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Enhancing energy efficiency in turning operations by optimizing cutting parameters

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Abstract

Improving energy and resource efficiency is becoming increasingly important in the absence of a typical industrial environment, mainly because of the expansion of global population and industrial demands. This research explores ways to improve the energy efficiency of CNC machines by optimizing key cutting parameters. The objective is to simultaneously reduce the energy consumption and increase the material removal rate (MRR) by adjusting the cutting speed, rate of progress, and depth of cut. Experiments were conducted using aluminum alloy as the material and the response surface method (RSM) to show the relationship between the cutting parameters and process results. Analysis of variance was used to assess the importance of each parameter, while the Artificial Bee Colony (ABC) algorithm was used to find the most efficient parameter configuration. The results indicated that the ideal result of reducing SCE without increasing MRR occurred at a cutting speed of 280 m/min, cutting depth of 4 mm, and feed rate of 1.6 mm/rev. The research findings suggest that adjusting cutting parameters can notably reduce energy usage and enhance machining productivity, thereby providing a sustainable manufacturing method.

Subject Classification: *68T20, 44A45.*

Keywords: *Energy efficiency, Cutting parameters optimization, ANOVA, Artificial bee colony (ABC) algorithm, Sustainable manufacturing, Tool wear reduction, Cutting speed optimization.*

1. Introduction

According to the IEA50, India's industrial sector accounted for 43.9% of the total electricity consumption in 2021 [1]. 25.3% was used by the residential sector, while 19.0% was utilized by agriculture, forestry, and commercial and public services accounted for 6.6%. Transport accounts for the smallest percentage (1.6%). Despite significant advancements in automotive technology aimed at enhancing fuel efficiency and reducing emissions, a critical research gap remains concerning the comprehensive minimization of energy consumption across the entire life cycle of automobiles. Existing studies have primarily focused on specific

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components or operational phases, such as engine efficiency or driving conditions, without fully integrating and optimizing energy-saving strategies throughout the production, usage, and end-of-life phases [2]. A comprehensive approach is required to effectively address the challenge of reducing energy consumption in the automobile industry. These include integrating energy management systems, using innovative materials, adopting sustainable manufacturing practices, and advancing propulsion technologies. These efforts can lead to significant, long-term energy savings for automotive production.

Today, the automotive industry is challenged to increase productivity and address its development goals. The inefficiency of energy consumption is another aspect that regarding the materialization of sustainable development needs to be improved in relation to the two production processes investigated. Hence, regulators, along with the consumers always encourage auto manufacturers to reduce the total energy consumption for new automobiles. One of the promising strategies among the listed ones is the enhancement of the cutting parameters in cutting processes. Thus, decisions in relation to cutting speed, advancement, and required depth are critical for the energy used in the fabrication of auto components, such as engines and chassis.

Although improvements in manufacturing technology have been felt in the industry, the prospects of utilizing enhanced cutting parameters to obtain even higher energy savings have not received much attention. Conventionally, the machining process has focused on the rates of throughput and the quality of the finished part. Energy efficiency has been given less consideration, but sustainability has become a greater issue. Thus, manufacturers realize that these concerns should be addressed by translating them into cutting parameters. It is also clear that the company can not only decrease the level of energy consumption but also prolong the shelf life of fermentation, minimize material losses, and increase production efficiency. This approach corresponds comprehensively to the principle of sustainable production, according to which it is possible to minimize the harm of production for the external environment while ensuring the corresponding economic benefits.

New technologies have been identified as effective in the application of modern computer simulation, modeling and machine learning to improve machining processes [3]. These technologies make it possible to set up rationalized scenarios of cutting by selecting the necessary parameters for reducing energy consumption without losses in quality of parts [4]. This is especially the case for automotive OEMs given the large number of firms active in this industry. The last one suggests that large-scale production means that even minor enhancement of energy use results in vast savings of both money and CO2 outputs [5]. However, current CNC machines with variable control decisions can vary the processing parameters to enhance the cutting in line. This is a significant improvement on earlier technologies related to the production of energy-efficient products.

