surface roughness · Tool wear · Non-linear regression analysis

1 Introduction
Face milling of structural materials such as AISI 1045 steel is very important for modern manufacturing applications. Products made from such materials are widely used in critical applications in the automotive, shipbuilding, and many other industries. Currently, for modern production, it becomes the most urgent task in addition to ensuring the requirements for machining accuracy (surface roughness), as well as the need to ensure the sustainability of production. Environmental and

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social aspects must be taken into account in order to ensure the efficient use of available resources. In this growing world, the demand for energy-efficient manufacturing processes is rapidly increasing because of strict environmental concerns. However, the power consumption and cost issues in manufacturing processes are two important factors from the perspective of the machining system that directly oblige the manufacturer to search for environmentally friendly processes [1]. Therefore, the main objective of this paper is to perform an experimental study especially related to two research objectives, i.e., power consumption measurement and cost estimation of the face milling process. Also, the complex influence of flank wear of face mills on such indicators as surface quality, power consumption measurement, and cost estimation is discussed. It is important to know such trends, and it is even better to be able to control such parameters as the tool wear increases. It is important to show this not only for some average wear values that are accepted for the disastrous but also to investigate the behavior of the output parameters of face milling outside these average wear values.

Face milling is a highly efficient machining process, widely used in manufacturing of flat surfaces [2–6]. At present, there are studies devoted to face milling of AISI 1045 steel (an analog of steel 45 considered in this article). Srivatsan et al. [7] presents the effect of cutting depth and tool speed on the residual stresses that occur when milling AISI 1045 steel. Padma Ooh et al. [8] in their article performed studies of residual stresses in AISI 1045 steel caused by milling. However, in these works [7, 8], the process of face milling is studied without taking into account tool wear. D’Errico et al. [9] investigated seven commercial inserts of metal-ceramic with dry face milling of carbon steel (AISI–SAE 1045). Richetti et al. [10] evaluated the flank wear curves for AISI 1045 and 8640 plates of steel using 1, 2, 3, and 6 inserts in a face milling cutter. Muñoz-Escalona et al. [11] developed the empirical models to predict tool wear mechanisms during milling AISI 1045. However, in these papers [7–11], the process of tool wear without examining the relationship with roughness is investigated. Moreover, it is important to ensure the critical characteristic of flat-surfaced workpieces, i.e., surface roughness $R_z$ (“maximum height of the assessed profile” according to ISO 4287:1999). Pimenov et al. [12] showed the influence of relative position of the cutter relative to the workpiece and the kinematics of milling on the components of the cutting forces, the spindle acceleration of the machine during the face milling of steel SAE 1045. Ali et al. [13] investigated the surface roughness, material removal rate, and cutting time for torch milling operations. Toledo et al. [14] analyzed the effect of the relationship between the length of the parallel surface of the secondary cutting edge and the feed per tooth $(b_f/f_f)$ on the surface roughness of AISI 1045 steel during face milling. Pimenov [15] introduced the influence of feed, cutting and on the roughness of flat surfaces in the face milling of steel 45. And this criterion is important for the quality of the treated surface.

At the same time, face milling consumes a significant amount of energy, which is caused by a larger tooth area. In addition, it is important to process to minimize machining energy. Henceforth, researchers have explored many strategies to minimize the machining energy (i.e., power) consumption. For instance, Hu et al. [16] strategically optimized the machining sequence to minimize the machine tool energy consumption. The machining scheme composed of milling and drilling operations on C45 steel. They have claimed that selecting the apt route can significantly reduce the power consumption in machining. In another paper, Hu et al. [17] attempted to reduce the energy consumption in machining for tool change and tool path; a 28.6% reduction is noticed in energy consumption caused by feature transitions. Even, that optimum change caused 27.95% reduction in machining time. Considering the extreme importance of energy consumption in machining, Li et al. [18] formulated specific energy consumption and power models for face milling operations with reliability above 96%. These models were formulated in terms of MRR and cutting speed, and authors claimed that those models are useful for estimation of power without measurement. Aramcharoen and Mativenga [19] identified the critical factors of energy modeling and influence of tool wear on energy intensity during machining. Their developed models predicted energy at 95% accuracy. They have also stressed that the reduction of tool wear can play effective role in reducing the energy consumption. An intelligent model was proposed by Garg et al. [20] for conserving the energy consumption in milling machining. They have employed the advanced evolutionary algorithm, i.e., multi-gene genetic programming technique. Another energy optimization study was reported by Albertelli et al. [21] with the novelty that they considered, in their model, the energy consumed by the auxiliary systems of a machine tool in face milling process. In fact, the authors have correlated the energy parameters with cutting parameters. Most notably, the influence of changes in tool wear in the machining process was incorporated in the model too. They have emphasized that the appropriate selection of process parameters is imperative to reduce the energy and time. On the other hand, Garg et al. [22] studied and modeled the tool life and power consumption for machining using three advanced modeling methods. The inputs of the models were cutting speed, nose radius, cutting depth, and feed rate. Then statistical comparison was conducted to suggest the best model—the genetic programming model. Shnfir [23] studies the machinability of AISI 1045 hardened steel during face milling using ceramic inserts based on SiAlON and whisker (SiCW). And it gives the influence of cutting parameters, milling configurations, edge preparation, and hardness of the processed material on machinability indicators, such as the resulting cutting force, power consumption,
and wear of the side tool. However, in the above studies, the cost of machining was not considered. In Khan et al. [24], multipurpose optimization was performed by integrating the Taguchi method, Grey’s relational analysis (GRA), and the non-dominant sorting genetic algorithm (NSGA-II). Where the output parameters are surface roughness and active cutting energy, taking into account the removal rate of the material, but excluding the cost of processing.

