Multi-objective optimization of turning process for hardened material based on hybrid approach

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Abstract

Energy and environmental issues have become pertinent to all industries in the globe because of sustainable development issues. This paper systematically investigates the turning process of the hardened material via process modeling, numerical experiments, and a hybrid algorithm. The objectives of this work are to reduce the specific cutting energy (SCE) and improve the energy efficiency (EF) based on the turning conditions optimization. The machining simulations were performed in conjunction response surface methodology (RSM) to generate the quadratic mathematical models of the specific cutting energy and energy efficiency in terms of machining parameters, including cutting speed, feed rate, nose radius, edge radius, and rake angle. An analysis of variance (ANOVA) was then adopted to examine the model adequacy and significant parameters. Subsequently, an evolutionary algorithm, namely non-dominated sorting genetic algorithm-II (NSGA-II) was used to find a much better spread of design solutions and better convergence near the true Pareto optimal front. A quantitative approach, namely entropy method was conducted to calculate the weight factors of multiple responses. In the last step, a TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) was applied to determine the best compromise solution. It was indicated that the energy efficiency was significantly improved using the optimal machining parameters and the specific cutting energy was effectively decreased in comparison with initial values. Moreover, the integrative approach performed very well in optimum performance of the machining process. Therefore, this work is expected as a contribution to improve the machining efficiency of the turning process of hardened steels.

Key words: Finite element method, Machining conditions, DOE, RSM, ANOVA, Multi-attribute decision-making method, Specific cutting energy

1. Introduction

Saving energy is an important issue in the development of new products and processes of manufacturers. Since the energy reduction is a new trend in the industrial applications, and manufacturing is an energy intensive sector. Machining is a common manufacturing process for shaping a variety of materials, thus the energy-efficient use in machining processes can contribute significantly to energy savings in manufacturing [Hironori et al., 2014, Joost et al., 2012,]. Machining processes of hardened materials were widely applied in a variety of industrial applications for making machine tool components, dies, tools, and shafts. Unfortunately, the energy consumption required is higher than conventional machining processes. Consequently, an effective approach for improving the energy efficiency of machining processes of hardened materials is an urgent demand.

Recently, reducing energy consumption in machining processes has drawn a great attention from many researchers. They have been proposed some optimization methods for the energy-efficient improvement in the machining. For reducing the environmental impact, optimizing parameters or changing the technologies and materials employed can be considered as the alternative solutions [Zhongde et al., 2012]. In this case, optimizing existing processes is less
expensive and has better social sustainability compared to making drastic changes, owing to the lower investment needed and user acceptance.

Realizing energy savings via parameter optimization have attracted many researchers. The energy-efficient improvement in machining processes can be divided into three levels: machine tool, process, and material removal. Mori et al. [2011] proposed a concept of power consumption per unit volume to assess the energy efficiency of a machine tool. The power measured was calculated through energy from cutting cycles, workpiece positioning, and spindle drive. Similarly, Mativenga and Rajemi [2013] attempted to minimize turning energy consumption through optimizing machining parameters. Their machine energy was estimated based on energy consumption from machine setup, cutting operations, tool change, and embedded energy in tool production. Furthermore, Neugebauer et al. [2012] proposed a holistic approach to optimize energy and resource efficiency in the development of high performance cutting and hybrid processes. An optimal inclination angle was determined to minimize energy consumption and maximized tool life during 5-axis machining process [Oda et al., 2012].

Among efforts aimed at increasing energy efficiency at the material removal level, some researchers have attempted to develop the energy models during the machining process. Astakhov and Xiao [2008] classified the cutting force into four elements and provided a mathematical expression for each energy mode. The machining power model was developed in order to increase accurate prediction for estimating forces with respect to various cutting conditions. However, optimal machining conditions and optimization approach for improving the energy efficiency did not describe. Additionally, Yoon et al., [2014] introduced a second-order regression model of material removal power in terms of process parameters and tool wear in the milling process. With the proposed model, the energy consumption of the milling machine could be estimated more precisely, and the tool-wear states could be more accurately predicted in terms of process parameters. Unfortunately, the constructed model did not consider the effects of cutting tool geometry on the cutting power and energy efficiency.

To overcome the challenge of reducing energy consumption and increasing machining efficiency, we introduce an energetic optimization to the turning process of the hardened AISI 4140 steel. This material was widely applied in a variety of industrial applications, such as automotive industry, aerospace, and machine tool manufacturing. Practical analysis shows that there is a potential improvement of the turning process for increasing the energy efficiency by parameter optimizations. We also carried out an investigation into the machining processes of hardened materials and found that the tool geometry is an important factor that affects cutting energy.

