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# Development of a Specific Energy Model and Optimization of Machining Parameters for Minimizing Energy Consumption

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**Abstract:** The objective of this research is to develop a specific energy model of the turning process of hardened material based on numerical experiments and Design of Experiments (DOE). Machining parameters considered include the process parameters (cutting speed and feed rate) and cutting tool geometry (rake angle) while the specific material removal energy is the objective. Firstly, a Finite Element (FE) based model was developed in order to describe the turning process behavior. Subsequently, numerical experiments were conducted based on the Box-Behnken Design (BBD) experiment of Response Surface Methodology (RSM) to render the relationship between machining parameters and energy consumed. An analysis of fitness check was used to investigate the model adequacy. Finally, a Genetic Algorithm (GA) was used to find optimal parameters and energy consumption. The results indicated that the cutting energy was decreased around 15%, compared to un-optimal case.

**Key words:** Energy consumption, machining parameters, simulation, DOE, turning process

## INTRODUCTION

Manufacturing dominates the industrial energy consumption (ABD, 2015). Cutting is a common manufacturing process of production in workshops and mechanic factories. Therefore, reducing energy consumed in cutting operations is a significant contribution to improving the energy efficiency in manufacturing. Energy saving technologies for cutting process can be divided into two solutions. The first solution mainly focuses on machine design and improvement as well as new cutting technologies used. The second solution pays attention to investigate the relationship among cutting conditions and energy consumption and leads to the development of energy consumption models and optimal parameters in terms of energy savings.

Design methodologies (ISO/TC 39/SC, 2012) and the intelligent control were proposed to improve the energy efficiency of cutting process. Apparently, the first branch based on hardware technologies is too costly to renew or replace existing devices. Improving the energy efficiency should be made firstly in existing machines and the second solution is an intelligent choice. Optimizing cutting process is less expensive and has better social sustainability compared to making drastic changes due to the lower investment needed and user acceptance (Pusavec *et al*., 2010). Consequently, optimal cutting conditions selection plays an important role in reducing energy consumption in cutting process.

To develop potential energy saving strategies, the realization of energy models in terms of machining parameters has described by many researchers. Kara and Li (2011) constructed a Specific Energy Consumption (SEC) model expressed in terms of the material-removal rate. Similar, Guo *et al*. (2012) developed this model with respect to various process parameters such as cutting depth, speed and feed rate. A mean cutting-power model as the function of the rotational speed, feed per tooth and depth of cut was expressed by Shao *et al*. (2004). Yoon *et al*. (2014) introduced a second-order regression model of material removal power in terms of process parameters and tool wear in three milling axis. However, the aforementioned publications often develop the energy model at the machine tool and process level. Developing specific energy models at the material removal level have not been thoroughly investigated. In addition to process parameters, the cutting tool geometries are an important factor affecting cutting force components (Tang *et al*., 2011).

To overcome the challenge of reducing energy consumption, an specific energy model for the turning of hardened AISI 4140 steel using a Finite Element (FE) model has considered. This material was chosen for study due to its wide application in automobiles, the aerospace industry and machine tools. Moreover, we found that altering various parameters such as the cutting speed,

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fedd rate andrake angle contributed to variations in cutting energy. Therefore, it is essential to have a reliable energy model with respect to process parameters and cutting tool geometry.

## MATERIALS AND METHODS

To develop the energy model, a simulation-based scientific framework is presented in Fig. 1. Firstly, a FE-based simulation model was developed with the support of DEFORM-3D V6.1 to simulate turning processes at various machining conditions.

A number of physical experiments with regard to the cnc turning machine were conducted to assess the accuracy of the FE model designed in the experimental plan. Secondly, a set of numerical simulations were performed through the experimental plans generated by the Box-Behnken Design (BBD) method to obtain data to generate the regression meta-model. Thirdly, Response Surface Methodology (RSM) was used to render the explicit relationships between process parameters and the performance of the objective functions. Furthermore, an analysis of model fitness check was conducted to verify the response significance. The effects of machining parameters on cutting energy also were investigated. Finnaly, optimal values of the objective and parameters were derived out with the support of the genetic algorithm.