Besides, tool wear increases along with the sliding distance (friction distance), and tool life determines the tool cost. In modern manufacturing, minimizing machining cost per workpiece is very important. It is therefore important in designing face milling operations to ensure the design surface roughness and minimize the power consumption and cost of machining at the same time. This approach allows for saving resources in manufacturing the end item.

Therefore, the current studies are dedicated to different machinability aspects of face milling. However, there is a scarcity of study regarding the sustainability achievement in machining by power consumption reduction and cost performance improvement. A comprehensive optimization study was conducted by Yang et al. [25] for face milling. They have optimized the cost of production, time, and rate of profit while maintaining the constraints of force, power, speed and feed and surface roughness. Yang et al. [26] employed advanced modeling technique, i.e., gene expression programming to model the energy consumption in face milling. Wang et al. [27] performed multi-response optimization for reducing the cost as well as the energy consumption using evolutionary algorithms for face milling. For instance, Sales et al. [28] investigated the performance of MQL in milling of AISI 4140 steel by considering surface roughness values, flank wear, and tool life as an input process parameter. Singh et al. [29] performed the milling experiments on Inconel-718 and the performance in terms of tool wear with respect to the milling process parameters was evaluated by an evolutionary algorithm. On the same content, Gupta et al. [30] applied the two evolutionary algorithms for optimizing the turning parameters under MQL conditions. Then, Siller et al. [31] discussed the influence of specially designed carbide tools on the performance (surface quality and tool life) of AISI D3 steel during the face milling operation. Cui and Zhao [32] examined the important machining indices in terms of tool wear mechanism, chip and surface characteristics in high-speed face milling of AISI H13 steel. In another face milling operation of Ti-10V-2Fe-3Al (Ti-1023), Houchuan et al. [33] discussed the effect of cutting speeds along with the average flank wear values on surface characteristics, defects of machining, micro-hardness, and microstructure variations values. Similarly, the influence of damaged inserts on surface roughness values during high-speed face milling of 17-4 PH steel was investigated by Liu et al. [34]. It is appreciable that general machinability aspects are studied by the above researchers. Some critical aspects such as cost, quality of the product, and power consumption are missing in many studied. This fact encouraged the authors to pursue this comprehensive study.

At present, many researchers use advanced modeling techniques to study surface roughness in face milling. Bruni et al. [35] implemented the artificial neural network technique to analyze the effect of lubricant-cooling techniques on surface roughness values during face milling of AISI 420 B steel. Sahu and Andhare [36] used the response surface methodology for estimation of power, productivity, tool wear, and surface roughness in high-speed milling of Ti6-AL-4V alloy. Siwarut et al. [37] investigated the machining behavior and wear properties of Co-WC coated inserts in dry face milling of cast iron. Studies use artificial intelligence to establish the correspondence between face milling parameters and the resulting surface roughness taking into account tool wear. However, no qualitative studies of the influence of face milling parameters on factors such as surface roughness, tool life, cutting power, and machining cost have been conducted in the literature. Managing cutting power and minimizing cost per workpiece enable us to promote sustainable manufacturing. It is also important to take into account tool life and flank wear that are affected by the cutting parameters.

The main objective of the technological process is to provide the required accuracy of processing. This is possible if there is dependence or model for predicting roughness on cutting conditions. Secondly, it is important to ensure the required surface roughness for the minimum material removal rate. Third, it is important to minimize processing costs by optimizing this parameter. Knowing the cutting force and cutting power, it is possible to choose the cutting conditions that reduce energy costs. In turn, this has reduced emissions from power plants for electricity generation. Thus it is important to have a complex relationship between the surface roughness, material removal rate, the processing cost, and cutting power at the outlet and inlet cutting conditions. It also requires multiparametric optimization of the entire complex of the data.

The aim of this study is to investigate patterns connecting feed per tooth \( f_z \), cutting speed \( v_c \), and the flank wear \( V_b \) to surface roughness \( R_z \), cutting power \( P_c \), material removal rate (MRR), sliding distance \( l_s \), and tool life \( T \) and determine the optimal cutting conditions, therefore, to provide for the design surface roughness while decreasing the cutting power and minimizing face milling costs at the same time.

### 2 Experimental procedure

The experiments were performed by considering the environmental aspects. The details of materials and equipment used in current work is discussed below.
2.1 Experimental conditions

For complex evaluation of surface roughness and minimizing the power consumed by the cutting operation as well as machining cost in fly milling, experimental studies have been conducted to measure the various tool flank wear values. The workpiece material used was AISI 1045 steel (the composition of high-quality structural carbon steel 45 in accordance with the Russian national state standard (GOST) 1050-99). The actual chemical compositions of test specimens are given in Table 1.

In general, the microstructure of the annealed/normalized AISI 1045 steel consists of ferrite and pearlite. As shown in Fig. 1a, the microstructure of the tempered specimen consists of ferrite (white areas) and tempered martensite (dark areas). In order to reveal the precipitates, the microstructure was examined using scanning electron microscopy (SEM). Consequently, as shown in Fig. 1b, dark and white areas represent ferrite and carbides, respectively.

For machining of a workpiece with the dimensions length \( L = 200 \) mm, width \( B = 75 \) mm, height \( H = 100 \) mm without cooling, an SF15 (6C12) vertical mill (LSZ, Lugansk, Ukraine) (Fig. 1) was used. The parameters of the cutting tool were as follows: cutting surface material (pentagonal cutter the Russian national state standard (GOST) 19021-80 (Kirovograd, Russia))—T5K10 (the composition of the hard T5K10 alloy of the titanium-tungsten cobalt group in accordance with GOST 3882–74 given in Table 2); mill diameter, \( D = 125 \) mm; main cutting edge angle, \( k_1 = 60^\circ \); side cutting edge angle, \( k_{1s} = 12^\circ \); rake angle, \( \gamma = 15^\circ \); clearance angle, \( \alpha = 8^\circ \); number of mill teeth, \( z = 1 \); insert side length, \( l = 1.0 \) mm; height insert, \( h = 5 \) mm; corner radius, \( r = 0.8 \) mm; cutting edge pitch angle, \( \lambda = 0 \). The workpiece hardness was measured at HB 190 using a TB 5004-03 Brinell hardness tester (Tochpribor, Ivanovo, Russia). The reference guide is used to select the input process parameters for the machining process, as tabulated in Table 3.