For this purpose, the aim of the present study is first to propose a finite element (FE)-based simulation method to perform the numerical experiments for the turning process of the hardened material. The approximate mathematical models of specific cutting energy and energy efficiency with respect to various turning conditions are then developed based on simulation results, design of experiments (DOE), and RSM [Chaiwateta et al., 2015, Xiaohui et al., 2014]. The optimal values of the objective functions and machining parameters are obtained using genetic algorithm (GA) [Mitsunobu et al., 2014] and TOPSIS method.

In the remainder of the paper, the scientific methodology used to resolve these issues is first introduced. Next, the reliable simulation model is developed; and numerical experiments as well as descriptive data analysis and optimization results are discussed. Finally, conclusions are drawn and future research is suggested.

2. Multi-objective optimization framework

2.1 Optimization problem

Turning is one of material removal processes, which is used to decrease the workpiece diameter and produce a smooth surface. The workpiece rotates in the lathe, with a certain spindle speed (n), at a given number of revolutions per minute (rev/min). At the machined point of the workpiece diameter, this will give rise to a cutting speed or surface speed (V) in m/min (Fig. 1). This is the speed at which the cutting edge machines the surface of the workpiece and it is the speed at which the periphery of the cutter diameter passes the cutting edge. The feed rate (f) in mm/rev is defined as the distance the tool travels during one revolution of the part. The cutting depth (d) in mm is the difference between un-cut and cut surface. It is half of the difference between the un-cut and cut the diameter of the workpiece.

The machining process is greatly affected by the tool geometry. The tool geometry is designed to cut various workpiece metals by forming chips in a smooth way, while also providing a strong cutting edge, and to break chips into manageable swarf. The geometric parameters of the cutting insert, including nose radius (R), edge radius (r), and rake angle (α) are illustrated in Fig. 2.
As previously discussed in Section 1, both response variables, including the specific cutting energy (SCE) and energy efficiency (EF) at the material removal level are optimized simultaneously by means of numerical experiments and a multi-objective optimization process. Specific cutting energy (SCE) was defined as the energy required to remove a specific volume of material from the work piece [David, et al., 2005]:

$$SCE = \frac{P_c}{dxfN} = \frac{F_cV}{dxfN} = \frac{F_c}{dxf}$$  \hspace{1cm} (1)

where $P_c$, $F_c$, $d$, $f$, and $V$ represent the cutting power, main cutting force, depth of the cut, feed rate, and cutting speed, respectively.

At the material removal level, the cutting power is transferred into the primary (shear power) and secondary deformation zones (friction power), as shown in Fig. 3. Therefore, the material removal power can be described as follows:

$$P_c = P_{sh} + P_{fr} = (F_c \cos \phi - F_t \cos \phi) \frac{V \cos \alpha}{\cos(\phi - \alpha)} + (F_t \sin \alpha + F_r \cos \alpha) r_c$$  \hspace{1cm} (2)

where $P_{sh}$, $P_{fr}$, $F_c$, $\phi$, $\alpha$, and $r_c$ denote the shear power, friction power, thrust force, shear plane angle, rake angle, and chip thickness ratio, respectively. The shear plane angle can be defined using Eq. (3):

$$\tan \phi = \frac{r_c \cos \alpha}{1 - r_c \sin \alpha}$$  \hspace{1cm} (3)

It can be observed that shear power is consumed to remove the material and the friction power used is essentially wasted. Therefore, energy efficiency (EF) can be defined as follows:

$$EF = \frac{P_{sh}}{P_c}$$  \hspace{1cm} (4)

The simulation results, including cutting force components and chip thicknesses are used to calculate the values of the specific cutting energy (SCE) and energy efficiency (EF) by means of above equations.

In this work, five parameters, namely, cutting speed ($V$), feed rate ($f$), nose radius ($R$), edge radius ($r$), and rake angle ($\alpha$), as well as their levels were selected according to the available literature (Mori et al., 1995, Mativenga et al., 2006) and recommendations data of SANDVIK cutting tools manufacturer (Table 1). According to the discussed analysis, multiple-objective optimization problems can be described in the below equation:

Find $X = [V, f, R, r, \alpha]$

Minimize specific cutting energy (SCE); Maximize energy efficiency (EF)

Subject to: $60 \leq V \leq 300$ (m/min), $0.10 \leq f \leq 0.16$ (mm/rev), $0.2 \leq R \leq 0.6$ (mm), $20 \leq r \leq 100$ (μm), $-10 \leq \alpha \leq 0$ (deg).
Table 1 Machining parameters and their levels.

| Level | Cutting speed \(V\) (m/min) | Feed rate \(f\) (mm/rev) | Nose radius \(R\) (mm) | Edge radius \(r\) (μm) | Rake angle \(α\) (deg) |
|-------|-----------------------------|--------------------------|------------------------|------------------------|------------------------|
| -1    | 60                          | 0.10                     | 0.2                    | 20                     | -10                    |
| 0     | 180                         | 0.13                     | 0.4                    | 60                     | -5                     |
| 1     | 300                         | 0.16                     | 0.6                    | 100                    | 0                      |

