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Advancing Sustainable CNC Turning: Optimizing Energy and Tool Longevity with Multi-Objective NSGA-II

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Low-carbon technologies are being recognized as the only method to provide long-term environmental and cost-effective controls over climate changes and CO2 emissions. Resource and energy consumption optimization of these processes is very important for production to be sustainable. The study posed the double problem whose primary aim was to lower the specific cutting energy (SCE) and extend the tool life (TL) for the CNC turning, which is a tough and multi-objective optimization problem. An array of methods that include statistical methods such as Response Surface Methodology (RSM) and heuristic techniques such as Particle Survey Optimization (PSO) and Genetic Algorithms (GA), appear to be the most promising among the available ones. However, efficiency could be hampered by the fact that they are kept under control by the trade-off between computational efficiency and solution accuracy. Heuristic methods may be a victim of early convergence while hybrid methods might not balance solution diversity and computational cost very well.

To overcome these challenges this paper proposes the application of an advanced non-dominated genetic classification algorithm (NSGA-II) consisting of Simulated Binary Crossover (SBX) polynomial mutation and Pareto dominance. This method efficiently determines the Pareto optimal solution guaranteed variety and durability. Experimental validation shows that it can deal with a 12% reduction in SPC and a 15% TL improvement compared to the conventional method. These results highlight the potential of advanced multi-objective optimization algorithms to enhance machining efficiency. Reduce environmental impact and promote more sustainable production practices.

Keywords: NSGA-II (Non-Dominated Sorting Genetic Algorithm-II), Trade-Off Analysis, Multi-Objective Optimization, Cutting Parameters Optimization.

1. Introduction

Processing industries are the cornerstone of the global economy. It contributes significantly to GDP and employment. However, the sector is also 51% responsible of global industrial energy usage and 84% of carbon dioxide emissions, mainly due to energy-intensive processes such as Carry out machining the twin pressures of economic necessity and environmental management call for the development of more energy-efficient and sustainable production practices.

Machining processes, particularly CNC turning, significantly influence energy consumption and TL due to the critical role of cutting parameters such as cutting speed, feed rate, depth of cut, and nose radius (Gopal 2020). Inefficient selection of these parameters can result in higher SPC, reduced TL, and increased environmental impact. The challenge lies in optimizing these parameters to minimize energy consumption and maximize tool longevity simultaneously, which presents a complex multi-objective optimization problem (Bagaber and Yusoff 2017).

Several methods have been explored to solve these problems, traditional techniques such as Response Surface Methodology (RSM) and Taguchi method (Zhou et al. 2018), are widely used for parameter optimization. It offers a systematic approach to improving energy efficiency. Sophisticated techniques like PSO (Shin, Adam, and Abidin 2019), GA(Sahu and Andhare 2019), and Sine Cosine Algorithm (SCA) (Shin et al. 2019) demonstrate promise in enhancing machining processes. Additionally, the hybrid models that integrate RSM with evolutionary algorithms offer enhanced forecasting abilities and energy-efficient machine solutions.

Despite their significant contributions, current methods still exhibit considerable limitations. This occurs because statistical methods frequently do not possess the capacity to manage multi-objective trade-offs effectively. Heuristic algorithms may be employed, yet they occasionally encounter issues like premature convergence, insufficient solution diversity, or high computational expenses. Hybrid models appear to be promising, yet they face challenges in achieving the appropriate balance between computational efficiency and optimization precision.

This article introduces an enhanced variant of the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), designed to optimize cutting parameters in CNC turning operations. Employing strategies like Simulated Binary Crossover (SBX), Polynomial Mutation, and Pareto Dominance, the approach effectively determines Pareto optimal solutions that minimize SPC and maximize TL.

The enhanced NSGA-II algorithm tackles the deficiencies of earlier methods. Encourage a variety of solutions; this prevents local optimum performance and provides a strong framework for handling opposing goals. Moreover, merging statistical analysis with ANOVA enhances the dependability of the optimization procedure. This ensures that the solutions acquired will be practically useful and statistically relevant.