Surface roughness \( R_z \) was measured using a profilometer Abris-PM7.0, which is a stylus-instrument (GCI SI VNIIMS, Moscow, Russia). The readings were taken for the base length \( L = 0.4 \) mm at the start, the middle, and the end of the pass of the mill. Every experiment had, therefore, \( 3 \times 5 \) iterations \( (k = 15) \).

The flank wear values, as well as machined surface values, were noted after each pass of the mill. This way, the experimental points of surface roughness were obtained for various flank wear areas and fly milling parameters. Statistical processing was then carried out on the experimental data to achieve the statistical design reliability of 0.95. The average values of the measured parameter were established based on the data from 5 experiments. Homogeneity of the sampling variance was checked using Cochran’s \( Q \) test. Figure 2 presents the flank tooth of the fly mill.

Table 4 lists the experimental and estimated data for the cutting parameters presented in Table 3.

2.2 Calculations for various stages of fly milling

Sliding distance, \( l_s \), is determined by Eq. (1):

\[
ls = (D_{ST} \cdot l_1)/(1000 \cdot fz),
\]

where \( D_{ST} \) is the length of the tooth mill sliding trajectory \((D_{ST} = 80.4 \) mm).

Processing time (tool life) \( T' \) is determined by Eq. (2):

\[
T' = (L + l_1)/(n \cdot z \cdot fz),
\]
Table 3 Cutting parameters for various stages of fly milling

| No. | Fly milling stage | Milling depth, $a_p$, mm | Feed per tooth, $f_z$, mm/tooth | Cutting speed, $v_c$, m/min | Spindle rotation speed, $n$, rpm |
|-----|------------------|--------------------------|---------------------------------|-----------------------------|-------------------------------|
| 1   | Finishing        | 1                        | 0.125                           | 392.6                       | 1000                          |
| 2   | Finishing        | 1                        | 0.16                            | 392.6                       | 1000                          |
| 3   | Semi-finishing   | 1                        | 0.25                            | 392.6                       | 1000                          |
| 4   | Semi-finishing   | 1                        | 0.25                            | 247.3                       | 630                           |
| 5   | Initial          | 1                        | 0.32                            | 196.3                       | 500                           |

where $l_1$ is the allowance length ($l_1 = 5$ mm); $f_z$ is the feed per tooth; $z$ is the number of mill teeth; $n$ is the spindle rotation speed.

Equation (3) is used to evaluate the cost of one part, i.e., $C_i$:

$$C_i = \left( \left[ (C_{\text{Main}} \cdot T') + \left( C_{\text{Toolmin}} \cdot T' \right) + C_{\text{w}} \right] \right) \cdot l / L$$

where $T'$ represents the tool life, i.e., $T' = (L + l_1) / (n \cdot z \cdot f_z)$, $n = (1000 \cdot v_c) / (3.141 \cdot D)$, $C_{\text{Main}}$ termed as the machining cost/hour, i.e., $(C_{\text{CF15}} (6C12)) (C_{\text{Main}} = $4), tool holder cost, i.e., $(C_{\text{Toolh}} = $50), tool holder life, i.e., $(L_{\text{Toolh}} = T \cdot 5$ years $\cdot 365$ days $\cdot 24$ h $= T \cdot 43,800$ min), tool inserts cost, i.e., $(C_{\text{In}} = $3.5), $k/3$ is the setup insert ($k'$ = 5); $z$ represents the cutting edge number, i.e., $(z = 1)$, workpiece per unit cost i.e., $(C_w = $8), $T$ represents as tool life, tool cost/min, i.e., $C_{\text{Toolh}} = [((C_{\text{Main}} + C_{\text{Toolh}}) / (T \cdot k)] + (C_{\text{Toolh}} \cdot L_{\text{Toolh}})$.

The initial and final values used to estimate the cost are prescribed in Table 5.

Cutting power, $P_c$, is determined by Eq. (4) [38]:

$$P_c = \left( K_1 \cdot f_z \cdot R_m \cdot \tan \psi \cdot \sum_{i=1}^{\infty} \frac{\sigma_i}{\cos \psi_i} \cdot \cos \beta \cdot \sin \psi_i \cdot \cos \beta \cdot dl + \frac{R_m \cdot f_z}{\cos \psi_i} \cdot \sum_{i=1}^{\infty} \int_{\psi_i}^{\beta} \left( k_0 \cdot V_B \cdot K_3 - f_z \cdot \left( 1 - e^{-x \cdot \psi_i} / x \right) \cdot dt \right) \pi \cdot D \cdot n / 1000 \right)$$

where $K_1 = \frac{\sqrt{\sigma_0 \cdot \psi}}{\sqrt{\psi}} = 1.08$ is a coefficient that represents the ratio of normal cutting force and shear force components [38]; $K_2 = 0.41$ and $K_3 = 0.59$ described as the coefficient of horizontal asymptote and the degree of the damping exponents [39], $d'$ is equal to the absence of a portion of the radius section on the top of the tooth and is equal to $R_m(1 - \cos k_r)$ in the presence of that portion [39]; $b'$ is equal to $a_p$ [39]; $k_r$ is the angle of the mill tooth cutting point; $\beta$ is the angle of action; $\Phi$ is the angle of shear; $\sigma_i$ is the stress intensity [40] (see physical and mechanical properties of the steel 45 (AISI 1045 steel) in Table 6 [40]) (the intensity of stress is a function of the intensity of strain, $\varepsilon$, the strain rate, $\dot{\varepsilon}$, and the temperature, $T^0$, of the material: $\sigma_i = f(\varepsilon, \dot{\varepsilon}, T^0)$; $dl$ is the elemental length of the cutting edge; $V_B$ is the flank wear on the tool [40, 41]; $\psi_i$ is the angular coordinate of the $i$th tooth; and, $i = x, y, z$ represents each axis of the coordinate tool system).

