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AN ENERGY EFFICIENT TURNING PROCESS FOR HARDENED MATERIAL WITH MULTI-CRITERIA OPTIMIZATION

Summary

This paper presents a systematic procedure for the optimization of machining parameters such as cutting speed, feed rate, nose radius, edge radius, and rake angle to reduce specific material removal energy and improve energy efficiency in the hard turning of AISI 4140 steel. A simulation approach was applied in conjunction with the design of experiment (DOE), mathematical approximation with a meta-model to develop specific energy as well as an energy efficiency model in terms of cutting parameters. A hybrid approach that combines the Multi-Objective Particle Swarm Optimization (MOPSO) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) using entropy weights was adopted to determine the best solution from the Pareto set. The results showed that energy efficiency could be improved by 11%, whereas specific energy decreased by approximately 15% compared to a non-optimal case. Therefore, this study is expected as a contribution to making the turning process of hardened materials greener and more efficient.

Key words: *Multi-objective optimization; Hard turning; Machining parameters; Energy efficiency; Finite element method.*

1. Introduction

Consumer pressure, rising energy costs, and environmental legislation have combined to increase the importance of improving energy efficiency. Compared to major energy users, the industrial sector accounts for approximately 50% of the total energy consumption, in which the manufacturing process dominates [1, 2]. Since machining is a common manufacturing process for shaping a variety of materials, increasing the efficient use of energy in machining operations can contribute significantly to energy savings in manufacturing. Among metal cutting methods, the machining of hardened steel (45÷65 HRC) has become a normal practice in industrial applications due to improved productivity, compatible surface roughness, and low manufacturing costs [3, 4]. However, the amount of energy consumed for hardened steel machining is larger than that needed to cut normalized or non-hardened materials. Therefore, identifying potential solutions to increase the energy efficiency of hard machining process is needed.

In addition to retrofitting machines with advanced energy-saving devices that promise certain energy efficiency, optimization of machining parameters of existing systems at both the machine and higher levels has been discussed by many researchers. Munoz et al. [5] concluded that energy consumption depends on the cutting tool geometry, part geometry, and process parameters. Furthermore, cutting conditions can be optimized in an effort to reduce energy consumption in turning [6] and milling processes [7]. Reducing the cycle time and optimizing the parameters of hydraulic equipment are considered as effective solutions to reduce energy consumption in manufacturing lines consisting of multiple machines [8].

Among efforts aimed at reducing energy consumption at the level of material removal, some researchers have attempted to model the cutting energy during a machining process. Xu et al. [9] created a cutting force model based on motor spindle power with respect to tool wear. Likewise, Astakhov et al. [10] classified the cutting force into four elements and provided a mathematical expression for each energy mode. Yoon et al. [11] introduced a second-order regression model of material removal power in terms of process parameters and tool wear in a milling process. However, these models do not thoroughly consider the effects of cutting tool geometry. The fact is that, in addition to process parameters, the selection of the tool shape is an important factor that affects the cutting force components and the cutting energy [12].

Experimental studies into hard machining in general and hard turning in particular can be time consuming and expensive. Therefore, an understanding of the effects of machining parameters on energy consumption and efficiency is needed at an early stage of machining process planning. To overcome these problems, finite element method (FEM)-based approaches using well-defined material properties and numerical models can be considered as an intelligent choice instead of a practical experiment to obtain reliable results that simulate machining [13, 14, 15, 16]. Finite element (FE)-based models for investigating the effects of cutting parameters on chip formation [17], temperature, work piece stress, and shear angle have been developed [18]. Optimization of oblique turning operations while machining the AISI H13 tool steel was studied by Usama Umer et al. [19] with the aim to reduce cutting forces and temperature. Their results indicated that FEM is a powerful technique for predicting the cutting performance of hard machining process.

To respond to the challenge of reducing energy consumption and increasing machining efficiency, an energetic optimization approach using the developed FE model and a hybrid multi-objective evolutionary algorithm for the hard turning of AISI 4140 steel is introduced in this paper. The material selected for this research was chosen due to its wide use in automobiles, aerospace, and machine tool applications. It is essential to have reliable energetic models for conducting parametric studies in order to understand the process mechanisms and optimize the machining parameters. In addition, constantly changing cutting parameters such as cutting speed, feed rate, nose radius, edge radius, and rake angle contribute to variations in the cutting energy and energy efficiency. Therefore, an effective approach that optimizes cutting parameters in terms of energy efficiency can contribute significantly to energy reduction and this is therefore an important area of research. For this purpose, the aim of the present study was first to create mathematical models of specific material removal energy and energy efficiency with respect to various machining parameters based on numerical results. Subsequently, an integrated method combining the Multi-Objective Particle Swarm Optimization (MOPSO) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed to obtain optimal parameters in terms of improving energy efficiency and decreasing specific energy.