2.2 Hybrid-multi objective optimization framework

Integrated DOE, RSM, NSGA-II, and TOPSIS were regarded as the optimization method to optimize the specific cutting energy and energy efficiency simultaneously. Fig. 4 is a flow chart showing the steps to determine an optimal process setting. The theory of DOE and the approximation method used are discussed by Simpson et al., [2001]. First, we defined the design variables and constraints and performed a design of experiments. A 3-level, 5-factor, and 46-set the Box-Behnken design (Jeff Wu and Hamada, 2009) were then used to carry out virtual experiments. Thirdly, RSM was used to construct the second order regression models of the specific cutting energy and energy efficiency (the outputs) in terms of machining parameters (the inputs). Subsequently, an ANOVA analysis was performed to investigate the adequacy of the approximate models and determine the significant factors. Finally, the best optimal solution for the machining parameters, specific cutting energy, and energy efficiency was identified with the support of the non-dominated sorting genetic algorithm-II (NSGA-II) and TOPSIS method.

The values of the objective weights can be determined by employing the Entropy method. A multi-criteria decision-making method (MCDM) problem with \(m\) alternatives each having \(n\) criteria (or attributes) can be expressed in matrix format as follows (Hwang and Yoon, 1981):

\[
A = \begin{bmatrix}
C_1 & C_2 & \cdots & C_n \\
A_1 & x_{11} & x_{12} & \cdots & x_{1n} \\
A_2 & x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
A_m & x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]

\[
D = \begin{bmatrix}
A_1 & C_1 & C_2 & \cdots & C_n \\
A_2 & x_{11} & x_{12} & \cdots & x_{1n} \\
A_3 & x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
A_m & x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]

\[
W = (w_1, w_2, \ldots, w_n)
\]

Here, \(A_i\) and \(C_j\) presents the feasible alternative generated from NSGA-II and evaluation criteria, respectively. \(x_{ij}\) denotes the performance rating of alternative \(A_i\) under criterion \(C_j\), and \(w_j\) presents the weight of criterion \(C_j\).

The data in matrix \(D\) have different dimensions, thus it needs to be normalized in order to transform various criterion dimensions into the non-dimensional criterion, which allows comparison across the criteria. The matrix \(D\) is normalized for each criterion as:

Fig. 4 Flow chart of multi-objective optimization.
\[ p_{ij} = \frac{x_{ij}}{\sum_{m}x_{ij}}, \ j = 1, \ldots, n \]  \hfill (6)

As a consequence, a normalized decision matrix representing the relative performance of the alternatives is the following:

\[ P = (p_{ij})_{m \times n}, \ i = 1, \ldots, m; \ j = 1, \ldots, n \]  \hfill (7)

The amount of decision information contained in Eq. (11) and emitted from each criterion can thus be measured by the entropy value \( e_j \) as:

\[ e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), i = 1, \ldots, m; \ j = 1, \ldots, n \]  \hfill (8)

The degree of diversity of the information contained by each criterion can be calculated as:

\[ d_j = 1 - e_j, \ j = 1, \ldots, n \]  \hfill (9)

Thus, the objective weight for each criterion is given by:

\[ w_j = \frac{d_j}{\sum_{j=1}^{n}d_j}, \ j = 1, \ldots, n \]  \hfill (10)

To rank the given alternatives of the Pareto solutions, the technique for order preference by similarity to ideal solution (TOPSIS) was used to determine the positive ideal solution (\( S^+ \)) as well as the negative ideal solution (\( S^- \)). TOPSIS finds the best compromise solution, which is the closest to \( S^+ \) and the farthest from \( S^- \) based on the Pareto set according to the decision maker’s objective weights. The TOPSIS process for determining the best compromise solution is briefly presented as follows:

1. Input matrix \( D \), where the element \( x_{ij} \) is the \( j_{th} \) objective value of the \( i_{th} \) alternative.
2. Calculate the normalized decision matrix, as \( P \) using Eq. (7) to Eq. (8).
3. Construct the weighted normalized values using Eq. (9) to Eq. (10).
4. Determine \( S^+ \) and \( S^- \) as follow:

\[ S^+ = \{(\max_{j \in J_1} p_{ij}), (\min_{j \in J_2} p_{ij}), i = 1, 2, \ldots, m\} \]

\[ S^- = \{(\min_{j \in J_1} p_{ij}), (\max_{j \in J_2} p_{ij}), i = 1, 2, \ldots, m\} \]  \hfill (11)

where \( J_1 \) and \( J_2 \) denote the sets of benefit criteria and cost criteria, respectively.

