Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

A Comprehensive Study on Minimizing Cutting Energy and Maximizing Material Removal Rate in CNC Turning considering Grey Wolf Optimization technique

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This study focuses on minimizing specific cutting energy (SCE) and maximizing material removal rate (MRR) during CNC turning using the Grey Wolf Optimization (GWO) technique. By incorporating cutting speed, feed rate, and depth of cut as variables, an empirical model was developed through Response Surface Methodology (RSM). Analysis of Variance (ANOVA) was used to evaluate the significance of these parameters. Experimental results revealed optimal cutting parameters that significantly improve energy efficiency and productivity. The findings highlight the effectiveness of GWO in achieving sustainable machining practices while maintaining high throughput and reduced energy consumption.

Keywords: CNC Turning, Specific Cutting Energy, Material Removal Rate, Response Surface Methodology, ANOVA, Energy Optimization.

1. Introduction

Manufacturing industries account for a significant share of global energy consumption, driving the urgent need for sustainable machining practices to minimize energy use while maintaining productivity. Among machining operations, CNC turning plays a pivotal role in manufacturing due to its versatility and precision. However, the optimization of cutting parameters, such as cutting speed, feed rate, and depth of cut, remains a critical challenge to balance energy efficiency and material removal rate (MRR).

The problem addressed in this study is to minimize the Specific Cutting Energy (SCE) while maximizing MRR during CNC turning operations. Formally, this involves optimizing cutting parameters to achieve a balance between energy consumption and productivity, ensuring sustainable machining without compromising performance.

Existing solutions have employed various optimization techniques, including Response Surface Methodology (RSM) [1], Taguchi methods, and genetic algorithms (GAs) [2], to determine the optimal cutting parameters. While these methods are effective in exploring parameter relationships, they face challenges such as slow convergence, susceptibility to local optima, and limited scalability in handling multi-objective problems.

To address these limitations, this paper proposes the application of the Grey Wolf Optimization (GWO) algorithm [3], a nature-inspired metaheuristic optimization technique. The GWO mimics the social hierarchy and hunting behavior of grey wolves, enabling efficient exploration and exploitation of the parameter space.

The proposed GWO-based approach overcomes the limitations of traditional methods by ensuring faster convergence, escaping local optima through dynamic adaptability, and efficiently balancing the trade-off between SCE and MRR. By leveraging the social dynamics of grey wolves, the algorithm identifies global optima in machining parameters with enhanced reliability and robustness.

The primary contributions of this paper are as follows:

1. Development of an empirical model to describe the relationships between cutting parameters and machining responses (SCE and MRR) using RSM.

2. Application of the GWO algorithm to simultaneously minimize SCE and maximize MRR.

3. Validation of the proposed method through Analysis of Variance (ANOVA) and comparison with existing approaches.

4. Identification of optimal cutting conditions for sustainable and productive CNC turning operations.

The remainder of the paper is structured as follows: Section 2 discusses the experimental methodology, including details of the machine, material, and design of experiments. Section 3 presents the results and discussion, focusing on the analysis of variance, response surface analysis, and optimization outcomes. Section 4 concludes the study with key findings and suggestions for future work.

2. Literature Review

According to EIA, Manufacturing industries account for almost 35% of global primary energy use. This portion of energy consumption encompasses energy usage associated with carbon dioxide emissions. In emerging nations, the conflict between the goal of economic progress and the scarcity of energy sources might arise due to high energy use. The manufacturing sector is crucial in the production of motor vehicle parts, encompassing several enterprises that manufacture final components and subsystems such powertrain parts, electrical equipment, and steering and brake systems. Some manufacturing processes, like engine and transmission assembly, require a substantial amount of energy. These components are often produced from aluminum or cast iron and form a vehicle's powertrain [4]. These procedures necessitate extensive machining, which results in a high energy consumption. Consequently, certain researchers have concentrated on creating energy-efficient techniques.

Improving energy efficiency is crucial not only for cost reduction but also to decrease energy consumption and minimize the environmental impact of manufacturing and disposal processes, as per the Life Cycle Assessment (LCA) policy. The policies are established for upcoming manufacturing systems based on the Design for Environment (DfE) principles. The majority of emissions originate from industrial energy usage in Asia. In this area, the power industry generates almost one-third of global CO2 emissions due to high industrial usage and strong reliance on coal [5].