The objective of this study is to develop a predictive model to minimize energy consumption in the automotive industry by appropriately adjusting cutoff point parameters. This study analyzes existing studies that identify the main factors that influence energy use in production and proposes a structure for developing energy-efficient production strategies. It also examines how advanced materials and ferrule-cutting technologies can improve energy efficiency. It provides a comprehensive view of the latest trends and future possibilities in this important area. To address the gaps in manufacturing practices this study aims to support ongoing efforts to make the automotive industry more sustainable and resilient, in the face of changing environmental and economic challenges.

Motivation

The rationale for this research is to focus on energy efficiency and sustainability in industrial operations worldwide. This is especially true in the automotive and manufacturing industries. Manufacturers face pressure to implement energy use reductions without sacrificing productivity or product quality. This is attributed to higher levels of awareness concerning the availability of resources and the scourge on the environment. This research aims to tackle this problem by first refining the cutting point parameters in machines, as the parameters can greatly influence energy consumption. This study had the following objectives: the environmental effects of industrial processing must be minimized, the amount of energy consumed must be reduced, and the amount of material removed from the substrate needs to be maximized to achieve the desired part dimensions. This supports current trends for greater sustainability in production processes that are demanded by the consumers and regulators.

Contribution

This study contributes to sustainable production by sharing experiments and optimizing turning processes using an aluminum group. The main achievement was to create a robust model to optimize machining parameters to reduce the specific cutting energy (SCE) and increase the material removal rate (MRR). This study presents a structured method to improve plant productivity using response surface methodology (RSM) to develop models and analysis of variance (ANOVA) to assess the importance of these factors. The research also presents an application of the Artificial Bee Colony algorithm (ABC) to determine the best cutoff parameters. The use of experimental data analysis and advanced optimization techniques provides a valuable framework for energy-efficient production processes, particularly in CNC machining.

Literature Review

Practical industrial applications include energy-intensive activities such as basic production operations. An effective energy harvesting process begins with a detailed analysis of energy flow. It is necessary to evaluate several levels of detail when discussing manufacturing activities. When examining a manufacturing plant for a machining line, specific information is usually categorized at the plant, workstation, or operational levels. Fysikopoulos et al. [6] presents a comprehensive analysis of energy flow in manufacturing processes, categorizing various degrees of detail and providing corresponding concise explanations. Duflou et al. [7] offers a thorough examination of the methodologies employed in discrete product manufacturing, with an emphasis on improving energy utilization and resource efficiency. The process begins at the unit level and progresses to the multi-machine level, followed by the industry level, multi-industry enterprise level, and, ultimately, the supply chain level [3]. The system boundary in this study on manufacturing processes is defined as encompassing a manufacturing facility. However, external logistics, material supply, waste treatment, and other related activities are not included in the specific manufacturing operations carried out within the production plant.

Anderberg and Kara [8] conducted a study in which they calculated the total energy consumption rate and determined the tool life using a flank wear criterion of 0.8 mm. Tool erosion was assessed following five machining operations using five distinct methods involving adjustments to the feed rate and depth of cut. The findings of this case study show that the direct energy expenses of machines significantly impact the overall cost, whereas indirect costs, including electricity expenses, have a minor influence compared to other machining costs. Manufacturers can achieve significant cost savings using energy-efficient machining techniques. Furthermore, this effectiveness can be attained with minimal energy usage owing to the high material removal rate, as indicated by [9] and [10].

The turning process is a crucial operation in the manufacturing sector such as in shipping, aircraft, and automobiles. During this operation, a revolving cylindrical work piece removes the material from its surface using a single point cutting tool. The cutting tool was advanced linearly in the direction of the axis rotation. Rajemi, Mativenga, and Aramcharoen [11] assert that turning is executed on a lathe, wherein power is utilized to rotate and shape the workpiece at a specified speed and feed rate relative to the cutting tool at a predetermined depth. The three key cutting parameters in turning operations that need to be improved are cutting speed, depth of cut, and feed rate [12]. Three cutting-force components were included in the turning process.

Macak and Hron [13] aimed to employ advanced techniques for optimizing cutting conditions in the wood processing industry by implementing a robust design in accordance with energy efficiency standards. The primary outcome of this planned experiment is the determination of the ideal control factor configurations that, in terms of energy consumption, render the wood-milling process resistant to change from noise. Increased S/N ratio values signify control-element configurations that mitigate the effects of noise-producing elements.