5. Develop a distance measure over each criterion to both ideal \( (D^+) \) and nadir \( (D^-) \):

\[ D_i^+ = \sqrt{\sum_{j=1}^{n} w_j(p_j^+-p_{ij})^2} \]  \hfill (12)

\[ D_i^- = \sqrt{\sum_{j=1}^{n} w_j(p_j^- - p_{ij})^2} \]

6. Calculate relative closeness \( D_i \) for each Pareto solution according to the following equation:

\[ D_i = \frac{D_i^-}{D_i^++D_i^-} \]  \hfill (13)

7. Choose the best compromise solution whose relative closeness \( D_i \) is the closest to 1.

NSGA-II is an improved multi-objective evolutionary algorithm based on NSGA, which is widely used for obtaining finite Pareto solutions to resolve constrained multi-objective optimization problems. To overcome the drawbacks of NSGA, NSGA-II keeps the diversity without specifying any additional parameters and obtains reliable optimal solutions by the elite-preserving and a phenotype crowd comparison operator. The operating procedure of the NSGA-II algorithm is illustrated in Fig. 5.
NSGA-II creates a random initial generation \( P_n \) and then generates offspring \( Q_n \) through the genetic operation (selection, crossover, and mutation) of previous parents. The offspring is created from the parents by simulated binary crossover. The random simplest mutation operator is applied randomly to create a solution from the entire search space. After the objective function of all individuals in \( R_n \) (combining parents \( P_n \) and offspring \( Q_n \)), the solutions are classified into various non-dominated fronts. The crowded tournament selection operator is employed to select the better solution and trim the population to form the new generation \( P_{n+1} \) according to the two rules: a non-dominated front in the population and a local large crowding distance.

3. FE-based machining simulation

3.1. Turning process-based model

For the machining simulations, a FE-based turning process model was designed using a commercial explicit finite element software DEFORM-3D (Fig. 6). For the each cutting analysis, the updated Lagrangian finite element formulation and adaptive meshing technique were used in order to obtain reliable results. Four-node elements in both workpiece and tool models were used for deformations occurring during the simulation process. The meshing window technology was used to locally refined part of the work piece to increase the simulation accuracy. In the workpiece model, a mesh ratio of 3 was used, and the minimum mesh size was 0.03. A mesh size of 0.025 was utilized in the window meshing of the work piece. In addition, the cutting tool was meshed into 30,000 tetrahedral elements, and a mesh ratio of 4 was used. To minimize the simulation time, the turning tool was modeled as perfectly rigid, while the workpiece was considered to have plastic properties. The workpiece was fixed in the X, Y, and Z-directions. The length of the workpiece is 4 mm, the width is 1.2 mm, and the height is about 0.9 mm. The cutting tool was set to move in the Y-direction. The moving distance and displacement of the cutting tool are 3 and 0.005 mm, respectively. Cutting tools were generated using CATIA V5R20 and then transferred to DEFORM 3D by means of an STL-format file.

The initial temperature of the workpiece and the ambient was assumed to be 20°C. The free surfaces of the workpiece were under free convection with a convective heat transfer rate of 2 W/m². For each cutting simulation, the Cockcroft and Latham’s criterion (Cockcroft and Latham, 1968) was adopted to predict the effect of tensile stress on the chip segmentation. In addition, the Coulomb-type was employed to describe the frictional behavior between the tool and workpiece. A frictional coefficient of 0.40 was used to obtain the best simulation results in view of the cutting forces. A constant depth of cut of 0.6 mm was used for all numerical experiments. The analysis process was performed sequentially with varying input parameters to obtain response values.

3.2. Workpiece and tool properties

Cubic boron nitride (CBN) was employed as a cutting tool material. The thermal-physical properties of the workpiece obtained from the DEFORM-3D environment and cutting tool are given in Table 2.
Table 2 The properties of the workpiece and tool material.

| Material                        | AISI 4140 | CBN   |
|---------------------------------|-----------|-------|
| Young's modulus (GPa)           | 210       | 720   |
| Poisson’s ratio                 | 0.3       | 0.2   |
| Density (kg/m³)                 | 7850      | 15000 |
| Specific heat (J/kg K)          | 363       | 20000 |
| Thermal conductivity (W/m K)    | 41.7      | 60.0  |
| Thermal expansion (10⁻⁹/K)      | 11.9      | 4.5   |

Table 3 The Johnson-Cook material flow model's parameters.

| Parameters | Value |
|------------|-------|
| A (MPa)    | 1057  |
| B (MPa)    | 755   |
| C          | 0.014 |
| n          | 0.15  |
| m          | 1.46  |
| Tₘ         | 1793  |