In the remainder of the paper, a framework for solving the multi-objective optimization problem is introduced. Next, the developed reliable simulation model is mentioned. The energetic aspects are analysed and optimization problems are defined. Numerical experiments as well as descriptive data analysis and optimization results are then discussed. Finally, we present our conclusions and discuss potential areas of future research.

2. Optimization framework

To our best knowledge, there is no commercial simulation tool that directly generates mathematical models of specific material removal energy and energy efficiency. Additionally, determining the optimal parameters of the machining process using the usual analytical methods is ineffective. For these reasons, we have developed a framework to facilitate the optimization process based on a simulation model and numerical experiments (Fig. 1). This systematic procedure consists of four main steps:

1. Development of a three-dimensional simulation model for the hard turning process

2. Planning of numerical experiments using the design of experiment (DOE), performing a set of simulations, and developing mathematical models of the specific material removal energy and energy efficiency based on a meta-model.

3. Generation of finite Pareto solutions based on the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm.

4. Application of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method using entropy weights to obtain the best optimal solution.

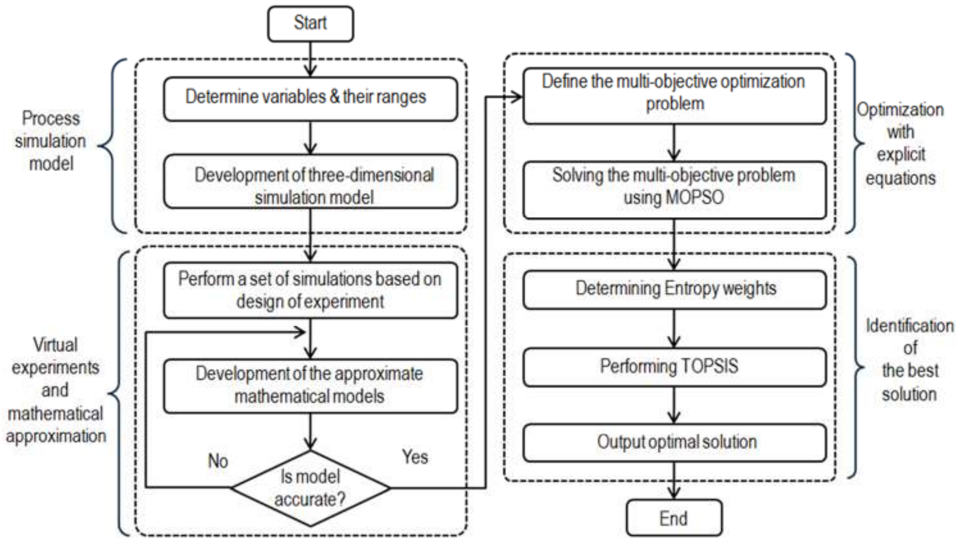


Fig. 1 Multi-objective optimization framework

An effective method based on a multi-dimensional sphere of design of the experiment, namely the Box-Behnken design [20], was adopted to organize the combination of machining parameters. In this way, all the design points lie on the same sphere with at least three or five points at the centre point. A set of numerical simulations was then done in order to obtain the data for generating the regression meta-model.

We suggest the second order response surface methodology (RSM) and radial basis function (RBF) as meta-models due to the moderate nonlinear behaviour of the machining process. RSM is a well-known mathematical approximation method that is widely used in engineering. RBF is a kind of neural network meta-modelling technique that the data points. Both RSM and RBF can be used effectively in the global optimization of expensive black-box functions for the computer simulation-based design. The theory of DOE, the approximation method, and the meta-model were mentioned in detail in the Ref. [21].

To solve the multi-optimization problem, MOPSO (a multi-objective exploratory technique that is well-suited for highly nonlinear design space) was used for solving trade-offs among objective functions. Many researchers have demonstrated that MOPSO is an efficient and viable technique to solve complex optimization problems [22, 23, 24]. Multi-objective optimization problems in which there is competition between objectives may have no single, unique optimal solution. Therefore, a Pareto solution is employed for trade-offs among objectives, and multiple-criteria decision-making (MCDM) should be used.

In this study, the finite Pareto optimal solutions were generated from the MOPSO technique. The entropy method was employed to derive the objective weights of evaluation criteria to avoid the influence of any subjective factors. Subsequently, TOPSIS was adopted as a MCDM method to rank the given alternatives of the Pareto solutions. A detailed explanation of specific procedures for TOPSIS with entropy weights can be found in Ref. [25, 26].

3. Process simulation via FEM

As previously mentioned in the introduction, FEM is an intelligent choice that reduces the experiment cost and time. Therefore, a FEM-based approach was utilized to investigate the influence of machining parameters on the specific cutting energy and energy efficiency. This section presents a FEM model and the procedure to simulate the hard turning process of AISI 4140 steel.

A three-dimensional turning model for semi-orthogonal cutting was developed using the DEFORM-3D explicit finite element software (Fig. 2). Four-node elements were used both in the work piece and cutting tool models of deformations taking place during the simulation process. An updated Lagrangian finite element formulation was employed in conjunction with continuous and adaptive meshing techniques in order to obtain reliable results.