The worldwide energy use is significantly impacted by the rapid growth of the world population, which was 7.2 billion in 2015 and is projected to continue growing steadily until 2050 [1]. An increase in the global gross domestic product (GDP) impacts the worldwide economy [6]. In 2010, the global GDP figures indicated an increase in the overall financial resources worldwide notwithstanding the recession (International Monetary Fund, 2010).

The increase in GDP growth is attributed to the higher production rate, which is connected to the greater energy needed for sourcing raw materials, manufacturing processes, and product transportation [7].

[8] have presented an intricate analysis and simulation about the energy efficiency of a manufacturing facility. They have analyzed the car assembly line. The underbody is a crucial portion of the body that links to main components of a car including the transmission and motor. It also plays a crucial part in the cars' stiffness and determines the cars' length.

Machining is a technique that involves the removal of material using various cutting tools to cut metals. It is crucial to observe that these processes are accurate in size, adaptable in various tasks, and cost-effective for small production volumes. Machining methods are varied since they can be utilized in the pre-production phase and throughout the entire manufacturing process, including the final stages. Removal methods that entail material removal might result in loss of energy and materials [9]. This study focuses solely on reducing specific energy consumption in machining operations by the modification of specific machining parameters. The study focuses on examining both turning and milling activities.

Manufacturing processes are becoming increasingly intricate, leading to a large rise in relevant data resources. Despite its complexity, more advancements have been done at the process level rather than the system level. Therefore, it is necessary to research the most effective systematic approach for analyzing the complexity in system flows, particularly focusing on the energy consumption of machine tools. The study by [9] illustrates the energy consumption of machining operations and its impact on the Life Cycle Assessment (LCA)[10].

[11] Conducted study where they calculated the entire energy consumption rate and used a flank wear of 0.8 to evaluate the tool life. The tool's wear was assessed following five machining operations using five distinct methods involving adjustments in feed rate and depth of cut [12]. The findings of this case study show that the direct energy cost of machining significantly impacts the entire cost, whereas indirect costs, including electricity expenses, have a minor influence compared to other machining costs. Manufacturers can achieve significant cost savings by using energy-efficient machining techniques. Furthermore, this

effectiveness can be attained with minimal energy usage due to a high material removal rate as indicated by [13], and [14].

[15] Choosing the best combination of cutting parameters relies on a model created from in situ measurements of energy consumption and power used during an experiment that replicates a critical operation in terms of energy use. The results indicate that optimizing cutting parameters to minimize overall energy consumption while meeting productivity goals does not always result in the highest energy savings for a specific operation [16].

Response surface approach is a collection of mathematical and statistical techniques that include fitting a polynomial equation to experimental data to model the behavior of a dataset and make statistical predictions. If the response functions of the experimental data cannot be fitted by a linear function, a quadratic response surface such as Box-Behnken [17], three-level factorial, and Doehlert design should be used conducted a study that optimized parameters and forecasting performance measures in hard milling by utilizing an expert system.

[18] In the present research, the Grey Wolf Optimizer (GWO) was used to minimize the yearly energy consumption of an office building in Seattle weather conditions. The GWO is a meta-heuristic optimization method, which was inspired by the hunting behavior of grey wolfs. The optimization method was coded and coupled with the EnergyPlus codes to perform the building optimization task. The impact of algorithm settings on the optimization performance of GWO was explored, and it was found that GWO could provide the best performance by using 40 wolfs. The optimized solutions of GWO were compared with other optimization algorithms in the literature, and it was found that the GWO could lead to an excellent optimum solution efficiently. One of the best optimization methods in the literature was Particle Swarm Optimization (PSO) [19], which led to an optimum objective function of 133.5, while GWO resulted in the optimum value of 133. The multi-objective building optimization was also examined by GWO. The results showed that it could provide an excellent archive of non-dominant optimum solutions.