Material removal rate, MRR, is determined by Eq. (5):

$$\text{MRR} = \frac{f_z \cdot v_c \cdot a_p}{}$$

Equations (1–5) were used to determine the values of the parameters listed in Table 4.

2.3 Optimization by Grey relational analysis

The optimization by the Grey relational analysis (GRA) is performed by considering the optimization problem as a “multi-objective optimization.” Whenever more than one response is optimized, GRA stands out as an effective method to solve the optimization. In the current study, the surface roughness, part processing cost, cutting power, and material removal rate are granted as the responses—in

Fig. 2 Left: flank wear of the mill tooth; right: machined surface of the workpieces at the milling depth $a_p = 1.0$ mm; feed $f_z = 0.125$ mm/tooth; cutting speed $v_c = 392.6$ mm/min; spindle rotation speed of the mill $n = 1.000$ rpm. a Fly milling cutter (first pass $V_b = 1.31$ mm). b Fly milling cutter (second pass $V_b = 4.6$ mm)
a total of four responses. GRA method combines these four responses into a single function and then optimizes the unified function. In the manufacturing region, numerous studies are reported using the GRA method. This method works in three modes depending on the target to the objective functions: minimization, maximization, and simultaneous maximization and minimization. The following steps are accounted:

I. Preprocessing of data: The surface roughness, part processing cost, cutting power, and material removal rate have a different scale of magnitudes. Before proceeding ahead, it is imperative to convert different scales into a single scale, from 0 to 1. This is done by normalization following Eq. 6 (minimization is the target) and Eq. 7 (maximization is the target).

\[ y_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \]  

(6)

\[ y_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \]  

(7)

II. Here, the experimental data (original) is indicated by \( x_i(k) \); the normalized preprocessed data is represented by \( y_i(k) \); also, the maximum and minimum values are presented by \( \max x_i(k) \) and \( \min x_i(k) \), respectively.

III. Grey relational coefficient: Next, the grey relational coefficient, which defines the relation of experimental value and ideal value, is calculated using Eq. 8.

Table 4  Experimental and estimated data for various stages of fly milling

| Exp. No. | Feed per tooth, \( f_z \), mm/tooth | Cutting speed, \( v_c \), m/min | Machined Length, \( l_m \), mm | Sliding distance, \( l_s \), m | Processing time (tool life), \( T \), min | Flank wear, \( V_{fb} \), mm | Roughness, \( R_z \), \( \mu m \) | The cost price of processing one part, \( C \), $ | Cutting power, \( P_c \), kW | Material removal rate (MRR), \( 10^3 \) mm³/min |
|---------|-------------------------------------|-------------------------------|-------------------------------|----------------|--------------------------|-----------------|------------------|-----------------------------|-----------------|-----------------|
| 1       | 0.125                              | 392.6                         | 5                             | 0              | 0                        | 0               | 3.2              | 320.000                      | 1.531           | 49.1            |
| 2       | 0.125                              | 392.6                         | 200                           | 128.6          | 1.64                     | 1.2             | 3.4              | 10.355                       | 2.407           | 49.1            |
| 3       | 0.125                              | 392.6                         | 400                           | 257.2          | 3.28                     | 3.6             | 4.5              | 6.358                        | 4.038           | 49.1            |
| 4       | 0.16                                | 392.6                         | 5                             | 0              | 0                        | 0.153           | 3.7              | 320.000                      | 1.930           | 62.8            |
| 5       | 0.16                                | 392.6                         | 200                           | 100.5          | 1.28                     | 1.35            | 3.9              | 10.355                       | 2.911           | 62.8            |
| 6       | 0.16                                | 392.6                         | 400                           | 201            | 2.56                     | 4.5             | 4.8              | 6.357                        | 5.019           | 62.8            |
| 7       | 0.25                                | 392.6                         | 5                             | 0              | 0                        | 0               | 4.1              | 320.000                      | 2.970           | 98.2            |
| 8       | 0.25                                | 392.6                         | 200                           | 64.3           | 0.82                     | 1.45            | 4.6              | 10.355                       | 4.045           | 98.2            |
| 9       | 0.25                                | 392.6                         | 400                           | 128.6          | 1.64                     | 5               | 6.5              | 6.356                        | 6.385           | 98.2            |
| 10      | 0.25                               | 247.3                         | 5                             | 0              | 0                        | 0               | 4.4              | 320.000                      | 1.785           | 61.8            |
| 11      | 0.25                               | 247.3                         | 200                           | 64.3           | 1.3                      | 1.25            | 4.9              | 10.089                       | 2.351           | 61.8            |
| 12      | 0.25                               | 247.3                         | 400                           | 112.53         | 2.28                     | 2.2             | 5.5              | 5.832                        | 2.728           | 61.8            |
| 13      | 0.32                               | 196.3                         | 5                             | 0              | 0                        | 0               | 6.2              | 320.000                      | 1.755           | 62.8            |
| 14      | 0.32                               | 196.3                         | 200                           | 50.3           | 1.28                     | 0.8             | 6.4              | 9.570                        | 2.068           | 62.8            |
| 15      | 0.32                               | 196.3                         | 400                           | 100.6          | 2.56                     | 1.75            | 6.9              | 5.571                        | 2.357           | 62.8            |