Energy consumption during precise cutting to produce 7050-T7451 aluminum alloy serrated HSM chips [14]. The three main components comprise the cutting energy used in the production process of serrated chips: the kinetic energy of the flowing chips, the tool and chip interface frictional work, and the plastic deformation energy in the primary distortion zone. Research has been conducted on the impact of tool rake angle, unreformed chip thickness, and cutting speed to reduce energy usage. The cutting speed range under investigation was established as 1000 - 4500 m/min, during which serrated chips were formed.

To reduce energy consumption in machine tools, the optimization model incorporates cutting specific energy consumption (CSEC) and processing time to enhance process factors [15]. The optimized parameters led to a 27.21% decrease in energy consumption compared with the preferred parameters, with the CSEC reduced by 32.07% and processing time by 34.11%. This approach offers an efficient solution for mitigating the environmental impact of energy consumption and promoting sustainable manufacturing practices. In metal cutting processes, significant energy losses occur owing to the improper selection of cutting parameters. Gu et al. [16] assert that energy efficiency can be significantly enhanced through the optimization of these parameters. This results in saving energy [17] and developing a model for energy use during the cutting process. Using milling as an example, an objective function was established to determine the energy consumption during the roughing and finishing steps. The experimental results show that optimizing the two cutoff parameters can achieve the objectives of reducing the energy consumption and maximizing the production rate simultaneously.

Experimental Process

To accurately determine how different cutting parameters affect the energy required for machines, it is important to carry out a well-planned trial process. This includes detailed preparation, precise execution, and careful analysis with a systematic approach using, making use of statistical data. The cutting parameters can be optimized to improve the efficiency of the production process.

In this study, the main inputs used to adjust the cutting performance are depth of cut, progress, and cutting speed. Values for these parameters were determined based on the clamping strength and manufacturer's recommendations, and the values are listed in Table 1 in the experimental test design. The combination of these shear parameters was calculated using RSM as detailed in Table 2.

Table 1

cutting parameters and their levels

Factor	Name	Units	Minimum	Maximum
A	Cutting Speed	m/min	100.00	280.00
B	Depth of Cut	mm	2.00	4.00
C	Feed Rate	mm/rev	0.2000	1.60

Table 2

Performance characteristics

Run	Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Specific Cutting Energy (Wh/cm3)	Material Removal Rate (mm3/sec)
1	280	2	0.2	0.177083	89.6
2	100	3.6	0.2	0.0983808	57.6
3	280	3.6	0.2	0.0983808	161.28
4	100	4	0.8	0.02214	256
5	160	4	0.8	0.02214	409.6
6	280	3.6	0.8	0.0245952	645.12
7	280	4	0.2	0.08856	179.2
8	100	4	0.2	0.08856	64
9	160	2	0.8	0.044244	204.8
10	100	2	1.6	0.02214	256
11	160	4	1.6	0.011052	819.2
12	160	2	1.6	0.02214	409.6
13	100	2.8	0.2	0.126468	44.8
14	280	2	0.8	0.04428	358.4
15	160	3.6	0.2	0.098352	92.16
16	220	2.8	0.8	0.031608	394.24
17	160	2.8	1.6	0.015804	573.44

Sensitivity Analysis

SCE plays an important role in the evaluation of the machining processes. It is highly sensitive to changes in advance rate, depth of cut, and cutting speed. By changing these necessary factors, energy efficiency can be increased. By carefully managing the increase in cutting force, cutting depth can be an effective way to reduce energy consumption. Because it has an inverse relationship with SCE, on the other hand, the relationship between cutting speed and SCE is more complicated. An appropriate speed limit is provided such that SCE is minimized without causing excessive wear of the tool.

The advanced rate also affects SCE, but the impact on the surface quality and shelf life of fermentation must be carefully balanced. This is because a higher advanced rate reduces SCE but can reduce the quality of the specimen and reduce shelf life. This analysis emphasizes the importance of finding balance in selecting machining conditions to minimize SCE, and at the same time maintaining the required part quality. Figures 1, 2, and 3 illustrate the special effects of these cutting factors on the SCE.