3.3. Material constitute model

In the machining model, a material constitutive model is required in order to describe the relationship between flow stress, strain, strain rate, and temperature. The Johnson-Cook (JC) [Moufki and Molinari, 2005] is the most widely used material model as it requires fewer material constants and also few experiments to evaluate these constants. The Johnson-Cook constitutive model can be represented by Eq. 14:

$$\sigma = \left[ A + B\varepsilon^n \right] \left[ 1 + C\ln\left( \frac{\dot{\varepsilon}}{\dot{\varepsilon}_0} \right) \right] \left[ 1 - \left( \frac{T - T_m}{T_m - 293} \right)^{m} \right]$$

(14)

where $A$, $B$, $C$, $n$, and $m$ are material constants, $\sigma$ is the equivalent stress, $\dot{\varepsilon}$ is the strain rate, $\dot{\varepsilon}_0$ is the reference strain rate, and $T$ and $T_m$ are the operating temperature and melting temperature. The coefficients for the Johnson-Cook model used in this paper are listed in Table 3.

3.4. Experimental confirmation

Fig. 7 shows the representative outputs, such as stress-effective and temperature distribution during the machining simulations. Then, turning experiments at various parameters are conducted to validate the FE simulations by means of Computer numerically controlled (CNC) lathe, namely HUYNDAI QUICKTURN 28N (Fig. 8). Cutting forces are recorded using charge amplifiers and a LABVIEW based data acquisition system. The workpiece is hardened 4140 steel bar of 400 mm long and the diameter is 100 mm. The machining conditions are the same as in the simulation (Table 4). Fig. 9 revealed that the main cutting force and thrust force have good agreement between the experiments and simulation (approximate 5%). Consequently, the FE model developed can be used to perform turning simulations and the optimization process.

Table 4 An experimental plan for validating the FE model.

| No | V (m/min) | f (mm/rev) | R (mm) | r (μm) | α (deg) |
|----|-----------|------------|--------|--------|---------|
| 1  | 60        | 0.16       | 0.4    | 60     | -5      |
| 2  | 300       | 0.16       | 0.4    | 60     | -5      |
| 3  | 180       | 0.13       | 0.2    | 20     | -5      |
| 4  | 180       | 0.13       | 0.6    | 20     | -5      |
| 5  | 180       | 0.13       | 0.4    | 20     | -10     |
| 6  | 180       | 0.13       | 0.4    | 100    | -10     |
| 7  | 180       | 0.13       | 0.2    | 60     | -10     |
| 8  | 180       | 0.13       | 0.2    | 60     | 0       |

(a) Stress-effective.  
(b) Temperature distribution.

Fig. 7 Representative output of machining simulation.
4. Numerical results
4.1 Development of mathematical predicted models

The relationship between the factors and the performance measures was modeled by quadratic regressions. The simulation results obtained from 46 numerical experiments according to the DOE method were used to construct the approximate models for the two response variables, including the specific cutting energy (SCE) and energy efficiency (EF). The regression equations obtained were as follows:

\[
\text{SCE} = a_0 + a_1 V + a_2 f + a_3 R + a_4 \alpha + a_5 V_f + a_6 V_r + a_7 V \alpha + a_8 f R + a_9 f \alpha + a_{10} f R^2 + a_{11} f \alpha^2 + a_{12} f^2 + a_{13} R R + a_{14} R \alpha + a_{15} \alpha R + a_{16} V^2 + a_{17} f^2 + a_{18} R^2 + a_{19} \alpha^2 \tag{15}
\]

\[
\text{EF} = b_0 + b_1 V + b_2 f + b_3 R + b_4 \alpha + b_5 V_f + b_6 V_r + b_7 V \alpha + b_8 f R + b_9 f \alpha + b_{10} f R^2 + b_{11} f \alpha^2 + b_{12} f^2 + b_{13} R R + b_{14} R \alpha + b_{15} \alpha R + b_{16} V^2 + b_{17} f^2 + b_{18} R^2 + b_{19} \alpha^2 \tag{16}
\]

The coefficients of Eq. (15) and Eq. (16) were determined by a regression method, and their values are shown in Table 5.

Before application of these quadratic polynomial models, it is necessary to validate the model accuracy. For this reason, the comparisons of the predicted and numerical values for the two response variables were depicted in Fig. 10 (a)-(b). The values of $R^2$ obtained by the RSM model of specific cutting energy and energy efficiency were 0.9941 and 0.9872, respectively. It could be observed that the predicted values are in agreement with the numerical data, which indicates that the developed regression models can yield high accurate results.
14.77%, nose radius (R) shows that the associated model with a large value of the coefficient of multiple determination (R²) based on its contribution (23.65%). The percentage contributions of feed rate (f) and edge radius (r) are the significant model terms associated with the specific cutting energy. Feed rate (f) was found to be the most effective parameter of any single term due to its high percentage contribution of 39.48%, followed by rake angle (α) with 18.77%, edge radius (r) with 18.77%, and cutting speed (V) with 14.77%, nose radius (R) with 5.60 %.