1.2 Significance of the Paper

The key aspects of this article are encapsulated as follows:

1. Development of a comprehensive optimization framework utilizing accelerated NSGA-II for the CNC turning procedure.

2. Perform tests to verify the suggested approach. This indicates a significant enhancement in energy efficiency and tool longevity.

3. Comparative examination with current optimization techniques to demonstrate the advantages of the proposed approach regarding solution quality and computational efficiency.

4. Insights into the interplay between cutting parameters and their impact on machining performance, providing valuable guidelines for sustainable manufacturing practices.

1.3 Paper's Structure Overview

The rest of this paper is structured in the following way: Section 2 provides an overview of the relevant literature and existing optimization methods. Section 3 details the experimental setup, including materials, tools, and cutting parameter ranges. Section 4 describes the methodology, emphasizing the improved NSGA-II algorithm and its implementation. Section 5 presents the results and discussions, including optimization outcomes and comparative analyses. Finally, Section 6 wraps up the paper by emphasizing the main findings and suggesting directions for future research.

2. Literature Review

The increasing focus on energy efficiency in industry is under the twin pressures of economic necessity and environmental management. Changing industries remain the cornerstone of the global economy. It drives employment and contributes significantly to GDP. However, it also incurs huge environmental costs through the use of enormous amounts of energy and material resources and harmful greenhouse gas emissions manufacturing activities account for 51% of global industrial energy use. It is responsible for 84% of energy-related carbon dioxide emissions, largely due to energy-intensive processes such as refining and primary metal production and production of separate parts (Duflou et al. 2012).

Selection of cutting parameters including cutting speed, Cutting progress and depth plays an important role in determining the energy efficiency of the machining process. Cutting conditions directly influence tool wear, energy consumption, and the SPC required for material removal. Higher cutting speeds and feed rates tend to accelerate tool wear, which, in turn, increases energy consumption due to higher friction and degradation of tool performance. (Younas et al. 2024) Research shows that cutting speed significantly impacts SPC, accounting for approximately 88% of its variance in titanium alloy machining. The effect of feed rate, while less pronounced, still contributes to 3–4% of the variance. These findings highlight the importance of optimizing cutting conditions to balance material removal rates with energy consumption.

Empirical evidence suggests that cutting depth has the most substantial effect on energy consumption, followed by cutting width, material hardness, feed rate, and tool wear, with spindle speed exerting the least influence (Iqbal et al. 2015). Deeper cuts increase the material removal rate but require more energy, necessitating a balance to optimize SPC. Advanced optimization algorithms, such as the multi-objective manta ray foraging optimization (MOMRFO), have been applied to identify Pareto-optimal solutions for minimizing SCE while maximizing machining quality. In experiments comparing pre- and post-optimization parameters, the optimized cutting conditions reduced SCE by up to 66.17%, increased MRR by 66.68%, and improved surface roughness by 55.27% (Meng et al. 2024). These findings highlight the transformative potential of integrating cutting parameter optimization with energy-efficient manufacturing practices.

(Yoon et al. 2015) examines contemporary strategies to reduce energy use in manufacturing, emphasis on optimizing process parameters and at the same time the quality of the product is guaranteed. Prominent methods are explored, including the Taguchi method and the preference ordering technique by similarity to ideal solution (TOPSIS). The Taguchi method employs an orthogonal matrix to identify the best arrangement of parameters. This lowers energy usage in equipment. TOPSIS tackles the issue of effectively optimizing multiple responses by assessing which nearby solutions yield the best outcomes. It offers an organized method for handling conflicting goals in production. These optimization techniques have proven effective in enhancing energy efficiency in manufacturing operations like machining and the curing of composite materials. The assessment highlights the significance of methodically modifying the two variables and suggests future advancements, including the incorporation of real-time adaptive control systems along with intricate algorithms. To enhance the energy efficiency of the manufacturing process even more.