### Finite element simulation

**FEM-based turning model:** For the machining simulations, a FE-based turning process model was designed using a commercial explicit finite element Software DEFORM-3D

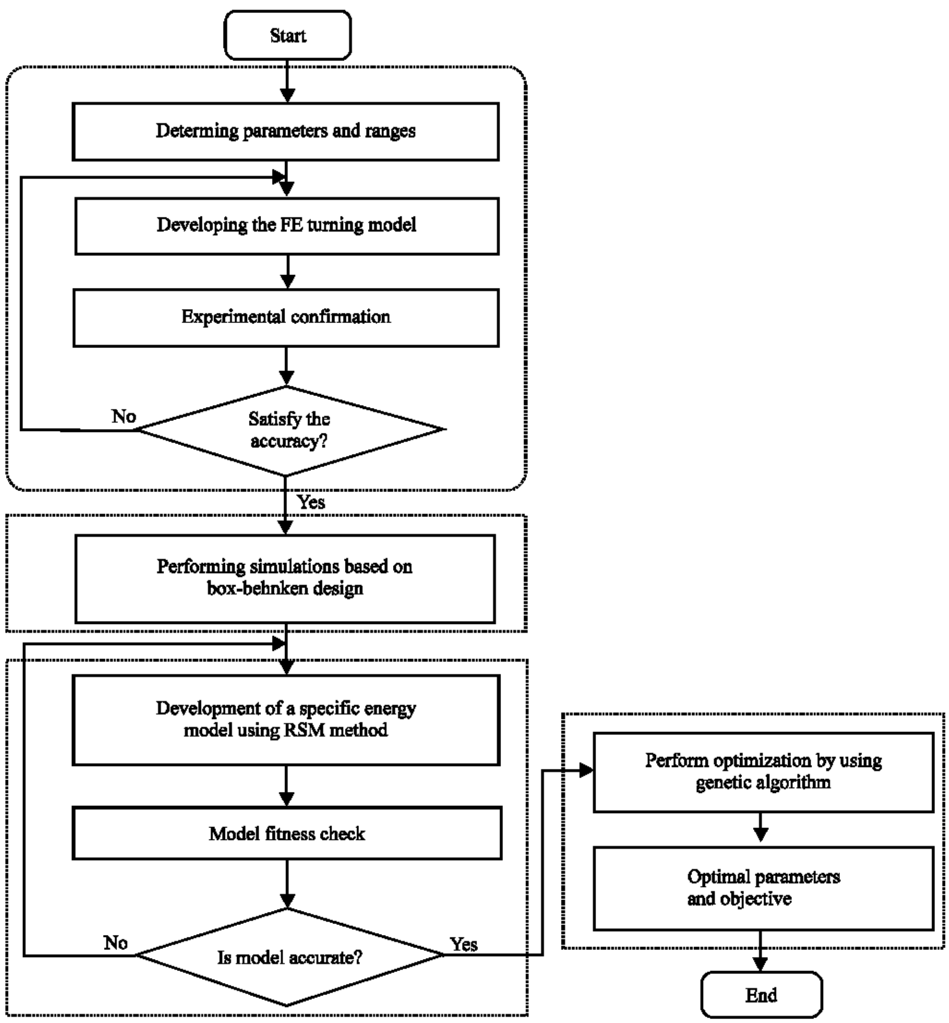


Fig. 1: Systematic procedure of simulation-based design of experiment and optimization

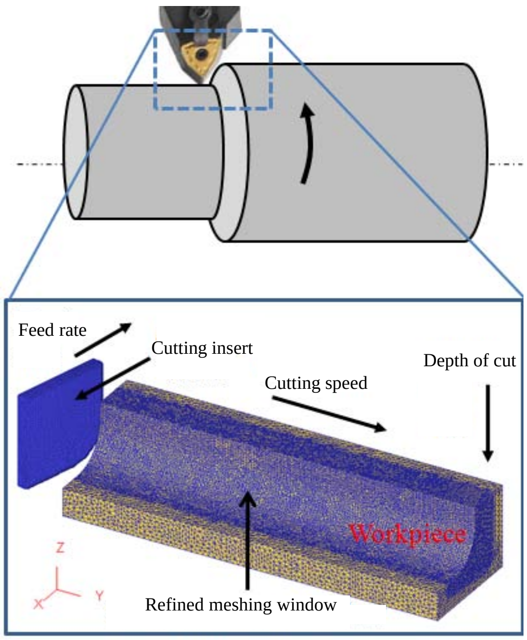


Fig. 2: Three-dimensional turning model

(Fig. 2). 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/m$^2$. For each cutting simulation, the Cockcroft and Latham (1968)'s criterion 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. Figure 3 shows the representative output with regard to turning hardened AISI 4140 steel.