Table 5  Initial and calculated values of the parameters for determining the cost price of processing one part

| Machining allowance section, \( l_m \), mm | Allowance length, \( l_1 \), mm | Diameter of cutter, \( D \), mm | Tool life, \( T \), min | Cost of machining /hour, \( C_{_tool, \$} \) | Cost of tool holder, \( C_{toolh, \$} \) | Life time of tool holder, \( LT_{toolh, \$} \) min | Cost of insert, \( C_{inset, \$} \) | Setup Insert, \( k \) | Number of teeth, \( z \) | Cost of tool minute, \( C_{toolmin, \$} \) | Cost of one workpiece, \( C_w, \$ \) |
|--------------------------------------------|-------------------------------|-------------------------------|-----------------|--------------------------|-----------------|--------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 200                                        | 5                             | 125                           | 3.28            | 4                        | 50              | 143,664                  | 3.5             | 5               | 1               | 0.214           | 8               |
| 200                                        | 5                             | 125                           | 2.56            | 4                        | 50              | 112,128                  | 3.5             | 5               | 1               | 0.274           | 8               |
| 200                                        | 5                             | 125                           | 1.64            | 4                        | 50              | 71,832                   | 3.5             | 5               | 1               | 0.428           | 8               |
| 200                                        | 5                             | 125                           | 2.93            | 4                        | 50              | 128,334                  | 3.5             | 5               | 1               | 0.239           | 8               |
| 200                                        | 5                             | 125                           | 3.84            | 4                        | 50              | 168,192                  | 3.5             | 5               | 1               | 0.183           | 8               |
\[ \vartheta_i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{0i}(k) + \zeta \Delta_{\max}} \]

IV. Here, the deviation sequence is presented \( \vartheta_{0i}(k) \). The following relations are used to present parameters of deviation sequence. Also, the distinguishing constant \( \zeta \) can have value within 0–1. For the current study, mid-value 0.5 is taken for further calculation.

\[
\begin{align*}
\Delta_{0i}(k) &= |y_{0i}(k) - y_i(k)| \\
\Delta_{\min} &= \min_{\forall i} \min_{\forall k} \Delta_{0i}(k) \\
\Delta_{\max} &= \max_{\forall i} \max_{\forall k} \Delta_{0i}(k)
\end{align*}
\]

V. Grey relational grade: As mentioned earlier, the multiple responses are combined to a single function, i.e., Grey relational grade (GRG). The grey relational coefficients are merged into GRG. The conversion is associated with particular weight values for each response. The typical calculation scheme for GRG is shown in Eq. 9. Depending on the manufacturer’s requirements, the weight value changes. In fact, controlling of weights to responses controls the ultimate optimum levels of parameters. For instance, in our current research, two different sets of weight values are accounted to address technological performance as well as the conservation of resources. The details are discussed later.

\[ \xi(y_{0i}, y_i) = \sum_{k=1}^{n} \omega_k \vartheta_k \]

VI. Grey relational order: Once the GRG is computed, the highest value of the GRG is ranked as 1. The rest are ordered as in descending order. The experiment number, ranked 1, is the optimum run.

3 Results and discussion

3.1 Multiple non-linear regression analysis

The multiple non-linear regression analysis was applied on the experimental data as presented in Table 4. In our case, it is advisable to use the mathematical apparatus of multiple classical correlations and regression analysis [42].

| Yield stress, \( \sigma_y \), MPa | Strain stress, \( \sigma_D \), MPa | Cutting speed, \( v_c \), m/min | Stress intensity, \( \sigma_i \), MPa |
|-------------------------------|-------------------------------|---------------------------------|-------------------------------|
| 550                           | 750                           | 100                             | 260                           |
| 150                           | 295                           | 300                             | 320                           |

Table 6 Physical and mechanical properties of the steel 45 (AISI 1045 steel) of the workpiece [40]
A preliminary assessment of the tabular data has established that an adequate mapping of the interrelations studied will provide non-linear regression equations. Given the combined nature of the non-linear relationship (positive and negative, increasing and decreasing, as well as equally accelerated and equally slow regressions) and successful experience of data approximation in work [43] are observed, the relationship between the four phenomena can be described by a second-order polynomial in four-dimensional space:

\[
y = d_0 + a_1 x_1 + b_1 x_2 + c_1 x_3 + a_2 x_1^2 + b_2 x_2^2 + c_2 x_3^2,
\]

where the sum of the coefficients with zero indices is denoted by \(d_0 = a_0 + b_0 + c_0\).

Since there is no universal method for selecting and rational regression curve, then we will judge the reliability of the approximation by the coefficient of determination \(R^2\), the value of which must be higher than 0.8 units.

As a result, a non-linear constrained optimization were selected coefficients to five equations for the normalized response function \(R_z^*\), cutting power \(P_c^*\), material removal rate (MRR\(^*\)), sliding distance \(l^*\), and tool life \(T^*\) reliability criterion:

\[
R_z^* = 1.907 + 0.229 f_z + 3.856 v_c^* + 0.281 V_B^*
\]
\[
+ 0.118 f_z^2 + 2.296 v_c^* + 0.011 V_B^2
\]

\[
P_c^* = -0.804 + 1.184 f_z^* + 0.607 v_c^*
\]
\[
+ 0.318 V_B^* - 0.426 f_z^2 + 0.092 v_c^* + 0.148 V_B^2
\]

\[
MRR^* = -1.354 + 2.452 f_z^* + 1.134 v_c^*
\]
\[
+ 0.000 V_B^* - 1.004 f_z^2 - 0.084 v_c^* + 0.000 V_B^2
\]

As a result, a non-linear constrained optimization were selected coefficients to five equations for the normalized response function \(R_z^*\), cutting power \(P_c^*\), material removal rate (MRR\(^*\)), sliding distance \(l^*\), and tool life \(T^*\) reliability criterion: \(R^2 = 0.98\).
Using the obtained equations, a quantitative analysis was conducted to study the influence of the input parameters on each of the specified response functions. For surface roughness $R_z$, it was found that with an increase of 0.1 units (0.032 mm/tooth) in a coded form of the feed parameter $f_z^*$, the roughness increases by 0.036 units (0.248 μm), with an increase of 0.1 units (39.260 m/min) in the coded form of the cutting speed $v_c^*$ parameter, the roughness decreases by 0.133 units (0.918 μm), and with an increase of 0.1 units (0.500 mm) in the coded as the flank wear parameter $V_B^*$, the roughness changes upward by 0.029 units (0.203 μm).