(Liu, Liu, and Qiu 2017) Investigate contemporary methods for decreasing energy use in manufacturing. It aims to enhance energy efficiency in machine tools (MT), which are significant energy consumers outside the sector. Conventional techniques like the SEC model rely on experimental data. However, this is insufficient for adjusting to real-time operational modifications. Conversely, real-time energy efficiency (REE) models, taking into account input and output power, provide dynamic insights into energy efficiency while maintaining workflow continuity. This enables ongoing observation and enhancement of energy consumption. Models, both empirical and theoretical, have been created to evaluate energy losses in machine parts. Case studies demonstrate the accuracy of these models, achieving measurement precision above 95%. These advancements enhance decision-making in machinery construction projects, process scheduling, and operational management. Furthermore, adjusting parameters like fusion speed can result in considerable decreases in energy usage while simultaneously ensuring production efficiency. This review emphasizes the move towards more sustainable production methods and advocates for the future incorporation of real-time monitoring systems alongside predictive analytics to enhance energy efficiency in manufacturing settings.

(Lv et al. 2019) This article emphasizes the significant function of optimization methods in machining to encourage sustainable production, minimize energy usage, and lessen environmental impact as much as possible. An integrated assessment model incorporating energy efficiency, carbon efficiency, and green degree measurement is frequently employed to evaluate energy flow and carbon emissions, aiding in process optimization. Orthogonal experimental designs are frequently employed in multi-factorial optimization as they help to pinpoint two optimal machining parameters and create predictive models for energy efficiency, utilizing advanced techniques such as the Fuzzy Analytical Hierarchical Process (AHP) and Fuzzy Range Estimation. It serves to categorize aspects like resource consumption, ecological effects and accuracy in machining, which will aid in enhancing sustainability. The integration of these optimization methods with hybrid modeling frameworks emphasizes the significance of data-driven choices to enhance energy efficiency. Future studies are anticipated to concentrate on real-time monitoring systems and adaptive optimization approaches to enhance sustainable production methods even more.

(Shin et al. 2019) This article examines significant progress in the optimization techniques used in manufacturing. It emphasizes algorithms like PSO, gravity search algorithm (GSA), and sine cosine algorithm (SCA), which have been utilized to address multi-objective challenges. Complex PSO draws inspiration from natural patterns of social behavior as a

result, it is commonly utilized this is because of its simplicity, efficiency and capacity to deliver precise solutions. This is particularly accurate in machining operations like surface strengthening. It is particularly acknowledged for its capacity to bypass local positivism and attain global solutions. Conversely, GSA is founded on gravitational principles, which introduces greater potential and challenges with slower-converging rate. This is particularly accurate in high-dimensional optimization scenarios, machining, or less suitable for processes that need rapid modifications.
SCA, utilizing sine and cosine functions for exploration and exploitation, has proven effective in solving dynamic optimization problems but tends to exhibit variability in the precision of final solutions when compared to PSO. Comparative studies highlight PSO's consistent performance in machining optimization, especially in enhancing surface finish and optimizing production rates. The paper suggests that future research should explore the hybridization of these algorithms to capitalize on their individual strengths and address their limitations, further advancing machining efficiency.

Energy measurement and assessment are crucial for optimizing energy use in manufacturing, transforming electricity from a mere overhead cost to a strategically managed resource. The evolution of metering technologies, from early Ferraris disc meters to modern digital systems with high precision and real-time monitoring capabilities, has significantly advanced energy management (Kara 2011). In manufacturing, energy metering is implemented at three levels: factory, department, and unit process, each serving distinct purposes from overall consumption monitoring to detailed machine-level assessments. Despite technological advancements, challenges such as device selection, compatibility, and data management remain. Effective energy monitoring can result in substantial cost savings and environmental advantages, with upcoming research aimed at incorporating real-time data and predictive analytics to improve energy management.