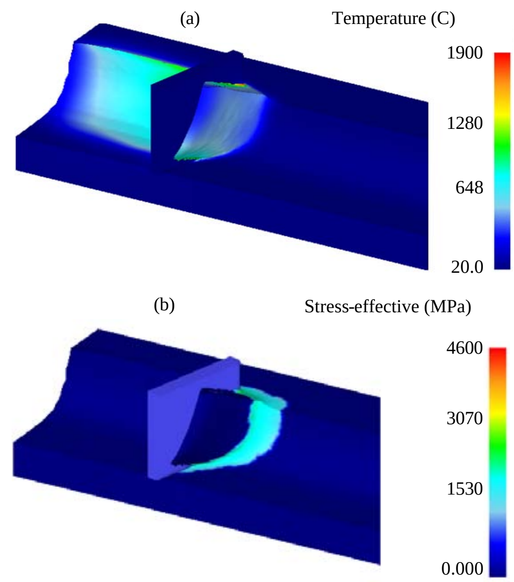


Fig. 3: a, b) Representative simulation outputs

Table 1: The properties of the workpiece and tool material

| Material | AISI 4140 | CBN |
|---|---|---|
| Young's modulus (GPa) | 210.0 | 720.0 |
| Poisson's ratio | 0.3 | 0.2 |
| Density (kg/m$^3$) | 7850.0 | 15000.0 |
| Specific heat (J/kg K) | 363.0 | 20000.0 |
| Thermal conductivity (W/m K) | 41.7 | 60.0 |
| Thermal expansion ($10^{-6}$/K) | 11.9 | 4.5 |

**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 1.

**Material consitutive model:** In the present research, Johnsone-Cook model has been adopted since it best describes the strain rate, non-linear material properties, high strain and strain hardening process involved in turning operation. The Johnson-Cook model can be expressed as follows:

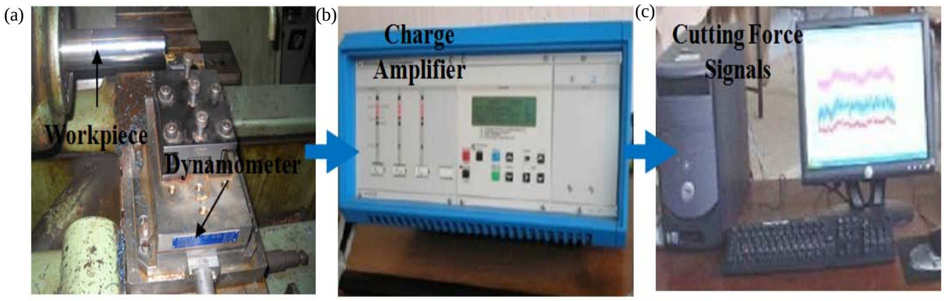


Fig. 4: a-c) Experimental facilities

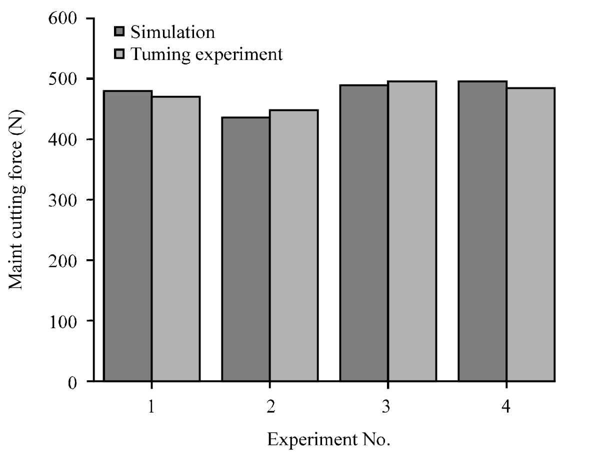


Fig. 5: Comparison of simulation and experimental results

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

Where

A, B, C, n and m = Material constants

$\sigma$ = The equivalent stress

$\varepsilon$ = The strain rate

$\varepsilon_0$ = The reference strain rate

T and $T_m$ = The operating and melting temperature

The coefficients for the Johnson-Cook model employed in this study are given in Table 2 (Moufki and Molinari, 2005). Based on an analysis of the machining parameters and the reference from previous studies (Shao *et al*., 2004; Yoon *et al*., 2013; Tang *et al*., 2011) three parameters, namely, cutting speed (V), federate (f) andrake angle ($\alpha$) were considered as design variables. The levels of the machining parameters have been selected according to the recommendations data of SANDVIK cutting tools manufacturer (Table 3).