The turning tool was modelled using rigid elements and was set to move in the Y-direction (cutting direction). Different geometries of cutting tools were designed using CATIA V5R20, and the models were converted to STL files and imported into the software. The work piece was set as a plastic object and was fixed in the X, Y, and Z-directions. The thermal-physical properties of the work piece (AISI 4140 steel) and the cutting tool made of cubic boron nitride (CBN) [18] are given in Table 1.

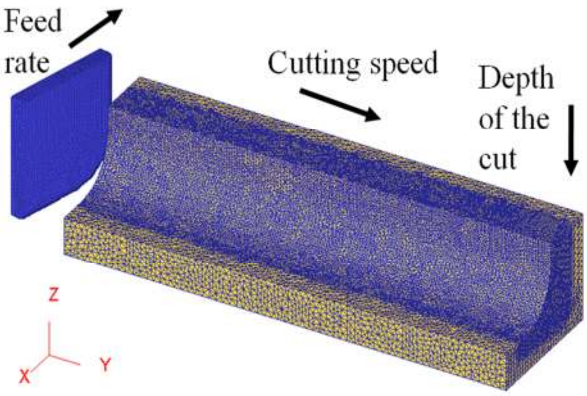


Fig. 2 FEM-based process model

Table 1 The properties of the work piece and tool material

Material	AISI 4140	CBN
Young’s modulus (GPA)	210	720
Poisson’s ratio	0.3	0.2
Density (kg/m^3)	7850	15000
Specific heat (J/kg K)	363	20000
Thermal conductivity (W/m K)	41.7	60.0
Thermal expansion (10^{-6}/K)	11.9	4.5

In order to reduce simulation time and improve accuracy, the meshing window technology was adopted to locally refine part of the work piece and the cutting tool. The initial temperature of the work piece, the cutting tool, and the ambient temperature were all assumed to be 20 °C.

The Cockcroft-Latham criterion [27] was adopted to predict the material separation and the damage criterion. Additionally, Coulomb-type behaviour was employed to describe the frictional law between the tool and chips. A frictional coefficient of 0.35 was used to obtain the best results with respect to cutting forces.

In this paper, we employed the Johnson-Cook model [28] to describe the behaviour of hardened AISI 4140 steel. This model produces excellent results in terms of describing the material behaviour and chip formation in constitutive plastic models. The Johnson-Cook model is capable of modelling large strains, high strain rates, and temperature dependency, and can be expressed as follows:

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

Here, A, B, C, n, and m are the material constants, σ 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 and melting temperatures, respectively (Table 2).

Table 2 Parameters of the Johnson-Cook material flow model

A	B	C	n	m	T_m
1057	755	0.014	0.15	1.46	1793

Five key machining parameters, namely, cutting speed (V), feed rate (f), nose radius (R), edge radius (r), and rake angle (γ) were considered as design variables based on the available literature [5, 12]. The levels of machining parameters were selected according to recommended data from the SANDVIK cutting tool manufacturer (Table 3). A constant cut depth of 0.6 mm was employed during machining simulations.

Table 3 Levels and respective values of machining parameters

Levels	Parameters				
	Cutting speed V (m/min)	Feed rate f (mm/rev)	Nose radius R (mm)	Edge radius r (μm)	Rake angle γ (deg)
1	60	0.10	0.2	20	-10
2	180	0.13	0.4	60	-5
3	300	0.16	0.6	100	0

The representative output of machining simulation is shown in Fig. 3. An experimental plan (Table 4) is a subset of the Box-Behnken design that is adopted to validate our FE model. A computer numerically controlled (CNC) lathe, namely HUYNDAI QUICKTURN 28N, and a dynamometer, charge amplifiers, and a data acquisition system were used to obtain the cutting forces. The lathe is equipped with a 22 kW spindle of a maximum speed of 3000 rpm. The work piece of 100 mm in diameter and 400 mm in length was adopted in the machining process (Fig. 4). Fig. 5 shows comparisons between the simulation and experimental results at various machining conditions. The small errors (approximately 6%) indicated that the developed model was able to simulate the turning process.