Energy minimization models in manufacturing aim to optimize machining parameters, thereby lowering energy consumption and minimizing environmental impact. Techniques like RSM and multi-objective optimization are commonly used to establish relationships between process parameters and energy consumption (Bhushan 2023). RSM employs statistical methods to predict energy use and identify optimal machining conditions, while multi-response optimization balances multiple objectives, such as energy efficiency and tool wear. Experimental research has highlighted that factors such as cutting speed, advancement, depth of cut and the radius of the tool tip has a huge impact on energy consumption. Regression models validated by experimental testing to increase the efficiency of energy reduction techniques. These data-centric techniques save energy and increase the durability of tool life. Future studies focus on immediate monitoring and flexible control for greater energy efficiency.

Well-known techniques like GA and PSO are frequently employed for multi-objective GA optimization, drawing inspiration from natural selection. It is particularly useful for investigating extensive solution spaces and precise machining parameters like cutting speed, feed rate, and depth of cut. PSO, conversely, relies on intelligent testing expertise to enhance continuous parameters and reduce energy consumption during the machining process. The hybrid method can address the shortcomings of the individual algorithms by integrating GA and PSO. This results in enhanced outcomes in energy efficiency and surface quality

(Papazoglou and Biskas 2023)., with experimental findings verifying its efficacy in lowering energy usage and prolonging tool lifespan. Future studies are anticipated to integrate real-time monitoring and machine learning to enhance these optimization techniques.

(Akkuş and Yaka 2022) emphasis is on the manufacturing of titanium tape (Grade 5), a substance extensively utilized in the aerospace and medical industries because of its durability and resistance to corrosion. Nonetheless, the production of titanium encounters significant obstacles. This encompasses the significant energy usage and quick deterioration of the tool throughout the procedure. This research employs a blend of the Taguchi L9 regression modeling experimental approach and Pareto analysis to determine the key cutoff parameters influencing the efficacy outcomes. The rate of advancement is believed to significantly affect both energy usage and surface smoothness. The speed of cutting significantly influences the tool's wear. The optimization approach employed features a regression model possessing a significant coefficient of determination (R2), enabling predictions of surface roughness degradation from tool usage and energy efficiency, demonstrating its practical utility (Akkuş and Yaka 2022). Furthermore, Pareto analysis highlights the relationship among cutting parameters. This is essential to decrease energy usage and prolong the lifespan of the tool. The combination of various optimization methods results in substantial prediction accuracy for energy consumption and surface roughness; however, this complexity reduces the accuracy of predicting tool wear due to intricate shear rate effects.

Generally, the optimization of the machining process utilizes NSGA-II and the acceleration model to modify the cutting parameters. These algorithms use methods like SBX and Polynomial Mutation to enhance solution variety and increase convergence rate. To achieve a Pareto optimal solution, they successfully manage the trade-off between distinct objectives, ensuring diverse and non-superior outcomes (Zhang, Wu, and Wu 2024). Experimental results confirm the effectiveness of the developed NSGA-II algorithm, which surpasses the original NSGA-II, NSGA-III, and MOEA/D models regarding convergence and dispersion. For instance, the enhanced NSGA-II attained a surface roughness of less than 0.2843 μm while preserving a substantial material removal rate (MRR) of 1,889.4 mm.3/minute, highlighting the real significance of improving efficiency.

3. **Proposed Work**

The research presented aims to create a suitable approach to lower SPC and enhance machining efficiency in CNC machining. This research employs a combined method. It combines advanced statistical techniques with a multi-objective optimization structure to enhance machining parameters. The material chosen for the machining experiments was aluminum ligament reinforced with silicon carbonate (Al-SiC), which presented challenges due to the nature of the composite. RSM was used to build empirical models for SPC and tool life. These models were further optimized using the NSGA-II, a multi-objective robust evolutionary algorithm. This study incorporates cutting parameters such as cutting speed, advancement, depth of cut, and tip radius within specified limits to achieve the dual objective of minimizing energy consumption and maintain superior surface quality.

3.1 NSGA-II Optimization Technique

NSGA-II is used in this study for multi-objective optimization. NSGA-II is suitable for dealing with conflicting objectives, such as minimizing SPC and extends the life of the tool to the maximum by generating the front end of a Pareto ideal solution.