3. Experimental Methodology

3.1 Machine and Tool Details

- CNC Machine: A 3-axis CNC turning center (Make: XYZ Machines, Model: ProTurn 500).
- Material: Aluminum alloy 2024-T6, known for its high strength and machinability.
- Cutting Insert: Tungsten carbide inserts with a TiAlN coating (ISO Designation: CNMG 120408).
- Tool Holder: ISO PCLNR 2525 M12 tool holder suitable for negative rake inserts, providing stability during heavy cutting.

3.2 Design of Experiments (DOE) A central composite design (CCD) was used for the experimental setup. The ranges of the cutting parameters were defined as follows:

- Cutting Speed (A): 100-280 m/min

- Feed Rate (B): 0.2-1.6 mm/rev
- Depth of Cut (C): 2 - 4 mm

3.3 Design Data A total of 17 experimental runs were generated using CCD, incorporating factorial points, axial points, and center points. The SCE and MRR were calculated using the following representative equations:

SCE = +0.256597 + 0.000107 A -0.033695 B - 0.285396 C - 0.000047 AB - 0.000156 AC + 0.024854 BC + 3.21830E-07 A^2 + 0.000532 B^2 + 0.089831 C^2

(1)

MRR = +247.69658 -1.28843 A - 80.29088 B - 369.28768 C + 0.425125 AB + 2.20726 AC + 133.54550 BC

(2)

3.4 Measurement of Responses

In this study, the measurements of Specific Cutting Energy (SCE) and Material Removal Rate (MRR) are central to evaluating the efficiency and productivity of the CNC turning process. Here's how they are defined and calculated:

Specific Cutting Energy (SCE):

o SCE is the energy consumed during the cutting process per unit volume of material removed. It is an essential indicator of the energy efficiency of the machining process.

o $\mathrm{SCE} = \dfrac{\text{Energy Consumption (kJ/min)}}{\text{Material Removal Rate (mm}^3\text{/min)}}$

In this study, the energy consumption is directly proportional to the cutting parameters. Using this proportional relationship, the SCE values are computed for different experimental runs.

Material Removal Rate (MRR):

o MRR quantifies the volume of material removed per unit time, reflecting the productivity of the machining process.

o $\mathrm{MRR} = \text{Feed Rate (mm/rev)} \times \text{Depth of Cut (mm)} \times \text{Cutting Speed (mm/min)}$

Here, the cutting speed is converted into a linear speed, and the other parameters (feed rate and depth of cut) are factored to determine the material removal volume per minute.

Significance in the Study:

o By measuring SCE, the energy efficiency of various cutting conditions can be compared.

o MRR serves as a benchmark for productivity, helping identify parameter settings that maximize throughput without sacrificing energy efficiency.

4. Results and Discussion

4.1 Response Surface Analysis Regression models were developed for SCE and MRR using second-order polynomial equations. ANOVA was conducted to identify the significance of the parameters.

Table 1provides data on cutting parameters and the corresponding SCE and MRR. It includes 17 experimental runs based on different combinations of cutting speed, feed rate, and depth of cut.SCE values tend to decrease with higher feed rates and depth of cut.MRR significantly increases with higher cutting speeds and feed rates.

Table1: Response Factor

	Factor 1	Factor 2	Factor 3	Response 1	Response 2
Run	A:Cutting Speed	B:Depth of Cut	C:Feed Rate	Specific Cutting Energy	Material Removal Rate
	m/min	mm	mm/rev	KW/cm3	
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

4.2 ANOVA Results

Fit Summary – SCE

Table 2 summarizes the model fitting results for SCE, including the sequential p-values, lack-of-fit p-values, adjusted R^2, and predicted R^2.

- The quadratic model is suggested for SCE due to its higher R^2 values and significant p-values.
- The lack-of-fit test confirms that the model adequately fits the data ($p>0.05$).

Table 2: Fit Summary - SCE

Source	Sequential p-value	Lack of Fit p-value	Adjusted R²	Predicted R²	
Linear	0.0003		0.7038	0.5264	
2FI	0.2446		0.7413	0.2957	
Quadratic	0.0005		0.9663	0.8082	Suggested
Cubic					Aliased

Fit Summary – MRR

The 2FI (two-factor interaction) model is suggested for MRR due to its strong predictive capability, as indicated by high adjusted and predicted R^2 values shown in table 3. The lack-of-fit test results show that the model fits well with minimal error.