Table 4 An experimental plan for validating the FE model

No	V (m/min)	f (mm/rev)	R (mm)	r (μm)	γ (deg)
1	60	0.10	0.4	60	-5
2	300	0.10	0.4	60	-5
3	60	0.13	0.2	60	-5
4	60	0.13	0.6	60	-5
5	180	0.13	0.2	20	-5
6	180	0.13	0.2	100	-5
7	180	0.13	0.4	20	-10
8	180	0.13	0.4	20	0

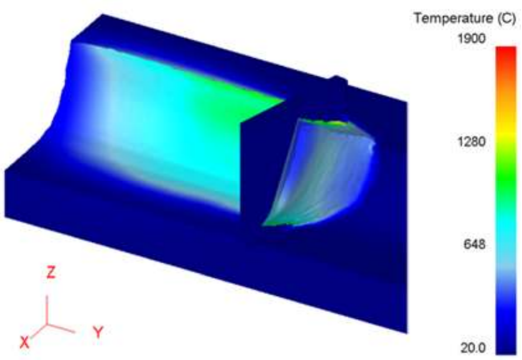


Fig. 3 Temperature field in the cutting zone

Fig. 4 Experimental facilities

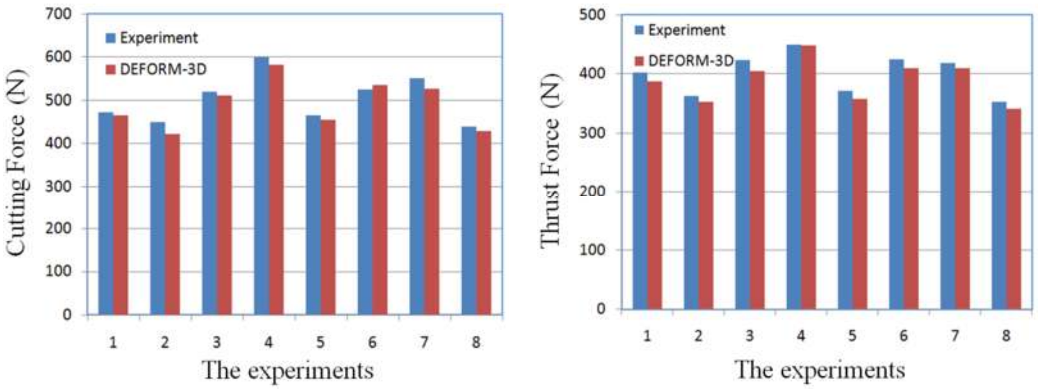


Fig. 5 Comparison between the experimental results and the simulation results

4. Analysis of energetic aspects and optimization problems

As mentioned in Sec. 1, the aim of this study was to reduce specific material removal energy and improve energy efficiency of the turning of hardened AISI 4140 steel based on the simulation approach and multi-objective optimization process. Specific material removal energy (SE) was defined as the energy required for removing a specific volume of material from the work piece:

$$SE = \frac{U_c}{MMR} = \frac{U_c}{d \times f \times V} \tag{2}$$

Here, U_c, MRR, d, f, and V represent the material removal energy, the material removal rate, the depth of the cut, the feed rate, and the cutting speed, respectively. The material removal energy was dissipated principally in two zones, namely, the primary zone and the secondary zone. To facilitate the approximation process, total energy consumption was approximately classified in two main categories: shear energy and friction energy (Fig. 6). Therefore, the energy consumption (U_c) was defined as:

$$U_c = U_{shear} + U_{friction} = F_c V \tag{3}$$

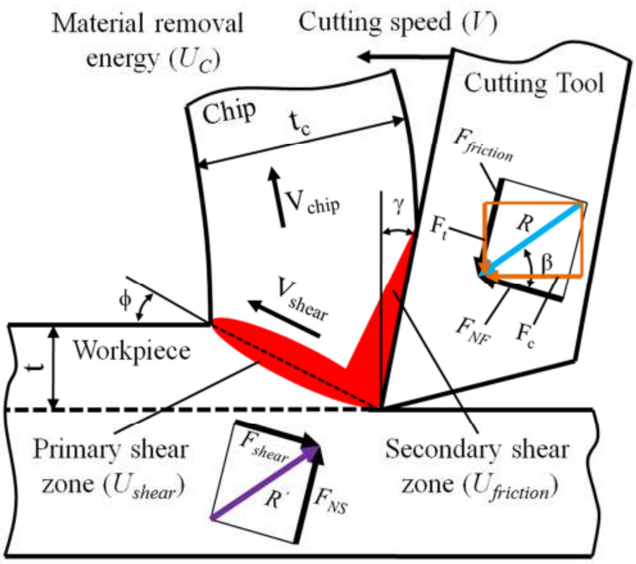


Fig. 6 Energetic components of material removal in the turning process

Here, U_{shear}, $U_{friction}$, and F_c represent the shear energy, the friction energy, and the main cutting force, respectively [29]. The two components of the shear and the friction energy can be defined as shown in Eq. (4) and Eq. (5), respectively:

$$U_{shear} = F_{shear} V_{shear} \tag{4}$$

$$U_{friction} = F_{friction} V_{friction} \tag{5}$$

Here, F_{shear}, $F_{friction}$, V_{shear}, and V_{chip} represent the shear force, the friction force, the velocity of the chip relative to the work piece, and the velocity of the chip relative to the tool face, respectively. The shear force (F_{shear}) and the velocity of the chip relative to the work piece (V_{shear}) can be calculated using Eq. (6) and Eq. (7), respectively:

$$F_{shear} = F_c \cos\phi - F_t \cos\phi \tag{6}$$

$$V_{shear} = \frac{V\cos\gamma}{\cos(\phi-\gamma)} \tag{7}$$

The friction force ($F_{friction}$) and the velocity of the chip relative to the tool face (V_{chip}) are defined as:

$$F_{friction} = R\sin\beta = \sqrt{F_c^2 + F_t^2}\,\sin\beta \tag{8}$$

$$V_{chip} = Vr_c = V\frac{t}{t_c} \tag{9}$$

where F_t, γ, φ, β, and r_c denote the thrust force, the rake angle, the shear plane angle, the friction angle, and the chip thickness ratio, respectively. The shear plane angle and the friction angle can be defined using Eq. (10) and Eq. (11), respectively:

$$\tan\phi = \frac{r_c \cos\gamma}{1 - r_c \sin\gamma} \tag{10}$$

$$\tan\beta = \frac{F_t + F_c \tan\gamma}{F_c - F_t \tan\gamma} \tag{11}$$

Shear energy is a significant component of the total energy consumed for material removal. On the other hand, the energy used to overcome frictional resistance is essentially wasted. Therefore, the material removal energy efficiency (*EF*) can be defined as the ratio of shear energy to material removal energy. Energy efficiency can thus be described as:

$$EF = \frac{U_{shear}}{U_c} \tag{12}$$

In the FEM-based approach, the specific material removal energy and the energy efficiency were calculated based on the measured values of the cutting force components and the chip thickness. In other words, two mathematical energetic models were generated as functions of the specified machining parameters.

As shown in Sec. 3, a total of five machining parameters were selected comprising cutting speed (*V*), feed rate (*f*), nose radius (*R*), edge radius (*r*), and rake angle (*γ*). According to the aim and the decision space, the optimization process was formulated using the following expression:

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

Minimize specific material removal energy (*SE*)

Maximize energy efficiency (*EF*)

Subject to: $60 \le V \le 300$ (m/min), $0.10 \le f \le 0.16$ (mm/rev), $0.2 \le R \le 0.6$ (mm),
$20 \le r \le 100$ (μm), $-10 \le \gamma \le 0$ (deg).

5. Results and discussions

5.1 Mathematical prediction models

According to the Box-Behnken experimental design, the data obtained from 46 numerical experiments was used to establish the relationships between the machining parameters and the specific material removal energy (*SE*) as well as the energy efficiency (*EF*). Both RBF and RSM models were employed for comparison. Fig. 7 presents a comparison between the predicted and the numerical experimental values obtained by the RBF and RSM models. In this study, we have chosen RSM as the preferred metal model because the RSM model has a better R^2 value (a measure of the goodness of fit) for the objectives than RBF. Additionally, the specific energy and the energy efficiency values of R^2 obtained by the RSM model were 0.9941 and 0.9835, respectively, indicating highly accurate results when regression models are concerned. Consequently, the developed mathematical models can be used in the optimization process. The regression response surface models showing the specific material removal energy (*SE*) and the energy efficiency (*EF*) are expressed as follows:

$$\begin{aligned} SE &= 12.9948 - 0.00916V - 92.6548f - 0.01312R + 0.00924r - 0.2718\gamma \\ &+ 0.02199Vf - 0.0016VR + 0.0000007Vr - 0.0001V\gamma - 24.47917fR \\ &- 0.11589fr + 1.63889f\gamma - 000028Rr + 0.0096R\gamma + 0.00013r\gamma \\ &+ 0.000011V^2 + 339.1537f^2 + 7.3675R^2 + 0.00016r^2 + 0.00383\gamma^2 \end{aligned} \tag{13}$$

$$\begin{aligned} EF &= 74.43565 - 0.012119V + 103.63426f - 15.77083R - 0.12609r \\ &+ 1.05833\gamma + 0.000001Vf + 0.013542VR + 0.00057Vr - 0.00096V\gamma \\ &+ 12.5fR - 0.1875fr - 0.83333f\gamma + 0.034375Rr - 0.825R\gamma - 0.001375r\gamma \\ &+ 0.000053V^2 - 844.90741f^2 - 3.80208R^2 + 0.00055r^2 - 0.02475\gamma^2 \end{aligned} \tag{14}$$