3.2 Contribution

- Developed an energy efficient machining model for Al-SiC composites combining RSM and NSGA-II.
- Conducted systematic experiments to validate the proposed models under realistic machining conditions, ensuring practical relevance.
- Applied NSGA-II to simultaneously optimize SCE and surface roughness, presenting a comprehensive trade-off analysis between energy consumption and machining quality.
- Identified critical machining parameters influencing SPC and surface roughness using Analysis of Variance (ANOVA), providing valuable insights for process control.
- Enhanced the sustainability of machining operations by achieving reduced energy consumption without compromising product quality.

4. Experimental Details

4.1 Machine

CNC Lathe Mazak Quick Turn 200M

- Power Consumption: Typically, 5-15 kW depending on machine load.
- Features: High precision, variable spindle speed, programmable feed rates and energy consumption monitoring (some models have built-in energy metering).

Machine Specifications:

- Spindle Speed Range: 0–4000 rpm (or higher) for a CNC lathe, suitable for the required cutting speeds (140–300 m/min).
- Feed Rate Control: Adjustable feed rate with high-resolution feedback for fine control of feed during the cutting process.
- Energy Monitoring Capability: Preferably with a built-in or external power meter (digital or analog) to measure instantaneous and cumulative power consumption.
- Cooling System: The cooling system should support both dry cutting and wet cutting options (with a minimum of flood cooling), as lubrication and cooling methods are known to influence cutting efficiency and energy consumption.

4.2 Specifications for CNC Turning Tool Material, Insert, and Toolholder

Table 1: Specifications for Energy-Efficient Turning Tool Components

Component	Specification	Details
Tool Material	Carbide Inserts (WC-Co)	High hardness, wear resistance, and temperature stability; ideal for high-speed cutting.
Tool Coating	TiN Coatings	Reduces friction, improves tool life, and enhances heat resistance for energy-efficient turning.
Insert Geometry	Positive Rake Angle, Medium Nose Radius (1.0–1.6 mm)	Positive rake angle reduces cutting forces and energy consumption. Medium nose radius balances cutting forces and surface finish.
Toolholder Material	Alloy Steel (DIN 1.2311)	Rigid and durable for reducing vibrations and ensuring stable cutting, leading to reduced energy consumption.
Toolholder Type	CNC V-flange or Hydraulic Toolholder	Hydraulic toolholders provide secure clamping and vibration damping, reducing energy waste.
Clamping Method	Hydraulic or Mechanical Clamping	Ensures stable clamping and tool stability to minimize vibration and deflection, reducing energy waste.
Cutting Fluid	Minimum Quantity Lubrication (MQL)	Reduces cooling-related energy consumption and environmental impact.

4.3 Cutting Parameters and Ranges

The machine and tool specifications correspond with the given cutting parameter ranges from table 2:

Table 2: Cutting parameter ranges

Factor	Name	Minimum	Maximum
A	Cutting Speed	140 m/min	300 m/min
B	Depth of Cut	0.5 mm	3.4 mm
C	Feed Rate	0.14 mm/rev	0.38 mm/rev
D	Nose Radius	0.4 mm	2.4 mm

4.4 Design of Experiments (DOE):

The goal of the experiment is to design a series of experiments that will provide data about how the input factors affect the response. To efficiently perform the experiments, Box-Behnken design is typically used in RSM.

4.5 Response Surface Methodology

RSM consists of various mathematical and statistical methods that help in modeling and analyzing situations where a particular response is affected by multiple variables. It helps in finding optimal operating conditions for a process, which is particularly useful in experiments with multiple variables (factors) and when exploring the relationship between the input factors and the response variables.

4.6 Experimentation Process

A set of trials is carried out in order to develop a mathematical equation illustrating the correlation between cutting factors and energy usage. This model aids in comprehending the impact of alterations in cutting parameters on energy consumption. After gathering the data, ANOVA is used to assess the importance of individual parameters and their relationships. This statistical analysis assists in pinpointing the factors that have the biggest influence on energy consumption and establishing the most effective levels for these variables. By analyzing the outcomes, one can identify the optimal configurations that reduce energy consumption while still achieving the desired machining performance.