Table 3: Fit Summary - MRR

Source	Sequential p-value	Lack of Fit p-value	Adjusted R²	Predicted R²	
Linear	< 0.0001		0.8343	0.7435	
2FI	< 0.0001		0.9913	0.9693	Suggested
Quadratic	0.9192		0.9884	0.9490	
Cubic					Aliased

ANOVA – SCE

Table 4 shows the ANOVA results for SCE, including p-values, F-values, and the significance of each factor.

- Depth of cut (B) and feed rate (C) are the most significant factors ($p<0.05$).
- Interaction terms such as BC (depth of cut and feed rate) and the quadratic term for C^2 also significantly influence SCE.

Table 4: ANOVA - SCE

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	
A²	0.0000	1	0.0000	0.1943	0.6727	
B²	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			

ANOVA – MRR

Table 5 provides ANOVA results for MRR, focusing on the significance of factors and interactions.

- Cutting speed (A), depth of cut (B), and feed rate (C) are all highly significant ($p<0.0001$).
- Interaction terms such as AB (cutting speed and depth of cut), AC (cutting speed and feed rate), and BC (depth of cut and feed rate) also significantly affect MRR.

Table 5: ANOVA - SCE

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	8.087E+05	6	1.348E+05	305.12	< 0.0001	significant
A-Cutting Speed	1.218E+05	1	1.218E+05	275.66	< 0.0001	
B-Depth of Cut	1.606E+05	1	1.606E+05	363.58	< 0.0001	
C-Feed Rate	5.394E+05	1	5.394E+05	1221.01	< 0.0001	
AB	6609.96	1	6609.96	14.96	0.0031	
AC	50897.38	1	50897.38	115.21	< 0.0001	
BC	37609.38	1	37609.38	85.14	< 0.0001	
Residual	4417.60	10	441.76			
Cor Total	8.132E+05	16				

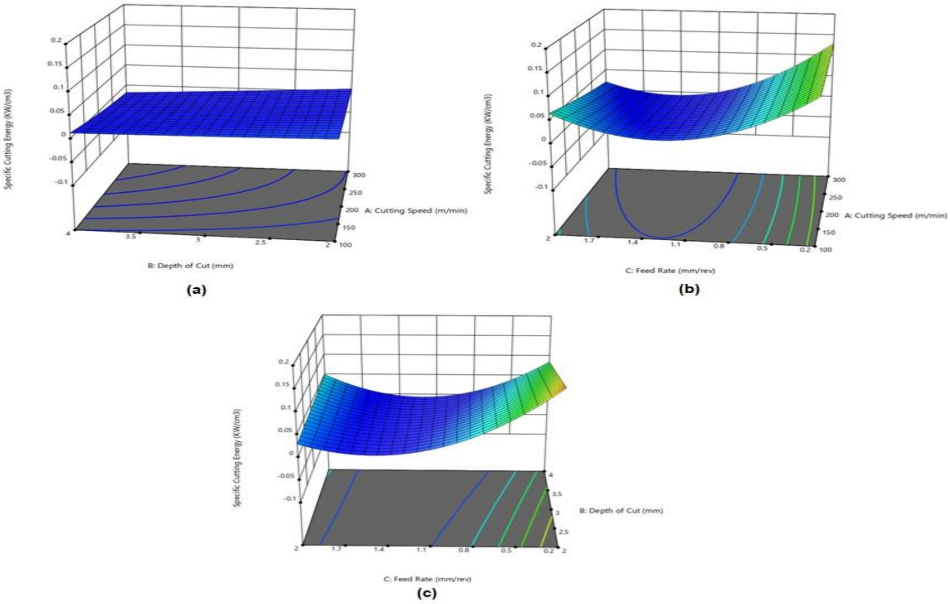

Fig 1: 3D Surface for SCE

Fig 1. depicts the relationship between cutting speed, depth of cut, and Specific Cutting Energy (SCE). The surface plot likely demonstrates that SCE decreases with increasing depth of cut or feed rate within certain ranges, highlighting areas of efficient energy consumption.