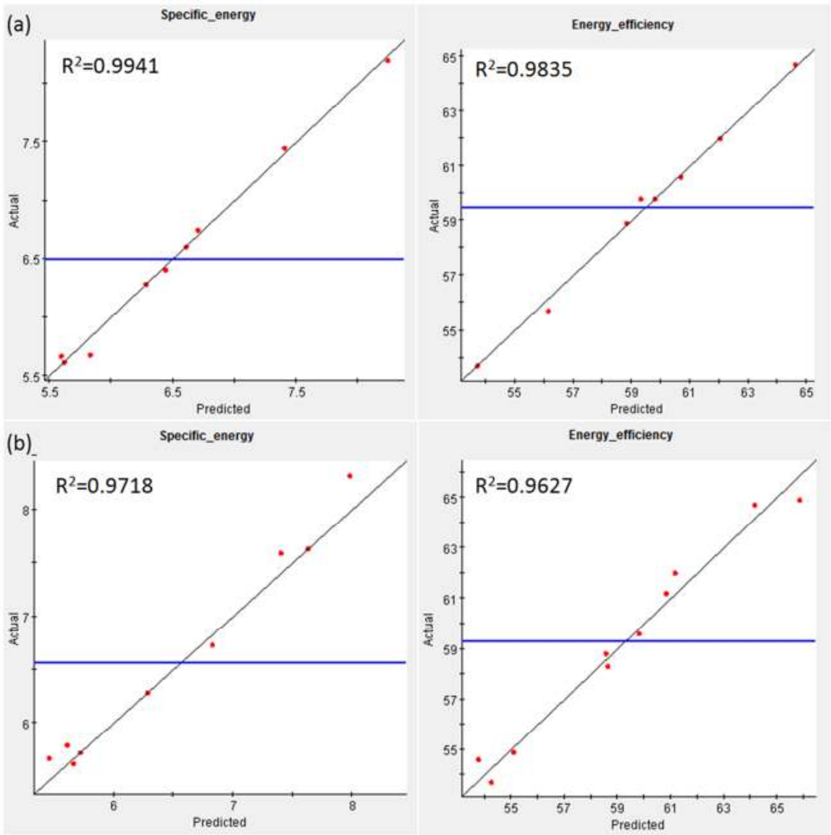


Fig. 7 Comparisons between the predicted and the numerical values obtained by (a) RSM model, (b) RBF model

5.2 Effect of the parameters on the objectives

Fig. 8 and Fig. 9 show the 3-D response surface plots between machining parameters and the specific energy as well as the energy efficiency within the ranges of factors considered in this study. Each sub-figure presents the effects of two parameters on the objectives, while the other design variables are kept at the initial value. Specific energy has a tendency to decrease at increased cutting speeds and feed rates. The optimum set of parameters for achieving the lowest specific energy was obtained with a smaller nose radius and a smaller edge radius. The tool becomes sharper with an increased rake angle, which results in less deformation and thus a decreased specific energy. Additionally, decreasing the edge radius and the nose radius causes the energy efficiency to increase. The cutting speed and the rake angle have significant effects on the energy, and thus high efficiency can be achieved by increasing both. It can be observed that the design variables have complex effects on the objective functions. Some parameters used in the study adversely influence the multi-criteria optimization. Therefore, implementation of the optimization process is required in order to find an optimal solution which can meet the objectives.

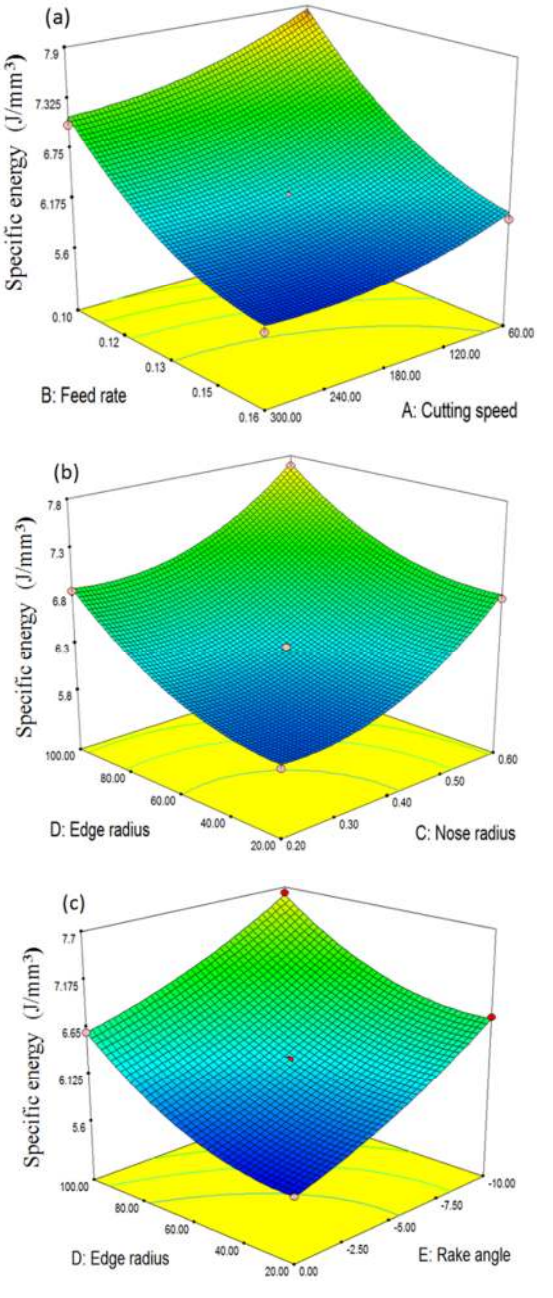


Fig. 8 (a) 3-D surface plots of the interaction effects of cutting speed and feed rate, (b) nose radius and edge radius, (c) rake angle and edge radius on specific energy.