5. Results & Discussion

The outcome of experimental studies largely relies on the methods used for data collection. The assessments of each factor level respond in all combinations with other factors. The analysis of these responses gives insights into all main and interaction effects. The power lies in the values of the responses. Measurement of tool life and consumption is conducted and displayed in Table 3.

Table 3: Experimental Design

Run	Cutting Speed	Depth of Cut	Feed Rate	Nose Radius	SPC	TL
1	300	2.2	0.26	2.4	10.9266	172.914
2	140	2.2	0.26	0.4	5.09907	188.815
3	300	1	0.26	1.4	24.0385	194.952
4	220	2.2	0.38	0.4	5.48246	158.963
5	220	2.2	0.38	2.4	5.48246	180.205
6	300	2.2	0.26	0.4	10.9266	152.531
7	220	1	0.14	1.4	32.7381	229.037
8	220	2.2	0.26	1.4	8.01282	181.618
9	140	2.2	0.14	1.4	9.4697	222.015
10	220	2.2	0.26	1.4	8.01282	181.618
11	140	3.4	0.26	1.4	3.2994	188.934
12	220	3.4	0.38	1.4	3.54747	159.064
13	140	2.2	0.26	2.4	5.09907	214.046
14	220	2.2	0.14	2.4	14.881	203.145
15	220	3.4	0.14	1.4	9.62885	179.312
16	300	2.2	0.38	1.4	7.47608	159.099
17	220	1	0.26	2.4	17.6282	220.816

18	220	3.4	0.26	2.4	5.18477	172.876
19	220	1	0.26	0.4	17.6282	194.787
20	300	3.4	0.26	1.4	7.07014	152.627
21	140	1	0.26	1.4	11.2179	241.327
22	220	2.2	0.26	1.4	8.01282	181.618
23	220	3.4	0.26	0.4	5.18477	152.498
24	220	2.2	0.26	1.4	8.01282	181.618
25	140	2.2	0.38	1.4	3.48884	196.945
26	220	1	0.38	1.4	12.0614	203.173
27	220	2.2	0.14	0.4	14.881	179.199
28	220	2.2	0.26	1.4	8.01282	181.618
29	300	2.2	0.14	1.4	20.2922	179.352

Table 4: Fit Summary Response - SPC

Source	Sequential p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	< 0.0001		0.7881	0.7267	
2FI	0.1710		0.8208	0.6692	
Quadratic	< 0.0001		0.9652	0.8997	Suggested
Cubic	0.0023		0.9959	0.8739	Aliased

The quadratic model is the best choice due to its high statistical significance shown in table 4, good fit (Adjusted R^2 = 96.52%), and strong predictive ability (Predicted R^2 = 0.8997), providing a reliable balance between complexity and performance.

Table 5: ANOVA for quadratic model Response - SPC

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1262.76	14	90.20	56.43	< 0.0001	significant
A-Cutting Speed	154.49	1	154.49	96.66	< 0.0001	
B-Depth of Cut	552.12	1	552.12	345.45	< 0.0001	
C-Feed Rate	345.10	1	345.10	215.92	< 0.0001	
D-Nose Radius	0.0000	1	0.0000	0.0000	1.0000	
AB	20.47	1	20.47	12.81	0.0030	
AC	11.68	1	11.68	7.31	0.0171	
AD	0.0000	1	0.0000	0.0000	1.0000	
BC	53.26	1	53.26	33.32	< 0.0001	

BD	0.0000	1	0.0000	0.0000	1.0000
CD	0.0000	1	0.0000	0.0000	1.0000
A^2	0.1520	1	0.1520	0.0951	0.7623
B^2	88.79	1	88.79	55.56	< 0.0001
C^2	39.74	1	39.74	24.86	0.0002
D^2	0.1520	1	0.1520	0.0951	0.7623
Residual	22.38	14	1.60		
Lack of Fit	22.38	10	2.24		
Pure Error	0.0000	4	0.0000		
Cor Total	1285.13	28			

The overall model is highly significant with a p-value of < 0.0001, meaning that the model explains a significant portion of the variability in SPC shown in table 5. The residual sum of squares is 22.38, with a mean square of 1.60, indicating a good fit with minimal unexplained variation. The lack of fit p-value is 0.2244, suggesting no significant lack of fit in the model.