Thus, compared with the influence of cutting speed $v_c^*$, the roughness value of the feed $f_z^*$ effect is 3.7 times less, and the flank wear $V_B^*$ is 4.5 times less. Graphic dependencies of the surface roughness $R_z$ with experimental and calculated by Eq. (11) points are shown in Fig. 3.

From Fig. 3, it has been observed that the increase in flank wear $V_B$ at fixed feeds $f_z$ and cutting speed $v_c$ involves increasing the surface roughness $R_z$ by linear dependencies, respectively.

For power cutting $P_c^*$, it is established that with an increase of 0.1 units (0.032 mm/tooth) in a coded form of the feed parameter $f_z^*$, the power increases by 0.072 units (0.457 kW), with an increase of 0.1 units (39.260 m/min) in the coded form of the cutting speed parameter $v_c^*$, the power increases by 0.071 units (0.452 kW), and with an increase of 0.1 units (0.500 mm) in the coded as the flank wear parameter $V_B^*$, the roughness changes upward by 0.029 units (0.203 μm).
0.1 units (0.500 mm) in the encoded form of the flank wear \( V_B^* \) parameter, the power changes upward by 0.048 units (0.307 kW). Thus, compared with the effect of the feed \( f_z^* \), the effect of the cutting speed \( v_c^* \) on the power value is 1.01 times less, and the flank wear \( V_B^* \) is 1.5 times less. Graphic dependencies of cutting power \( P_c \) with the points calculated by Eq. (4) and calculated by Eq. (12) are shown in Fig. 4.

From Fig. 4, it can be seen that an increase in the flank wear \( V_B \) with a fixed feed \( f_z \) and a cutting speed \( v_c \) involves an increase in power \( P_c \) in a parabolic relationship.

For the material removal rate \((MRR^*)\), it was established that with an increase of 0.1 units \((0.032 \text{ mm/tooth})\) in the coded form of the feed parameter \( f_z^* \), the productivity increases by 0.135 units \((13.232\cdot10^3 \text{ mm}^3/\text{min})\), with an increase of 0.1 units \((39.260 \text{ m/min})\) in the coded form of the cutting speed parameter \( v_c^* \), material removal rate increases by 0.104 units \((10.227\cdot10^3 \text{ mm}^3/\text{min})\), and the influence of the flank wear parameter \( V_B^* \) on the \( MRR \) is missing (the corresponding zero wound coefficients). Thus, compared with the effect of the feed \( f_z^* \), on the material removal rate \( (MRR) \), the effect of the cutting speed \( v_c^* \) is 1.3 times less. Graphical dependencies of the material removal rate with the points calculated by Eqs. (5) and (13) are shown in Fig. 5.

Figure 5 shows that the flank wear \( V_B \) on the material removal rate is not affected.

For sliding distance \( l_s^* \), it is established that with an increase of 0.1 units \((0.032 \text{ mm/tooth})\) in a coded form, the feed parameter \( f_z^* \), sliding distance decreases by 0.075 units.

### Table 7 Preprocessing sequence

| Exp. No. | Roughness, \( R_z \) | The cost price of processing one part, \( C \) | Cutting power, \( P_c \) | Material removal rate, \( MRR \) |
|----------|---------------------|----------------------------------|-------------------|------------------|
| 1        | 1.0000              | 1.0000                           | 1.0000            | 0.0000           |
| 2        | 0.9459              | 0.5006                           | 0.8195            | 0.0000           |
| 3        | 0.6486              | 0.0000                           | 0.4835            | 0.0000           |
| 4        | 0.8649              | 1.0000                           | 0.9178            | 0.2790           |
| 5        | 0.8108              | 0.5006                           | 0.7157            | 0.2790           |
| 6        | 0.5676              | 0.0002                           | 0.2814            | 0.2790           |
| 7        | 0.7568              | 1.0000                           | 0.7035            | 1.0000           |
| 8        | 0.6216              | 0.5006                           | 0.4821            | 1.0000           |
| 9        | 0.1081              | 0.0006                           | 0.0000            | 1.0000           |
| 10       | 0.6757              | 1.0000                           | 0.9477            | 0.2587           |
| 11       | 0.5405              | 0.5570                           | 0.8311            | 0.2587           |
| 12       | 0.3784              | 0.2231                           | 0.7534            | 0.2587           |
| 13       | 0.1892              | 1.0000                           | 0.9539            | 0.2790           |
| 14       | 0.1351              | 0.6671                           | 0.8894            | 0.2790           |
| 15       | 0.0000              | 0.3338                           | 0.8298            | 0.2790           |
(19.401 m), with an increase of 0.1 units (39.260 m/min) in the coded form of the cutting speed parameter \( v_c \) sliding distance increases by 0.371 units (95.519 m), and with an increase of 0.1 units (0.500 mm) in the coded form of the flank wear parameter \( V_B \) sliding distance is changed upwards by 0.057 units (17.732 m). Thus, as compared with the influence of the cutting speed \( v_c \), the value of the sliding distance impact feed \( f_z \) is less than 4.9 times, and flank wear \( V_B \) is less than 6.5 times. Graphic dependencies of sliding distance \( l_s \) with experimental and calculated by Eq. (14) points are shown in Fig. 6.