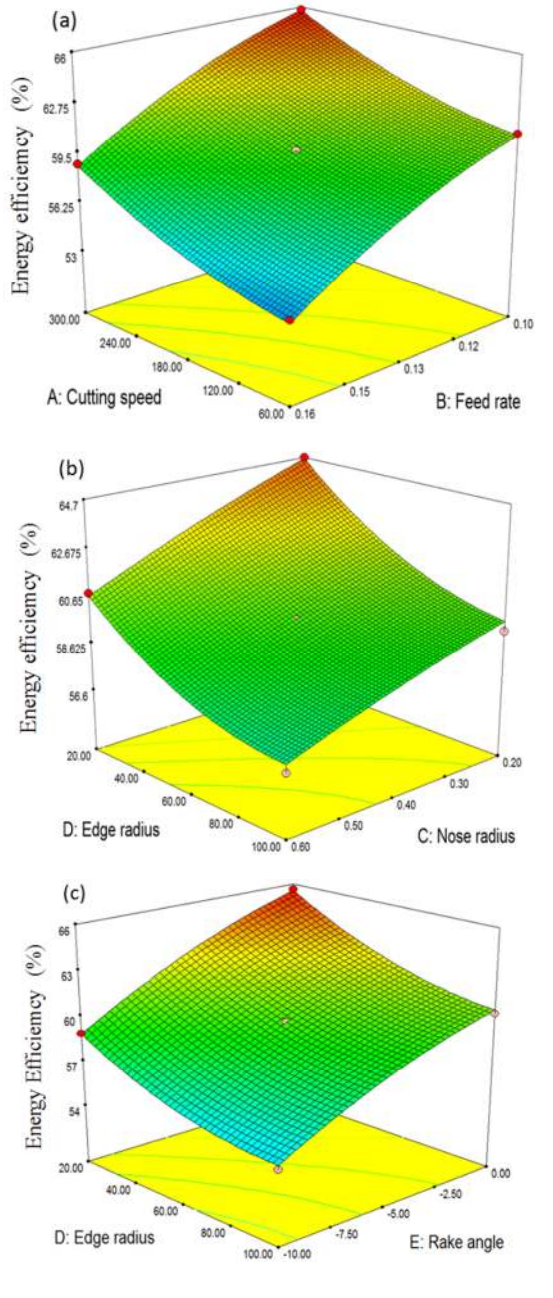
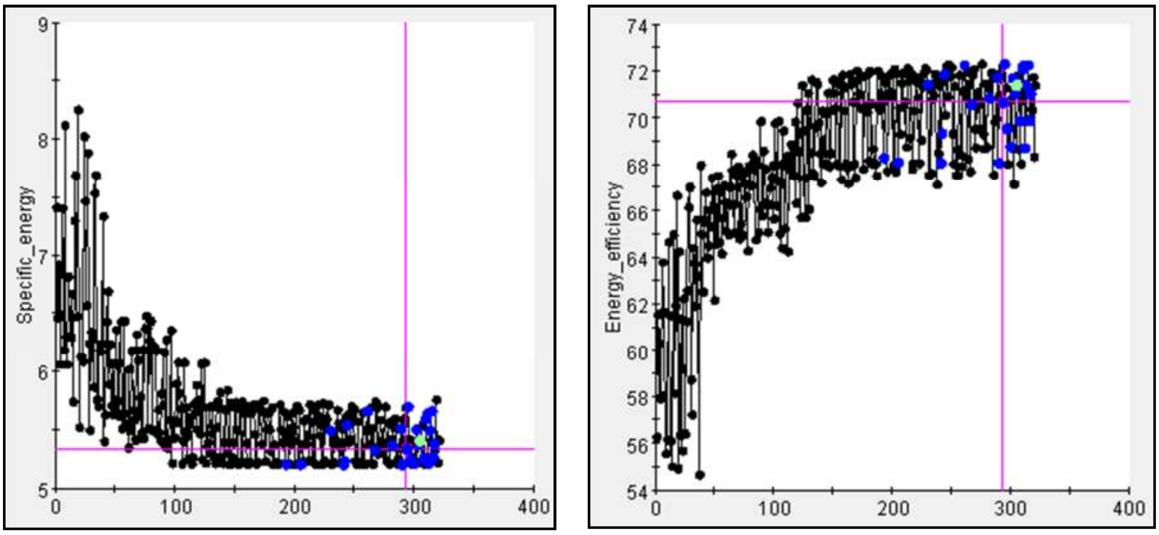


Fig. 9 (a) 3-D surface plots of the interaction effects of cutting speed and feed rate, (b) nose radius and edge radius, (c) rake angle and edge radius on energy efficiency.