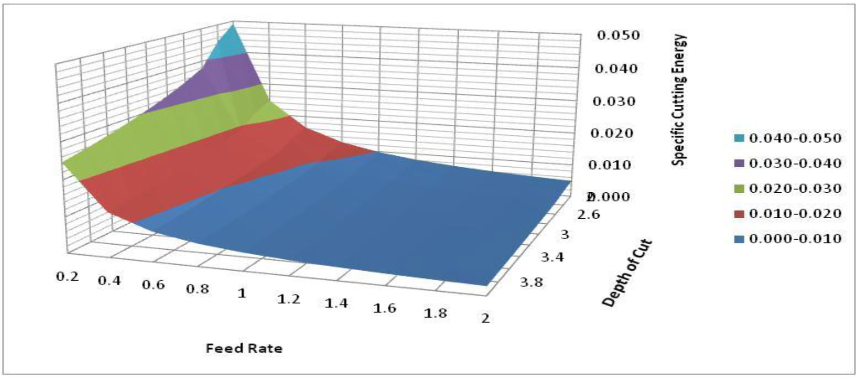


Figure 1

Effect on specific cutting energy by feed rate and depth of cut

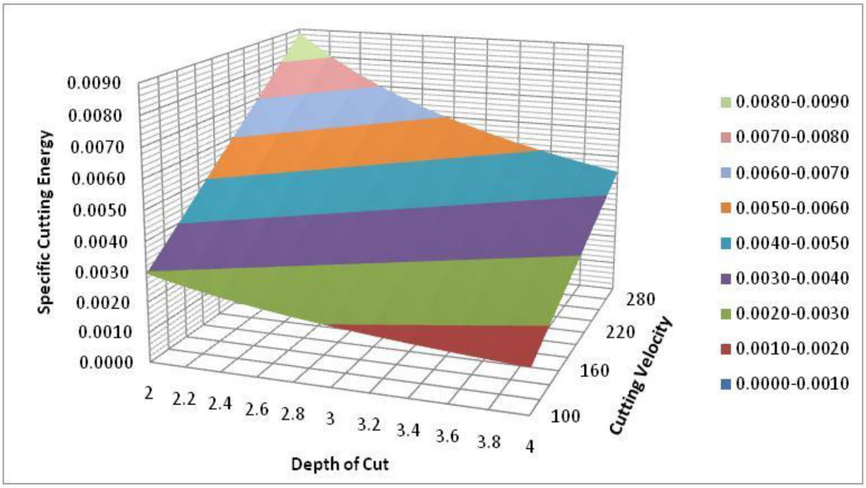


Figure 2

Effect on specific cutting energy by depth of cut and cutting velocity

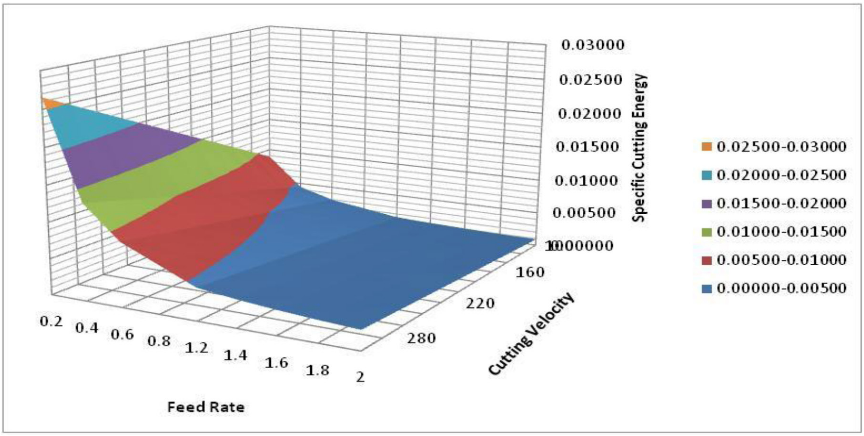


Figure 3

Effect on specific cutting energy by feed rate and cutting velocity

Artificial Bee Colony (ABC) Algorithm for Power Consumption Minimization

The (ABC) algorithm is a nature-inspired optimization technique that can be effectively applied to minimize the power consumption in machining processes by considering machining parameters.