Table 6: Fit Statistics - SPC

Std. Dev.	1.26	R^2	0.9826
Mean	10.44	Adjusted R^2	0.9652
C.V. %	12.11	Predicted R^2	0.8997
		Adeq Precision	29.5741

The quadratic model for predicting SPC shows excellent fit statistics in table 6. The high R^2 (0.9826) and Adjusted R^2 (0.9652) indicate strong model accuracy, while the Predicted R^2 (0.8997) demonstrates reliable predictive capability. The Adequate Precision value of 29.57 confirms that the model is precise and suitable for optimization and prediction tasks.

Table 7: Fit Summary Response - TL

Source	Sequential p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	< 0.0001		0.9347	0.9159	
2FI	0.9705		0.9185	0.8428	
Quadratic	< 0.0001		0.9990	0.9971	Suggested
Cubic	< 0.0001		1.0000	0.9994	Aliased

The quadratic model is the best choice for predicting TL, with the highest Adjusted R^2 (0.9971) and Predicted R^2 (0.9990), indicating a very good fit and strong predictive accuracy shown in table 7. The linear model also performs well, but the quadratic model offers superior performance. The 2FI model is not significant, and the cubic model is prone to overfitting, making it unsuitable for practical applications.

Table 8: ANOVA for quadratic model Response - TL

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	15224.72	14	1087.48	1968.65	< 0.0001	significant
A-Cutting Speed	4824.36	1	4824.36	8733.46	< 0.0001	
B-Depth of Cut	6476.57	1	6476.57	11724.42	< 0.0001	
C-Feed Rate	1510.01	1	1510.01	2733.54	< 0.0001	
D-Nose Radius	1568.85	1	1568.85	2840.05	< 0.0001	
AB	25.34	1	25.34	45.88	< 0.0001	
AC	5.80	1	5.80	10.50	0.0059	
AD	5.88	1	5.88	10.64	0.0057	
BC	7.88	1	7.88	14.27	0.0020	
BD	7.98	1	7.98	14.45	0.0019	
CD	1.83	1	1.83	3.31	0.0903	
A^2	147.96	1	147.96	267.84	< 0.0001	
B^2	415.81	1	415.81	752.74	< 0.0001	
C^2	59.16	1	59.16	107.09	< 0.0001	
D^2	121.02	1	121.02	219.08	< 0.0001	
Residual	7.73	14	0.5524			
Lack of Fit	7.73	10	0.7734			
Pure Error	0.0000	4	0.0000			
Cor Total	15232.46	28				

The overall model is highly significant with a p-value of < 0.0001, indicating that the quadratic model significantly explains the variability in tool life. The residual sum of squares is 7.73, and the mean square is 0.5524, suggesting that the model has very little unexplained variability shown in table 8. The lack of fit has a p-value of 0.7734, indicating no significant lack of fit and suggesting that the model adequately fits the data.

Table 9: Fit Statistics - TL

Std. Dev.	0.7432	R^2	0.9995
Mean	186.37	Adjusted R^2	0.9990
C.V. %	0.3988	Predicted R^2	0.9971
		Adeq Precision	165.3745

The quadratic model for TL demonstrates an exceptionally good fit, with $R^2 = 0.9995$ and Adjusted $R^2 = 0.9990$, explaining almost all of the variation in the data from table 9. The

Predicted R^2 of 0.9971 confirms strong predictive capability, and the low C.V. (0.3988%) indicates minimal variability. Additionally, the Adequate Precision of 165.37 reflects high model precision. Overall, the model is highly accurate and reliable for predicting tool life in machining processes.