Table 2: The Johnson-Cook material flow model's parameters

| Variables | Values |
|---|---|
| A (MPa) | 1057.000 |
| B (MPa) | 755.000 |
| C | 0.014 |
| N | 0.150 |
| M | 1.460 |
| $T_m$ | 1793.000 |

Table 3: Machining parameters and their levels

| Level | Cutting speed V (m/min) | Feed rate f (mm/rev) | Rake angle $\alpha$ (deg.) |
|---|---|---|---|
| -1 | 60 | 0.10 | -9 |
| 0 | 180 | 0.13 | -6 |
| 1 | 300 | 0.16 | -3 |

Table 4: Experimental plans to validate the FE model

| V (m/min) | f (mm/rev) | $\alpha$ (deg.) | $F_{csimul}$ (N) | $F_{cexper.}$ (N) |
|---|---|---|---|---|
| 60 | 0.10 | -6.00 | 478 | 470 |
| 300 | 0.16 | -6.00 | 434 | 446 |
| 180 | 0.10 | -9.00 | 488 | 492 |
| 180 | 0.16 | -9.00 | 493 | 484 |

**Simulation verification:** A Computer Numerically Controlled (CNC) lathe, namely a huyndai quickturn 28N was employed to perform the physical experiments. The workpiece dimensions were 100 mm (diameter) and 400 mm (length) for the machining process (Fig. 4). Cutting forces were obtained with a dynamometer, charge amplifiers and a data acquisition system (Fig. 4). The experimental plan shown in Table 4 is a subset of the box-behnken design used to check the accuracy of the FE model.

The comparisons revealed that the current simulation results were in good agreement with the experimental data with an average error of 5% (Fig. 5). These observations indicated that the developed three-dimensional model was exact enough to simulate machining processes.

## RESULTS AND DISCUSSION

**Development of an energy model:** The Specific Cutting Energy (SCE) is defined as the power consumed ($U_c$) to remove a unitary volume of material (Stephenson and Agapiou, 2005):

Table 5: Simulation results

| V (m/min) | R (mm) | α (deg) | Fc (N) | SCE (J/mm$^3$) |
|---|---|---|---|---|
| 300 | 0.10 | -6 | 434 | 7.2333 |
| 180 | 0.16 | -3 | 510 | 5.3125 |
| 60 | 0.16 | -6 | 582 | 6.0625 |
| 180 | 0.13 | -6 | 494 | 6.3333 |
| 300 | 0.16 | -6 | 527 | 5.4895 |
| 180 | 0.13 | -6 | 498 | 6.3846 |
| 300 | 0.13 | -9 | 504 | 6.4615 |
| 180 | 0.13 | -6 | 492 | 6.3076 |
| 180 | 0.10 | -9 | 488 | 8.1333 |
| 180 | 0.13 | -6 | 486 | 6.2307 |
| 60 | 0.13 | -3 | 525 | 6.7307 |
| 300 | 0.13 | -3 | 460 | 5.8974 |
| 60 | 0.13 | -9 | 563 | 7.2170 |
| 60 | 0.10 | -6 | 478 | 7.9666 |
| 180 | 0.10 | -3 | 420 | 7.0000 |
| 180 | 0.16 | -9 | 593 | 6.1771 |
| 180 | 0.13 | -6 | 490 | 6.2821 |

$$SCE = \frac{U_c}{MRR} = \frac{U}{d \times f \times v} = \frac{F_c}{d \times f} \tag{2}$$

where, MRR, $F_c$, d and f represent the material removal rate, main cutting force, depth cut and feed rate, respectively. According to the box-behnken design scheme, we performed 17 simulation runs and obtained the response data for generating approximate models (Table 5). The regression response surface model showing the Specific Cutting Energy (SCE) expressed as:

$$\begin{aligned} SCE = {} & 14.8979 - 0.0086V - 94.2274f - 0.056524\alpha + \\ & 0.01114Vf - 0.00005V\alpha + 0.74653f\alpha + \\ & 0.00001V^2 + 255.07479f^2 + 0.01316\alpha^2 \end{aligned} \tag{3}$$

**Model fitness check:** Adequacy of the developed models was also investigated through examination of the residuals. The residuals which are the differences between the respective observed responses and predicted responses were examined. The normal probability plots and plots of the residuals versus the predicted response can be seen in Fig. 6. If the model was adequate, points on the normal probability plots of the residuals should form a straight line. Figure 6a shows that the residuals did not exhibit any particular trend and that errors were distributed normally. The residual versus the predicted response plot in Fig. 6b also revealed that there were no obvious patterns or unusual structures. Consequently, the developed second order models with regard to the machining parameters could be used to determine optimal values.