A population of artificial bees (solutions) was randomly generated within a feasible range of the cutting parameters. Each solution represents a combination of depth of cut, feed rate, and cutting speed. The employed bees assessed the efficacy of their solutions through the application of a fitness function. Inverse of the power usage defines the fitness function. Lower power consumption implies a higher fitness value. Onlooker bees observe the employed bees and select solutions based on their performance metrics. Solutions with higher fitness values had a higher probability of being selected. If an employed bee cannot improve its solution after a certain number of cycles, then it becomes a scout bee. Scout bees randomly generate new solutions. Both the onlooker bees and the employed modify their solutions based on the selected solution and a random vector. This process helps to explore the search space and find better solutions.

The fitness function is defined as the inverse of the power consumption. The power consumption can be calculated using empirical models or simulation tools. Incorporate constraints related to tool life, surface finish, and other relevant factors in fitness function. Experiments were conducted with different parameters of the ABC algorithm, such as population size, maximum cycle number, and solution update mechanism, to optimize its performance.

Results

Achieving efficient material removal and at the same time minimizing SCE requires determining the optimum balance between the cutting parameters. This is a fundamental part of the machining process optimization by carefully managing the advance rate to control the cutting speed, cutting depth, cutting force and energy requirements. The objective was to identify the best combination of these factors to increase efficiency. Reduce energy consumption and decrease wear and tear of equipment. Ideal configurations, along with improving the overall machine efficiency, are generally determined using experimental data and analysis.

ANOVA

Powerful statistical tools, such as Analysis of Variance (ANOVA) help to identify factors that have a significant impact on a specific response variable. In practice, ANOVA can be used to understand how different process parameters affect the SCE. By identifying the most important factors we can adjust the settings to reduce SCE and increase the overall efficiency of the machining process.

Table 3

Sequential Model for Specific Cutting Energy

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	0.0631	1	0.0631			
Linear vs Mean	0.0279	3	0.0093	13.67	0.0003	
2FI vs Linear	0.0029	3	0.0010	1.63	0.2446	
Quadratic vs 2FI	**0.0054**	**3**	**0.0018**	**23.27**	**0.0005**	**Suggested**
Cubic vs Quadratic	0.0005	7	0.0001			Aliased
Residual	0.0000	0				
Total	0.0999	17	0.0059			

As shown in the Sequential Model Sum of Squares analysis in Table 3, the linear terms explained most of the variability in the response variable and were found to be statistically significant. Although cubic terms and two-factor interactions did not considerably improve the model fit, the addition of quadratic terms did. The low residual variance suggests that the model fits the data reasonably well. However, further validation is required.

Table 4

Fit Summary

Std. Dev.	0.0088	**R^2**	0.9853
Mean	0.0609	**Adjusted R^2**	0.9663
C.V. %	14.45	**Predicted R^2**	0.8082
		Adeq Precision	22.7440

The Predicted R^2 value indicates how well the model predicts the new or unseen data. A value of 0.8082 suggests in table 4 that the model has good predictive capability, as it explains approximately 80.82% of the variability in the new data. This strongly indicates that the model is likely to perform well when applied to the new datasets.

Table 5

Quadratic model response for specific cutting energy

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.0363	9	0.0040	51.99	< 0.0001	significant
A-Cutting Speed	0.0001	1	0.0001	1.06	0.3373	
B-Depth of Cut	0.0011	1	0.0011	13.74	0.0076	
C-Feed Rate	0.0018	1	0.0018	22.86	0.0020	
AB	0.0001	1	0.0001	0.8080	0.3986	
AC	0.0002	1	0.0002	2.00	0.1997	
BC	0.0012	1	0.0012	15.41	0.0057	
A^2	0.0000	1	0.0000	0.1943	0.6727	
B^2	4.620E-07	1	4.620E-07	0.0060	0.9406	
C^2	0.0050	1	0.0050	65.08	< 0.0001	
Residual	0.0005	7	0.0001			
Cor Total	0.0368	16				

The model exhibits strong significance, as evidenced by its low p-value (< 0.0001), indicating that it effectively explains the variability in specific cutting energy given in table 5. The model had a low residual sum of squares, indicating a strong fit for most of the variability accounted for by the model.