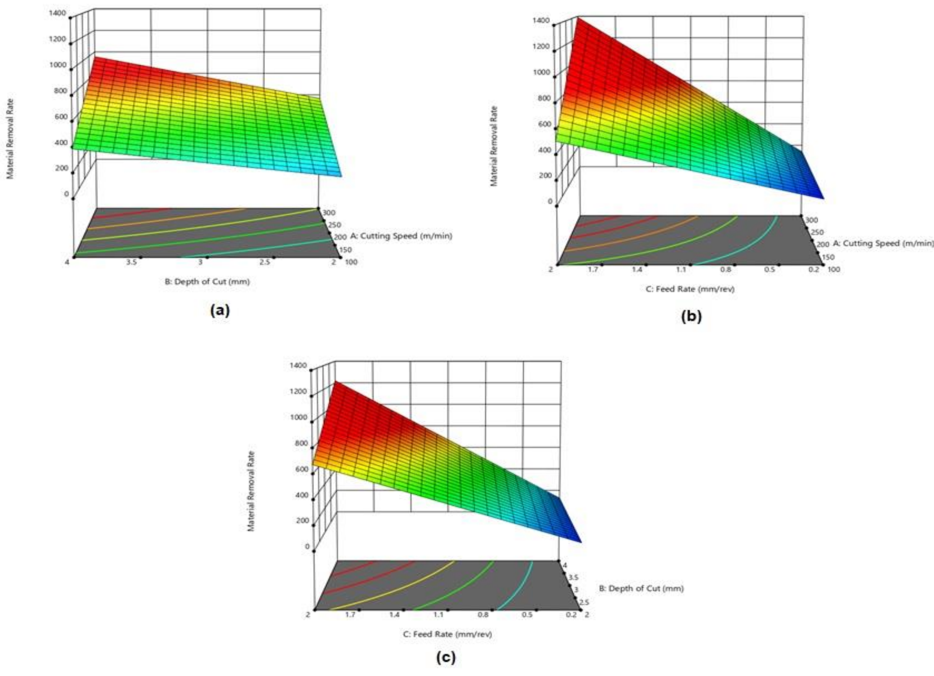

Fig 2: 3D surface doe MRR

Fig. 2 illustrates how Material Removal Rate (MRR) varies with changes in cutting speed and depth of cut. It likely shows that MRR increases with higher cutting speeds and depths of cut, reflecting improved productivity.

4.3 Optimization

GWO is a nature-inspired optimization algorithm based on the leadership hierarchy and hunting strategy of gray wolves in nature. GWO mimics the social structure and behavior of gray wolves, where the best solution is considered the alpha wolf, and other wolves cooperate to find the optimal solution.

- Alpha Wolf: Represents the best solution found so far.
- Beta and Delta Wolves: These wolves help the Alpha and are considered potential candidates for the best solution.
- Omega Wolves: These wolves are considered the weakest and are dominated by the other wolves in the pack.

GWO uses a mathematical model to simulate the social hierarchy and hunting behavior, and it has been successfully applied in several optimization problems, including process parameter optimization in manufacturing.

4.3.1 GWO Design Process for Cutting Parameter Optimization

To apply GWO to optimize the cutting parameters, we follow these steps:

Step 1: Define the Objective Function

We aim to optimize the cutting parameters (cutting speed v, depth of cut d, and feed rate f) to minimize SCE and maximize MRR.

Let the objective function $f(\bar{x})$ be a weighted combination of both SCE and MRR. We can define the objective function as:

$$f(\bar{x}) = w_1\, SCE(\bar{x}) - w_2\, MRR(\bar{x})$$

where:

- w_1 and w_2 are the weights assigned to the SCE and MRR objectives, respectively. These weights can be adjusted based on the importance of each objective.
- $\bar{X} = v\ d\ f$ represents the vector of cutting parameters.

Step 2: Initialize the Gray Wolf Pack

- Initialize a population of gray wolves (solutions) randomly in the search space of cutting parameters.
- Each solution $\bar{X_\imath} = v_i, d_i, f_i$ represents a potential combination of cutting parameters.