**Effect of the parameters on the responses:** Figure 7 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

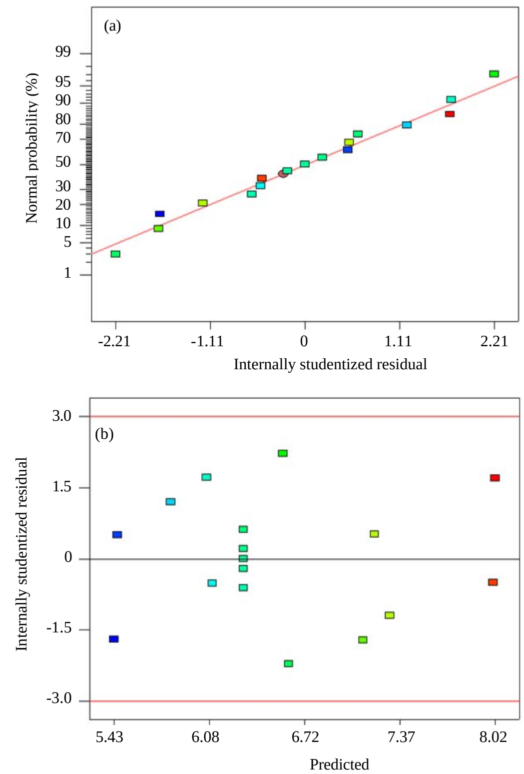


Fig. 6: Model fitness check: a) Normal probability plots for the residuals and b) Plots of residual and predicted values

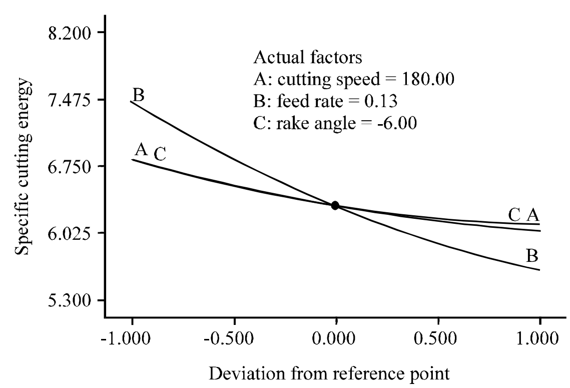


Fig. 7: Perturbation plot showing the effect of all factors on the specific cutting energy

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. 8. To visualize these effects of the machining parameters on the specific cutting energy, 3D surface contour plots were generated within ranges of the factors