Final Equation in Terms of Specific Factors

The second-order regression constants were determined using the experimental data presented in Equations 1 and 2, and the resulting regression equations described the response characteristics based on the three input process parameters investigated in the experiments.

$$\textbf{SCE} = +0.256597 + 0.000107 * A - 0.033695 * B - 0.285396 * C - 0.000047 * A B - 0.000156 * A C + 3.21830E\text{-}07 * A^2 + 0.000532 * B^2 + 0.089831 * C^2 \quad (1)$$

$$MRR = 247.69658 - 1.28843 A - 80.29088 B + 0.425125 AB + 2.20726 AC + 133.54550 BC \quad (2)$$

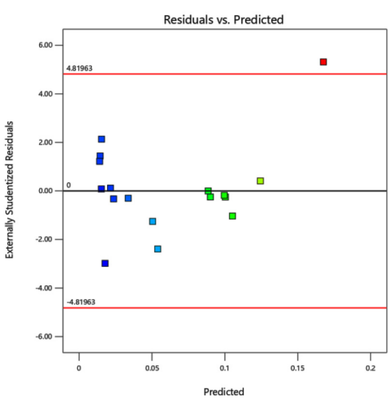


Figure 4

Residual Vs Predicted

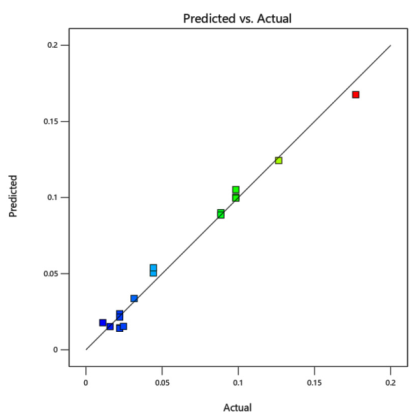
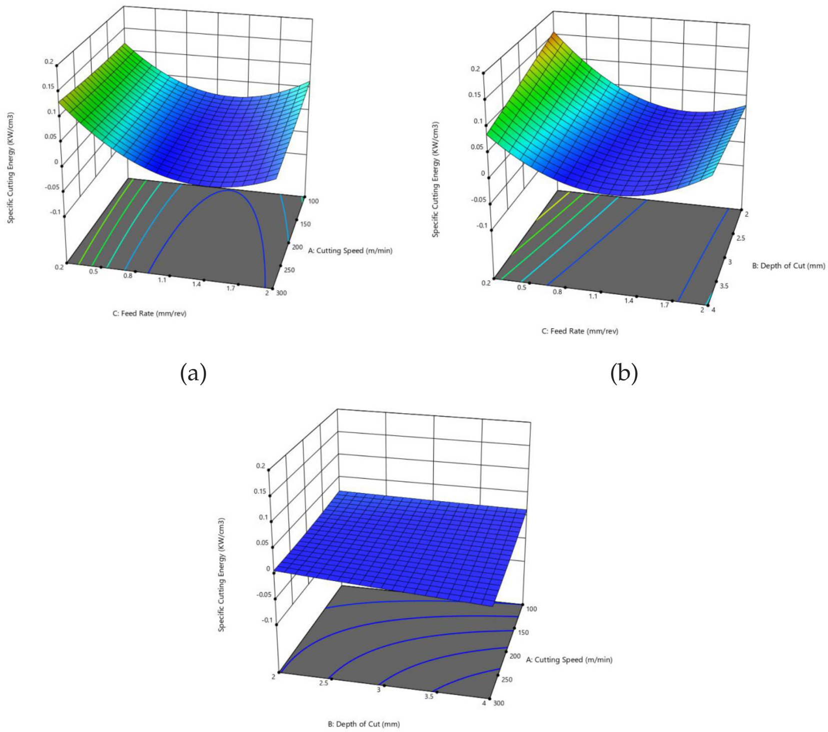


Figure 5

Predicted Vs Actual

In figure 4 shows that maximum point fall within the limits this indicate that the model adequately represents the data and meets the assumptions of regression analysis and in figure 5 Predicted vs Actual shows that maximum point lines near the reference line which indicate that the model is performing well and the predicted values are close to the actual values.