5.3 Optimization results

In comparing cost simulations based on the FEM in the computational approach, Eq. (13) and Eq. (14) were found to produce a much simpler and more efficient way to predict the values of response variables within the limits of the specific factors studied. Fig. 10 shows the history of the optimization process of the objective functions using the MOPSO algorithm. Fig. 11 presents finite Pareto optimal solutions in which each blue point indicates the feasible optimum point. The two objectives appeared to be in conflict with each other, such that there was no point in attempting to optimize the two energetic models simultaneously. Therefore, we used the TOPSIS approach to determine the best solution from the Pareto optimal set.



(a) Specific energy (b) Energy efficiency

Fig. 10 Optimization history of objective functions

The weighting factors calculated using the entropy method of specific energy objective function and energy efficiency objective function are 0.7 and 0.3, respectively. Using the TOPSIS approach, the first 5 efficient alternatives with the highest TOPSIS score were obtained, as shown in Table 5, with the Pareto optimal solution numbers, the values of functions, and the ranking. The solution having the highest TOPSIS score is the compromise suite. Therefore, the solution no. 294 was selected as the best solution among all alternatives, which is shown as the point with crossed lines in Fig. 11. A comparison between the values of all design variables and objective functions before and after optimization is shown in Table 6.

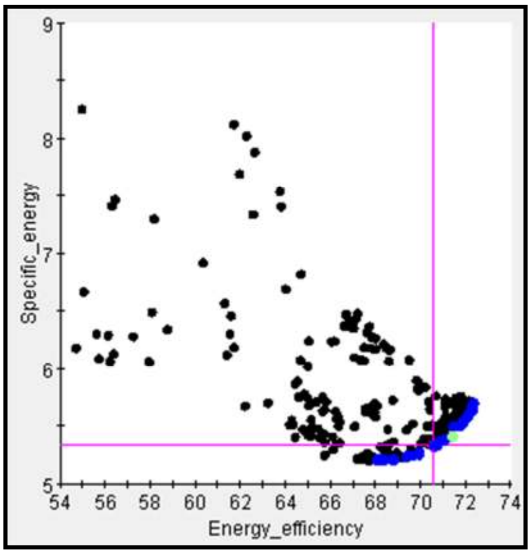


Fig. 11 Pareto optimal solutions

Table 5 TOPSIS ranking results of alternatives

No	*SE* (J/mm^3)	*EF* (%)	Score	Ranking
294	5.331	70.6	0.9286	1
246	5.444	71.4	0.9264	2
250	5.361	71.0	0.9251	3
270	5.379	71.2	0.9238	4
260	5.555	71.8	0.9223	5

The optimization results listed in Table 6 were regarded as machining parameters of the hard turning process to simulate the correspondence between the specific energy (*SE*) and the energy efficiency (*EF*). Importantly, it can be observed that the specific energy exhibited an approximate reduction of 15% compared to a non-optimal case and the energy efficiency is improved by about 11%. The research results indicated the efficiency and practical potential of the proposed optimization method.

Table 6 Results of multi-objective optimization process

Parameters	Explanatory variables					Responses	
	V (m/min)	f (mm/rev)	R (mm)	r (µm)	γ (deg)	SE (J/mm^3)	EF (%)
Un-optimal case	180	0.130	0.4	60	-5	6.282	59.6
Optimized value	300	0.138	0.2	20	0	5.331	70.6

6. Conclusions

In summary, the hard turning process of AISI 4140 steel was systematically investigated in order to find the optimal parameters such as cutting speed, feed rate, nose radius, edge radius, and rake angle based on the developed mathematical models of specific energy and energy efficiency. A FE-based three-dimensional model was employed in conjunction with the Box-Behnken experimental design to analyse the turning process through simulation. Mathematical models of the specific energy and of the energy efficiency were created using a mixed regression model as well as a response surface method to increase the predictive accuracy. The best design point was determined using the TOPSIS method with entropy weights based on the finite Pareto optimal solutions generated by the MOPSO algorithm.

Using the proposed approach, specific material removal energy can be reduced by approximately 15%, while increasing the energy efficiency by 11% compared to an arbitrary non-optimal case or initial value of machining parameters. Therefore, the proposed model can help manufacturing engineers to effectively identify optimal parameters for hard turning process in terms of energy efficiency. However, we have also noted that the total machine energy consumption is strongly influenced by variations in machining parameters. Thus, an energetic model integrating other elements such as basic energy, spindle energy, and stage energy should be developed.

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NOMENCLATURE

U_c = Material removal energy (W)

U_{shear} = Shearing energy (W)

$U_{friction}$ = Friction energy (W)

SE = Specific material removal energy (J/mm^3)

MRR=Material removal rate (mm^3/s)

EF = Energy efficiency (%)

d = Depth of the cut (mm)

V = Cutting speed (m/min)

f = Feed rate (mm/rev)

R = Nose radius (mm)

r = Edge radius (µm)

γ = Rake angle (deg)

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