Figure 10 Comparisons of the predicted and numerical values.

Table 5 The values of coefficients in Eqs. (15) and (16).

| Coefficient | Value   | Coefficient | Value   | Coefficient | Value   | Coefficient | Value   |
|-------------|---------|-------------|---------|-------------|---------|-------------|---------|
| a₀          | 12.7238 | a₁₁        | -0.1333 | b₀         | 63.41481 | b₁₁        | 0.45833 |
| a₁          | -0.0093 | a₁₂        | 1.6389  | b₁         | 0.07484  | b₁₂        | 3.33333 |
| a₂          | -88.5870| a₁₃        | -0.0048 | b₂         | -11.99074| b₁₃        | 0.01563 |
| a₃          | -0.2773 | a₁₄        | -0.0064 | b₃         | -54.64583| b₁₄        | 0.4500  |
| a₄          | 0.0119  | a₁₅        | 0.00013 | b₄         | -0.08021 | b₁₅        | -0.00014|
| a₅          | -0.2629 | a₁₆        | 0.00001 | b₅         | -0.29625 | b₁₆        | -0.00014|
| a₆          | 0.0220  | a₁₇        | 323.9257| b₆         | 0.08333  | b₁₇        | 488.4259|
| a₇          | -0.0016 | a₁₈        | 7.4656  | b₇         | 0.00938  | b₁₈        | 52.2396 |
| a₈          | 0.000004| a₁₉        | 0.00016 | b₈         | -0.00005 | b₁₉        | -0.00036|
| a₉          | -0.0001 | a₂₀        | 0.00416 | b₉         | 0.00146  | b₂₀        | -0.02542|
| a₁₀         | -22.3090|            |         | b₁₀        | -8.3333  |            |         |

4.2 ANOVA analysis

The statistical significance was tested for those quadratic models by the ANOVA. Backward processes were conducted in order to eliminate insignificant terms. Table 6 gives the ANOVA results of the quadratic model of specific cutting energy. Accordingly, the regression model has a larger value for the coefficient of multiple determination (R² = 0.9941). This implies that the proposed quadratic model is statistically significant. The large model F-value of 209.57 indicates the significance of the regression model. There is only a 0.01% chance that a “Model F-value” this large could occur due to noise. The associated P-values of the developed model, which are less than 0.05, indicate that the model terms are statistically significant, and the effect of the model terms with a P-value greater than 0.1 are insignificant. Additionally, the backward process was used to eliminate the insignificant terms. Therefore, the single terms (A, B, C, D, E), interaction terms (AB, BC, BD, BE) and quadratic terms (A², B², C², D², E²) are the significant model terms associated with the specific cutting energy. Feed rate (f) was found to be the most effective parameter of any single term due to its high percentage contribution of 39.48%, followed by rake angle (α) with 18.77%, edge radius (r) with 14.77%, nose radius (R) with 13.64 %, and cutting speed (V) with 6.67%.

Similarly, the ANOVA results of the quadratic model of the energy efficiency are listed in Table 7. The ANOVA shows that the associated model with a large value of the coefficient of multiple determination (R² = 0.9872) is adequate to represent the simulation results. There is very little chance that noise can lead to such large “Model F-value”. The associated P-values of the developed model, which are less than 0.05, indicate that the model terms are statistically significant, and the effect of the model terms with a P-value greater than 0.1 are insignificant. For the energy efficiency model, the single terms (A, B, C, D, E), interaction terms (AE) and quadratic terms (A², C², D², E²) were found to be significant model terms. Moreover, rake angle (α) can be considered as the most significant parameter based on its contribution (23.65%). The percentage contributions of feed rate (f), cutting speed (V), edge radius (r), and nose radius (R) were 23.16 %, 16.67 %, 13.56 %, and 12.97 %, respectively.
Table 6 ANOVA table for the specific cutting energy after backward process.