(a) (b)

(c)

Figure 6

Specific cutting energy changes with respect to depth of cut, cutting speed and feed rate

Figure 6 shows the cutting speed on power consumption, feed rate and impact of depth of cut. The observation that power consumption increases with Cutting Speed, as shown in the 3D Surface Plot, indicates that higher Cutting Speeds require more energy for the cutting process. This trend reflects a direct relationship between cutting speed and Specific Cutting Energy, and by extension, power consumption.

Optimization of cutting parameters

In the ABC optimization process, we employed standard parameters, specifically setting the population size to 50 and the maximum number of evaluations to 1000 while using the basic ABC algorithm. To address both the MRR and SCE, we formulated a multi-objective optimization problem. This was achieved by applying a weighted sum approach to integrate the two objectives into a single scalar objective, which was then optimized using the ABC algorithm. The weights are adjusted to reflect the relative importance of each objective.

When it comes to machining and optimization, the objective is frequently to find a balance or to optimize multiple competing goals, such as reducing SCE while increasing the MRR. The optimization depends heavily on cutting factors, such as the cutting velocity (*V*),feed rate (*f*) and depth of cut (*d*).

$$\text{Objective} = \tfrac{F}{d \times f} - \gamma \times (V \times d \times f)$$

where γ is the scaling factor used to adjust the influence of the MRR on the overall objective.

Constraints

$$V_{min} \le V \le V_{max}$$
$$d_{min} \le d \le d_{max}$$
$$f_{min} \le f \le f_{max}$$

The ABC algorithm generated a minimum SCE of 0.003074 Wh/cm3 and MRR of 77.64 cm^3/min. The optimization results identified suitable process parameters, such as a cutting speed of 280 m/min, cutting depth of 4 mm, and breakthrough. 1.6 mm/rev according to the proposed fitness function.

Conclusion

This study focuses on the experimental and analytical optimization of aluminum league using high-speed fermentation (HSS) to obtain quality results and a good cost-benefit ratio. We conducted an experiment to explore the effects of SCE and MRR usage parameters. A robust model forum was developed using RSM to evaluate the efficacy results. The importance of each machining parameter is analyzed using ANOVA, and the RSM model was combined with the ABC algorithm to identify the ideal process parameters. This allowed us to determine the best input configuration to minimize SCE and maximize MRR. For future research, we investigate advanced optimization techniques, including machine learning models and real-time monitoring systems, to enhance the precision of cutting parameters in turning operations. Furthermore, examining sustainable materials and coolant strategies could yield significant energy savings, promoting environmentally conscious manufacturing practices while maintaining productivity and cutting efficiency.

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Writing-review & editing: Chandrashekhar Meshram; S. B. Thakre; Subhash Khatarkar

Declarations

Conflict of Interest: The authors certify no conflict of interest.
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References

[1] A. Giampieri, J. Ling-Chin, Z. Ma, A. Smallbone, and A. P. Roskilly, "A review of the current automotive manufacturing practice from an energy perspective," *Appl. Energy*, vol. 261, no. July 2019 (2020), doi: 10.1016/j.apenergy.2019.114074.

[2] B. Li, X. Tian, and M. Zhang, "Modeling and Multi-objective Optimization Method of Machine Tool Energy Consumption Considering

Tool Wear," *Int. J. Precis. Eng. Manuf. - Green Technol.*, vol. 9, no. 1, pp. 127–141 (2022), doi: 10.1007/s40684-021-00320-z.

[3] F. Z. El Abdelaoui, A. Jabri, and A. El Barkany, *Optimization techniques for energy efficiency in machining processes—a review*, vol. 125, no. 7–8. Springer London (2023). doi: 10.1007/s00170-023-10927-y.