For tool life \( T^* \), it is established that with an increase of 0.1 units (0.032 mm/tooth) in a coded form, the feed parameter \( f_z \) processing time decreases by 0.010 units (0.032 min), with an increase of 0.1 units (39.260 m/min) in a coded form of the cutting speed parameter \( v_c \) processing time decreases by 0.014 units (0.045 min), and with an increase of 0.1 units (0.500 mm) in the coded form of the flank wear parameter \( V_B \) processing time changes to a larger direction by 0.067 unit (0.219 min). Thus, compared with the influence of flank wear \( V_B \), on the processing time value, the impact of the feed \( f_z \) is 6.8 times less, and the cutting speed \( v_c \) is 4.9 times less.

### Table 8 Deviation sequence

| Exp. No. | Roughness, \( R_z \) | The cost price of processing one part, \( C \) | Cutting power, \( P_c \) | Material removal rate, \( MRR \) |
|----------|----------------------|---------------------------------|----------------|------------------|
| 1        | 0.0000               | 0.0000                          | 0.0000         | 1.0000           |
| 2        | 0.0541               | 0.4994                          | 0.1805         | 1.0000           |
| 3        | 0.3514               | 1.0000                          | 0.5165         | 1.0000           |
| 4        | 0.1351               | 0.0000                          | 0.0822         | 0.7210           |
| 5        | 0.1892               | 0.4994                          | 0.2843         | 0.7210           |
| 6        | 0.4324               | 0.9998                          | 0.7186         | 0.7210           |
| 7        | 0.2432               | 0.0000                          | 0.2965         | 0.0000           |
| 8        | 0.3784               | 0.4994                          | 0.5179         | 0.0000           |
| 9        | 0.8919               | 0.9994                          | 1.0000         | 0.0000           |
| 10       | 0.3243               | 0.0000                          | 0.0523         | 0.7413           |
| 11       | 0.4595               | 0.4430                          | 0.1689         | 0.7413           |
| 12       | 0.6216               | 0.7769                          | 0.2466         | 0.7413           |
| 13       | 0.8108               | 0.0000                          | 0.0461         | 0.7210           |
| 14       | 0.8649               | 0.3329                          | 0.1106         | 0.7210           |
| 15       | 1.0000               | 0.6662                          | 0.1702         | 0.7210           |

### Table 9 Grey relational coefficient

| Exp. No. | Roughness, \( R_z \) | The cost price of processing one part, \( C \) | Cutting power, \( P_c \) | Material removal rate, \( MRR \) |
|----------|----------------------|---------------------------------|----------------|------------------|
| 1        | 1.0000               | 1.0000                          | 1.0000         | 0.3333           |
| 2        | 0.9024               | 0.5003                          | 0.7348         | 0.3333           |
| 3        | 0.5873               | 0.3333                          | 0.4919         | 0.3333           |
| 4        | 0.7872               | 1.0000                          | 0.8588         | 0.4095           |
| 5        | 0.7255               | 0.5003                          | 0.6375         | 0.4095           |
| 6        | 0.5362               | 0.3334                          | 0.4103         | 0.4095           |
| 7        | 0.6727               | 1.0000                          | 0.6278         | 1.0000           |
| 8        | 0.5692               | 0.5003                          | 0.4912         | 1.0000           |
| 9        | 0.3592               | 0.3335                          | 0.3333         | 1.0000           |
| 10       | 0.6066               | 1.0000                          | 0.9053         | 0.4028           |
| 11       | 0.5211               | 0.5302                          | 0.7475         | 0.4028           |
| 12       | 0.4458               | 0.3916                          | 0.6697         | 0.4028           |
| 13       | 0.3814               | 1.0000                          | 0.9155         | 0.4095           |
| 14       | 0.3663               | 0.6003                          | 0.8188         | 0.4095           |
| 15       | 0.3333               | 0.4287                          | 0.7461         | 0.4095           |
Graphic dependencies of processing time (tool life) \( T' \) with experimental and calculated by Eq. (15) points are shown in Fig. 7.

Approximate the response function \( C^* \) in the four-dimensional space, a second-order polynomial is not possible due to the harmonic nature of the dependence. Therefore, Fig. 8 shows the graphs of the cost price of processing one part \( C \) calculated by Eq. (3) points.

Figure 8 shows that the cost price of processing one part \( C \) decreases as the flank wear increases \( V_B \) decreases along a broken linear curve. In the characteristic inflection point of the curve, the rate of change of the parameter \( C \) decreases to almost zero. A further increase in tool wear above the characteristic value makes sense if the material removal rate is important with reduced requirements for roughness \( R_z \) and power \( P_c \).

After establishing the regularities of a complex multifactor process of milling, we proceed to find the optimal cutting conditions with a fixed flank wear \( V_B = \text{const} = 0 \). Since only, in this case, the minimum values of the optimum in a multicriteria search can be ensured.

| Exp. no. | Case 1: \( w_{R_z} = 1.0, w_C = 0.5, w_{P_c} = 0.5, w_{MRR} = 1.0 \) | Case 2: \( w_{R_z} = 1.0, w_C = 1.0, w_{P_c} = 1.0 \) and \( w_{MRR} = 0.5 \) |
|----------|-------------------------------------------------|-------------------------------------------------|
| Grey relational grade | Rank | Grey relational grade | Rank |
| 1  | 0.7778 | 2 | 0.9048 | 1 |
| 2  | 0.6178 | 6 | 0.6583 | 6 |
| 3  | 0.4444 | 13 | 0.4512 | 13 |
| 4  | 0.7087 | 3 | 0.8145 | 2 |
| 5  | 0.5680 | 8 | 0.5909 | 7 |
| 6  | 0.4392 | 15 | 0.4242 | 15 |
| 7  | 0.8289 | 1 | 0.8001 | 3 |
| 8  | 0.6883 | 4 | 0.5888 | 8 |
| 9  | 0.5642 | 8 | 0.4360 | 14 |
| 10 | 0.6540 | 5 | 0.7752 | 4 |
| 11 | 0.5209 | 10 | 0.5715 | 9 |
| 12 | 0.4597 | 12 | 0.4881 | 12 |
| 13 | 0.5829 | 7 | 0.7148 | 5 |
| 14 | 0.4951 | 11 | 0.5686 | 10 |
| 15 | 0.4434 | 14 | 0.4894 | 11 |