| Source       | Sum of Squares | Mean square | F-value | P-value | Contribution (%) |
|--------------|----------------|-------------|---------|---------|------------------|
| Model        | 23.76          | 1.19        | 209.57  | <0.0001 |                  |
| A-Cutting speed | 1.33          | 1.33        | 234.44  | <0.0001 | 5.60             |
| B-Feed rate  | 9.38           | 9.38        | 1654.30 | <0.0001 | 39.48            |
| C-Nose radius| 3.24           | 3.24        | 571.56  | <0.0001 | 13.64            |
| D-Edge radius| 3.51           | 3.51        | 619.07  | <0.0001 | 14.77            |
| E-Rake angle | 4.46           | 4.46        | 786.19  | <0.0001 | 18.77            |
| AB           | 0.025          | 0.025       | 4.42    | 0.0457  | 0.11             |
| BC           | 0.072          | 0.072       | 12.64   | 0.0015  | 0.30             |
| BD           | 0.10           | 0.10        | 18.04   | 0.0003  | 0.42             |
| BE           | 0.24           | 0.24        | 42.64   | <0.0001 | 1.01             |
| A²           | 0.21           | 0.21        | 36.89   | <0.0001 | 0.88             |
| B²           | 0.74           | 0.74        | 130.83  | <0.0001 | 3.11             |
| C²           | 0.78           | 0.78        | 137.27  | <0.0001 | 3.28             |
| D²           | 0.56           | 0.56        | 98.12   | <0.0001 | 2.36             |
| E²           | 0.094          | 0.094       | 16.63   | 0.0004  | 0.39             |
| Residual     | 0.14           | 0.0056      |         |         |                  |
| Core total   | 23.90          |             |         |         |                  |

Table 7 ANOVA table for the energy efficiency after backward process.

| Source       | Sum of Squares | Mean square | F-value | P-value | Contribution (%) |
|--------------|----------------|-------------|---------|---------|------------------|
| Model        | 1175.63        | 58.78       | 96.47   | <0.0001 |                  |
| A-Cutting speed | 196.00        | 196.00      | 321.68  | <0.0001 | 16.67            |
| B-Feed rate  | 272.25         | 272.25      | 446.82  | <0.0001 | 23.16            |
| C-Nose radius| 152.52         | 152.52      | 250.32  | <0.0001 | 12.97            |
| D-Edge radius| 159.39         | 159.39      | 261.60  | <0.0001 | 13.56            |
| E-Rake angle | 278.06         | 278.06      | 456.35  | <0.0001 | 23.65            |
| AE           | 3.06           | 3.06        | 5.03    | 0.0341  | 0.26             |
| A²           | 34.69          | 34.69       | 56.94   | <0.0001 | 2.95             |
| C²           | 38.11          | 38.11       | 62.54   | <0.0001 | 3.24             |
| D²           | 2.82           | 2.82        | 4.63    | 0.0412  | 0.24             |
| E²           | 3.52           | 3.52        | 5.78    | 0.0239  | 0.3              |
| Residual     | 15.23          | 0.61        |         |         |                  |
| Total        | 1190.86        |             |         |         |                  |

4.3. Effect of the machining parameters on the objective functions

The effects of process factor on the specific cutting energy and energy efficiency were evaluated in terms of perturbation and contour plots. The perturbation plots were used to compare the effect of all the factors at a centre point of the design space. The contour plots were used to investigate the effects of parameters considered in their full range, at each level of the focal position.

Fig. 11 is a perturbation plot which illustrates the effects of machining parameters on the specific cutting energy (SCE). It is evident from the results that all the input parameters have a significant effect on the output (SCE). Contour plots showing the effects of the machining parameters on the specific cutting energy are illustrated in Fig. 12. SCE decreases with an increase in cutting speed. In this case, the heat generated in deformation zones cannot dissipate quickly. Consequently, thermal softening of the workpiece does occur due to the increase in temperature in the deformation areas. Therefore, a decrease in the cutting forces takes place. Feed rate leads to a corresponding increase in the normal contact stress at the tool chip interface and in the tool chip contact area. Hence, the cutting forces were found to increase with feed rate. However, the feed rate is inversely proportional to the specific cutting energy, which is reduced due to an increase in the volume of the cut material in the same unit of time. An increase in the nose radius
results in an increase in the length of the cutting edge, requiring higher the cutting forces. Therefore, shear and friction energy increase with nose radius at the same time. Furthermore, the specific cutting energy increases gradually with increasing edge radius. As the edge radius increases, the tool becomes blunt; hence, more energy is consumed to overcome the frictional resistance. In contrast, the tool becomes sharper with an increase in rake angle, which results in less deformation leading to a reduction in the cutting forces.

Fig. 13 is a perturbation plot illustrating the effect of machining parameters on the energy efficiency ($EF$). It can be observed that the energy efficiency is sensitive to variations in input parameters. The contour plots of energy efficiency versus the employed parameters are shown in Fig. 14. As the cutting speed increases, the energy efficiency proportionally improves, too. High temperature at deformation zones achieved with high cutting speed would mean a lower the shear and friction power, which would increase the energy efficiency. An increase of feed rate results in improved energy efficiency due to the higher shear power (useful component) consumed. Regarding the nose radius and edge radius, it can be noticed that the two independent variables affect the energy efficiency in similar ways. An increase of nose radius or edge radius results in decreased energy efficiency due to the higher friction energy used. Furthermore, increasing the rake angle is the most effective way to minimize the energy efficiency through a reduction of the friction power.