[4] S. Pedrammehr, M. Hejazian, R. Qazani, H. Parvaz, S. Pakzad, M. Ettefagh, A. Suhail, "Machine Learning-Based Modelling and Meta-Heuristic-Based Optimization of Specific Tool Wear and Surface Roughness in the Milling Process," *Axioms*, vol. 11, no. 9 (2022), doi: 10.3390/axioms11090430.

[5] H. Zhu, X. Ge, Y. Wang, and Z. Ding, "Analysis and forecast of Tianjin's industrial energy consumption," *Int. J. Energy Sect. Manag.*, vol. 11, no. 1, pp. 46–64 (2017), doi: 10.1108/IJESM-06-2015-0003.

[6] A. Fysikopoulos, D. Anagnostakis, K. Salonitis, and G. Chryssolouris, "An empirical study of the energy consumption in automotive assembly," *Procedia CIRP*, vol. 3, no. 1, pp. 477–482 (2012), doi: 10.1016/j.procir.2012.07.082.

[7] J. R. Duflou, J. W. Sutherland, D. Dornfeld, C. Herrmann, J. Jeswiet, S. Kara, M. Hauschild, and K. Kellens, "Towards energy and resource efficient manufacturing: A processes and systems approach," *CIRP Ann. - Manuf. Technol.*, vol. 61, no. 2, pp. 587–609 (2012), doi: 10.1016/j.cirp.2012.05.002.

[8] S. Anderberg and S. Kara, "The 7th CIRP Conference on Sustainable Manufacturing Energy and cost efficiency in CNC machining," pp. 1–4.

[9] A. Dietmair and A. Verl, "A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing," *Int. J. Sustain. Eng.*, vol. 2, no. 2, pp. 123–133 (2009), doi: 10.1080/19397030902947041.

[10] H. Shao, H. L. Wang, and X. M. Zhao, "A cutting power model for tool wear monitoring in milling," *Int. J. Mach. Tools Manuf.*, vol. 44, no. 14, pp. 1503–1509 (2004), doi: 10.1016/j.ijmachtools.2004.05.003.

[11] M. F. Rajemi, P. T. Mativenga, and A. Aramcharoen, "Sustainable machining: Selection of optimum turning conditions based on minimum energy considerations," *J. Clean. Prod.*, vol. 18, no. 10–11, pp. 1059–1065 (2010), doi: 10.1016/j.jclepro.2010.01.025.

[12] L. B. Abhang and M. Hameedullah, "Power prediction model for turning EN-31 steel using response surface methodology," *J. Eng. Sci. Technol. Rev.*, vol. 3, no. 1, pp. 116–122 (2010), doi: 10.25103/jestr.031.20.

[13] T. Macak and J. Hron, "Robust parameter design for the optimisation of cutting conditions according to energy efficiency criteria," *Agric. Econ. (Czech Republic)*, vol. 62, no. 12, pp. 537–542 (2016), doi: 10.17221/330/2016-AGRICECON.

[14] B. Wang, Z. Liu, Q. Song, Y. Wan, and Z. Shi, "Proper selection of cutting parameters and cutting tool angle to lower the specific cutting energy during high speed machining of 7050-T7451 aluminum alloy," *J. Clean. Prod.*, vol. 129, pp. 292–304 (2016), doi: 10.1016/j.jclepro.2016.04.071.

[15] Z. Deng, H. Zhang, Y. Fu, L. Wan, and W. Liu, "Optimization of process parameters for minimum energy consumption based on cutting specific energy consumption," *J. Clean. Prod.*, vol. 166, pp. 1407–1414 (2017), doi: 10.1016/j.jclepro.2017.08.022.

[16] W. Gu, Z. Li, Z. Chen, and Y. Li, "An energy-consumption model for establishing an integrated energy-consumption process in a machining system," *Math. Comput. Model. Dyn. Syst.*, vol. 26, no. 6, pp. 534–561 (2020), doi: 10.1080/13873954.2020.1833045.

[17] M. Stojković, M. Madić, M. Trifunović, and R. Turudija, "Determining the Optimal Cutting Parameters for Required Productivity for the Case of Rough External Turning of AISI 1045 Steel with Minimal Energy Consumption," *Metals (Basel).*, vol. 12, no. 11 (2022), doi: 10.3390/met12111793.

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