Italicized numbers indicate the optimum runs

Fig. 9 Visualization of optimal surface roughness \( R_z \) values found using optimization by Grey relational analysis

Fig. 10 Visualization of optimal cutting power \( P_c \) values found using optimization by Grey relational analysis
Also as a result of studies of machining by milling AISI 1045 steel, it was possible to establish the following. The low plastic flow characteristics of AISI 1045 steel combined with its relatively high hardness made it easy to process and enabled good surface finish during its machining activities. The tool-workpiece brittle interaction leads to hard material separation resulting in better surface finish. Machined surface quality was degraded by increasing the feed rate and depth of cut. Higher cutting forces, friction, and worked incremental areas are, in fact, induced causing the poor surface finish manifesting in larger horizontal markings spacing. An increase of the depth of cut is also responsible for the growth of the vertical spacing separating peaks and troughs of the machined surface. Hence, increased feed rates and depth of cuts generally degrade the surface finish although they improve cutting performance. Consequently, it is highly important to find an optimum combination of the cutting parameters settings to reduce machining time and keep a high quality of surface finish. Optimization techniques (such as Grey relational analysis) or a “dense sampling” factorial design of experiment could be of great help to achieve the mentioned research motivation.

3.2 Optimization

Following the methodology of Section 2.2, multiple responses, i.e., roughness parameter, cost of the part, power consumption, and material removal rate, are simultaneously optimized using Grey relational analysis. The experimental/computed data of Table 7 are used in the optimization. The preprocessed sequence is developed by using Eqs. 3, 4 (for Rz, C, P) and using Eq. 5 (for MRR), and listed in Table 4.

The deviation sequence, computed using “1 – Preprocessing sequence,” is tabulated in Table 8

Later, the grey relational coefficient is computed using Eq. 3 and listed in Table 9.

For GRC, the distinguishing coefficient is taken as ζ = 0.5. At last, the Grey relational grade (GRG) is calculated by combining the GRCs of all the responses. The respective weights for the responses were determined from two perspectives. First, if the technologist is faced with the task of making the part with the greatest performance, the logical deduction is to emphasize on the product quality and on the material removal. That means the surface roughness and material removal rate are assigned higher weights than the other two responses. As such, in the current study, case 1 has considered \( w_{Rz} = 1.0, w_C = 0.5, w_Pc = 0.5, \) and \( w_{MRR} = 1.0. \) In the second case, if the main objective is to conserve resources maintaining product quality acceptable, then more importance is delegated to surface quality, cost of producing single part, and the consumption of power, and less weight is exerted on material removal rate. As such, the weights for case 2 are \( w_{Rz} = 1.0, w_C = 1.0, w_Pc = 1.0, \) and \( w_{MRR} = 0.5. \) Note that in both cases the product quality was not compromised.

Table 10 shows the GRG and respective rank for both cases. For case 1, experiment number 7 is found as the optimum run; the corresponding input parameters for this case are feed per tooth \( f_z = 0.25 \text{ mm/tooth}, \) cutting speed \( v_c = 392.6 \text{ m/min}, \) and machined length \( l = 5 \text{ mm}. \) For case 2, the optimum parameters values are feed per tooth \( f_z = 0.125 \text{ mm/tooth}, \) cutting speed \( v_c = 392.6 \text{ m/min}, \) and machined length \( l = 5 \text{ mm}. \) Therefore, it is visible that the change in the requirements from “performance” to “resource conservation” has entailed a different optimum result; here, the cutting speed and machined length though are the same, the feed per tooth is reduced from 0.25 to 0.125 mm/tooth.
4 Conclusions

The research conducted has shown that:

- The tabular dependence of input parameters (cutting speed \(v_c\), feed per tooth \(f_z\), and flank wear \(V_f\)) and output parameters (surface roughness \(R_z\), cutting power \(P_c\), material removal rate \(MRR\)) of fly milling of carbon AISI 1045 steel. In such an integrated formulation for milling AISI 1045 steel, the task was posed for the first time, which made it possible to evaluate the accuracy and resource-saving characteristics, including at high values of tool wear providing its cutting ability.

- For the first time with high accuracy (\(R^2 = 0.98\)) for face milling of AISI 1045 steel by multilayer regression analyses identified non-linear laws of surface roughness \(R_z\), cutting power \(P_c\), material removal rate \(MRR\), cost of producing single part \(C\), depending on feed per tooth \(f_z\), cutting speed \(v_c\), and flank wear \(V_f\), which can be easily integrated into CNC machines.

- Multi-objective optimization for the product obtained by the fly milling of carbon AISI 1045 steel using Grey relational analysis (GRA) showed that the optimum parameters for improving the manufacturing efficiency and reduce the machining time (case 1) are as follows: feed per tooth \(f_z = 0.25\) mm/tooth, cutting speed \(v_c = 392.6\) m/min, and machined length \(l = 5\) mm; for resource-saving (case 2), the optimum parameters are feed per tooth \(f_z = 0.125\) mm/tooth, cutting speed \(v_c = 392.6\) m/min, and machined length \(l = 5\) mm.

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