![Perturbation plot](image)

**Fig. 11** Perturbation plot showing the effect of all factors on the specific cutting energy.

(a) Interaction effects of cutting speed and feed rate.

(b) Interaction effects of nose radius and edge radius.

(c) Interaction effects of rake angle and edge radius.

**Fig. 12** 3-D surface plots of the interaction effects of machining parameters on the specific cutting energy.
5. Optimization results

The developed mathematical models for the specific cutting energy (SCE) and energy efficiency (EF) are optimized using NSGA-II which has the capacity of finding the optimal solution of a multi-objective problem. It is a tough work to determine the optimal process parameters for decreasing the cutting energy and improving the energy efficiency simultaneously. Moreover, machining parameters, such as cutting speed, feed rate, nose radius, and rake angle have complex effects on the evaluation criteria. The following parameters were listed based on the study to get optimal solutions with low computational effort:

1. Population size = 24
2. Maximum number of generations = 30
3. Crossover probability = 0.9
4. Crossover distribution index = 40.0
5. Mutation distribution index = 10.0

NSGA-II can converge to the feasible optimal solutions of both objectives, as shown in Fig. 15, which means that the formation of the Pareto front results in the final set of solutions. 721 Pareto solutions are obtained at the end of NSGA-II operation. Among the Pareto-optimal solutions, it is clearly found that none of the solutions is absolutely better than any other; any one of them is an acceptable solution. Therefore, an integrative approach, including the entropy method and TOPSIS technique is necessary to find the most appropriate solution. Based on the entropy method,
the weight factors calculated of the specific cutting energy and energy efficiency are 0.7 and 0.3, respectively. Coupled with the TOPSIS approach, the 4 efficient alternatives with the highest TOPSIS score were obtained and listed in Table 8 with the Pareto-optimal solution numbers, the objective values, the score, and the ranking. It can be stated that the no. 687 solution was selected as the best solution among all alternatives, which is shown with green color in Fig. 15. The optimal values listed in Table 9 indicated that the energy efficiency was improved by 18% and the specific cutting energy was decreased by 14%.

![Table 8 TOPSIS ranking results of alternatives.](image)

| No. solution | 687 | 647 | 638 | 527 |
|--------------|-----|-----|-----|-----|
| SCE (J/mm³)  | 5.397 | 5.388 | 5.382 | 5.379 |
| EF (%)       | 78.8 | 78.4 | 78.0 | 77.9 |
| Score        | 0.9461 | 0.9426 | 0.9384 | 0.9358 |
| Ranking      | 1 | 2 | 3 | 4 |

![Fig. 15 Pareto optimal solutions.](image)

### Table 9 Results of multi-objective optimization process.

| Parameters | Machining parameters | Objective functions |
|------------|----------------------|---------------------|
|            | $V$ (m/min) | $f$ (mm/rev) | $R$ (mm) | $r$ (μm) | $\alpha$ (deg) | $SCE$ (J/mm³) | $EF$ (%) |
| Initial values | 180 | 0.13 | 0.4 | 60 | -5 | 6.282 | 60.8 |
| Optimized values | 300 | 0.16 | 0.2 | 20 | 0 | 5.397 | 78.8 |

### 6. Conclusions

In this paper, a particular approach for simulation and optimization of the turning process of the hardened steel has been developed through the FE model, design of experiments, ANOVA analysis, genetic algorithm, and multi-criteria decision-making method. The machining parameters, including cutting speed, feed rate, nose radius, edge radius, and rake angle were optimized in order to reduce the specific cutting energy and improve energy efficiency. A FE-based turning process model was developed to perform a set of the machining simulation based on Box-Behnken experimental designs. The quadratic models of the objectives, including the specific cutting energy and energy efficiency, were created by the mixed regression model and response surface method. The adequacy of the developed mathematical models and the important parameters were validated using ANOVA techniques. The best optimal point was determined by adopting the TOPSIS technique with entropy weights based on Pareto-optimal solutions generated by NSGA-II algorithm. The following conclusions can be drawn from this investigation within factors considered:

1. The two polynomial models of the specific cutting energy and energy efficiency carried out by the Box-Behnken design experiment and RSM, which predicted the values of the responses with sufficient accuracy.

2. After optimization, the multi-objective optimization gave results representing an approximate 14% reduction of the specific energy and an increase of 18% in the energy efficiency compared to initial values.

3. The developed approach by coupling FE simulations, DOE, RSM, ANOVA, NSGA-II, and TOPSIS has been proved to be effective and will be a powerful tool to guide the optimal design of the process parameters and cutting tool geometry. This study can provide a valuable guidance for improving the energy efficiency of machining processes.
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