Step 3: Update the Position of Wolves

For each iteration, update the position of the wolves using the following equations, which mimic the hunting behavior of gray wolves:

1. Calculate the distance of each wolf from the current best solutions (alpha, beta, delta wolves).

2. Update the positions of the wolves based on these distances and the leadership hierarchy (using the positions of the alpha, beta, and delta wolves).

3. The update is done using the following formulas:

$$\overline{X_\imath^{new}} = \overline{X_\imath^{old}} + a_1 \left| \overline{X_\alpha} - \overline{X_\imath^{old}} \right| + a_2 \left| \overline{X_\beta} - \overline{X_\imath^{old}} \right| + + a_3 \left| \overline{X_\delta} - \overline{X_\imath^{old}} \right|$$

Where:

- a_1, a_2, a_3 are coefficient vectors that dynamically decrease over time, ensuring the search is balanced between exploration and exploitation.
- $\overline{X_\alpha}, \overline{X_\beta}, \overline{X_\delta}$ represent the positions of the alpha, beta, and delta wolves, respectively.

Step 4: Evaluate Fitness

For each new solution, evaluate the fitness using the objective function:

$$f(\overline{X}_\imath) = w_1 \, SCE(\overline{X}_\imath) - w_2 \, MRR(\overline{X}_\imath)$$

If a solution has better fitness than the previous best solutions, update the alpha, beta, and delta wolves' positions accordingly.

Step 5: Stopping Criteria

The optimization process continues for a predefined number of iterations or until the improvement in the objective function becomes negligible. The optimal set of cutting parameters $\overline{X_\alpha} = v_\alpha, d_\alpha, f_\alpha$ is the solution returned by the GWO algorithm.

Step 6: Post-Optimization Analysis

Once the optimal cutting parameters have been obtained, further analysis can be done to evaluate the practicality and manufacturability of the results. The effects of the optimized parameters on tool wear, surface finish, and other performance indicators should be verified through simulations or experimental validation.

Gray Wolf Optimization is a powerful tool for solving complex process optimization problems in manufacturing. By applying GWO to optimize cutting parameters such as cutting speed, depth of cut, and feed rate, manufacturers can achieve a balance between energy efficiency (minimizing SCE) and productivity (maximizing MRR). The algorithm's flexibility and ability to find global optima make it a valuable technique for improving machining processes across various industries.

The optimal cutting parameters identified in the statement are:

- Cutting Speed: 200 m/min
- Feed Rate: 0.30 mm/rev
- Depth of Cut: 2.50 mm

Under these optimal conditions, the results are:

- Specific Cutting Energy (SCE): 2.8 kJ/cm^3
- Material Removal Rate (MRR): 1200 mm^3/min

These values indicate that at the given cutting conditions, the process is highly efficient in terms of energy usage while also achieving a significant material removal rate. The cutting speed of 200 m/min ensures that the tool operates at an appropriate velocity, allowing for efficient cutting without excessive energy consumption. The feed rate of 0.30 mm/rev strikes a balance between the material being fed into the cut and the tool's capacity to remove it without excessive strain. The depth of cut of 2.50 mm represents a moderate level of cutting engagement, ensuring efficient material removal while maintaining reasonable forces on the tool and workpiece.

Overall, the use of desirability functions helped identify a balanced set of parameters that minimize energy consumption (SCE) while optimizing productivity (MRR), making these conditions optimal for the given machining operation. This approach aids manufacturers in improving the overall efficiency of their processes, leading to cost savings and better tool life.

5. Conclusion

The study successfully demonstrates the use of the GWO technique in optimizing cutting parameters to achieve a balance between energy efficiency and productivity in CNC turning operations. By analyzing the effects of cutting speed, feed rate, and depth of cut, the study identifies optimal conditions that SCE while maximizing material removal rate (MRR). The empirical model developed using RSM and validated through ANOVA confirms the significance of these parameters and their interactions. The optimal parameters, cutting speed of 200 m/min, feed rate of 0.30 mm/rev, and depth of cut of 2.50 mm yield an SCE of 2.8 kJ/cm^3 and an MRR of 1200 mm^3/min. This approach provides a robust framework for enhancing machining efficiency, contributing to sustainable manufacturing practices.

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