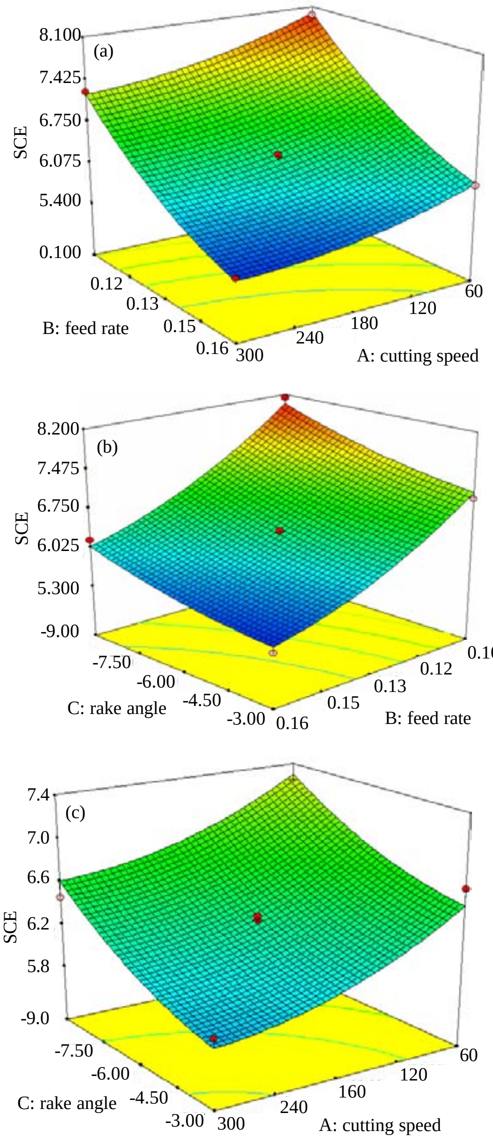


Fig. 8: 3D surface plots of the interaction effects of machining parameters on the specific cutting energy: a) Interaction effects of cutting speed and feed rate; b) Interaction effects of feed rate and rake angle and c) Interaction effects of rake angle and cutting speed

considered. Each sub-figure presented the effects of two parameters considered in the objectives while the other design variables were kept at their initial values (parameter values at level 0).

Figure 8 shows that the Specific Cutting Energy (SCE) is sensitive to variations in machining parameters. Reductions in the specific cutting energy could be achieved through an increase in both cutting speed and feed rate (Fig. 8a). An increase in cutting speed increased the temperature in the deformation areas, resulting in a lowering of the specific cutting energy. Increasing the feed rate increased the volume of the cut material in the same unit of time, thus resulting in a reduction in the specific cutting energy (Fig. 8b). The tool became sharper with an increase in rake angle, resulting in less deformation leading to a reduction in specific energy (Fig. 8c).

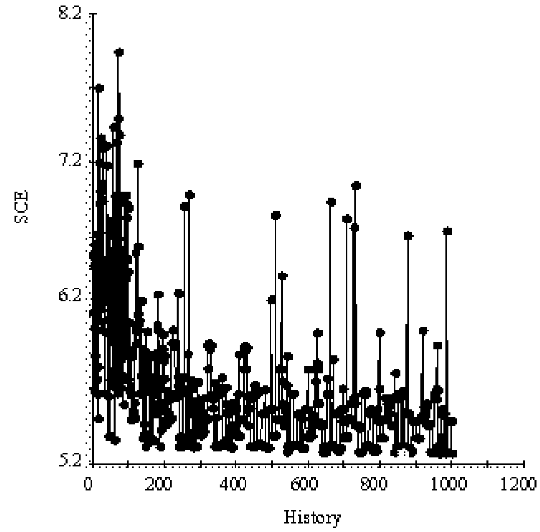


Fig. 9: Optimizing history

Table 6: Optimal parameters

| Parameters | Initial values | Optimized values |
|---|---|---|
| V (m/min) | 180.0000 | 300.0000 |
| f (mm) | 0.1000 | 0.1600 |
| α (deg.) | -6.0000 | -3.0000 |
| **Response** | | |
| SCE (J/mm$^3$) | 6.2307 | 5.2695 |

**Optimization results:** The optimization problem can be expressed as follows: Find X = [V, f, α], Minimize Specific Cutting Energy (SCE), Subject to: 60 = V= 300 (m/min), 0.10 =f =0.16; -9 = α = -3 (deg).

This optimization problem was solved by coupling the Eq. 3 by means of the Multi-Island Genetic Algorithm (MIGA). The following parameters were listed based on the study to get optimal solutions with low computational effort:

- Population size = 24
- Maximum number of generations = 30
- Crossover probability = 0.9
- Crossover distribution index = 40.0
- Mutation distribution index = 10.0

Figure 9 describes the history of the MIGA-based optimization process. Optimal parameters generated are listed in Table 6. Importantly, the cutting energy was decreased around 15%, compared to un-optimal case.

## CONCLUSION

In this study, a specific energy model of the machining of hardened AISI 4140 steel was developed. A three-dimensional model in the DEFORM-3D environment in conjunction with Box-Behnken experimental design was employed to simulate the process and to obtain simulation results. The adequacy of the mathematical model was validated by using the fitness check. The Multi-island Genetic Algorithm (MIGA) was used to obtain the optimal parameters. The following conclusions can be drawn from this investigation within factors considered: The polynomial model of the specific cutting energy carried out by the box-behnken design experiment and RSM which predicted the values of the responses with sufficient accuracy.

After optimization, the optimization gave results representing an approximate 15% reduction of the specific energy, compared to initial values. The developed approach by coupling FE simulations, DOE, RSM, GA 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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