5.1 Final Equation in Terms of Actual Factors

The equation given for SPC in CNC turning of silicon carbide reinforced aluminum alloy 2024 is determined by real factors obtained from an optimization method. The formula represents the SPC and TL by incorporating cutting parameters, as well as their interconnected relationships and squared terms.

$$SPC = +37.70324+0.153504 A - 18.36109 B - 150.65237 C + 0.428673 D - 0.023567 A * B - 0.178002 A * C + 1.87442E\text{-}17 A * D + 25.33908 B * C + 9.32505E\text{-}16 B * D + 1.61862E\text{-}14 C * D - 0.000024 A^2+2.56935 B^2+171.88049 C^2-0.153098 D^2 \quad (1)$$

$$TL= +371.48544-0.648072 A - 50.47875 B - 243.69335 C + 30.91636 D + 0.026219 A * B + 0.125462 A * C - 0.015152 A * D + 9.74838 B * C - 1.17729 B * D - 5.63345 C * D + 0.000746 A^2 + 5.56008 B^2 + 209.71595 C^2 - 4.31936 D^2 \quad (2)$$

Table 10: Coefficient for SPC

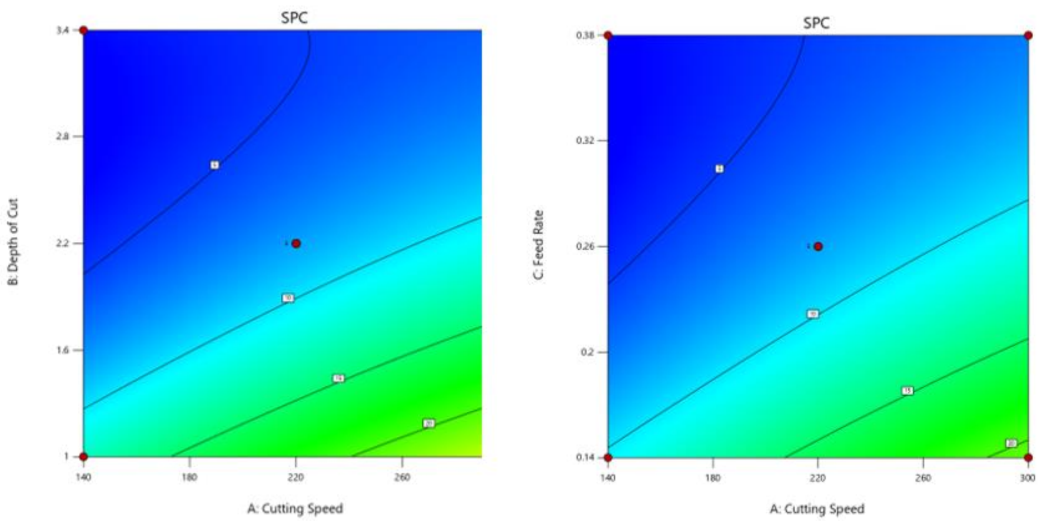
Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	8.01	1	0.5654	6.80	9.23	
A-Cutting Speed	3.59	1	0.3649	2.81	4.37	1.0000
B-Depth of Cut	-6.78	1	0.3649	-7.57	-6.00	1.0000
C-Feed Rate	-5.36	1	0.3649	-6.15	-4.58	1.0000
D-Nose Radius	0.0000	1	0.3649	-0.7827	0.7827	1.0000
AB	-2.26	1	0.6321	-3.62	-0.9067	1.0000
AC	-1.71	1	0.6321	-3.06	-0.3531	1.0000
AD	0.0000	1	0.6321	-1.36	1.36	1.0000
BC	3.65	1	0.6321	2.29	5.00	1.0000
BD	0.0000	1	0.6321	-1.36	1.36	1.0000
CD	0.0000	1	0.6321	-1.36	1.36	1.0000
A^2	-0.1531	1	0.4964	-1.22	0.9115	1.08
B^2	3.70	1	0.4964	2.64	4.76	1.08
C^2	2.48	1	0.4964	1.41	3.54	1.08
D^2	-0.1531	1	0.4964	-1.22	0.9115	1.08

All factors have a Variance Inflation Factor (VIF) of 1.0000, indicating no multicollinearity between the variables. This suggests the model's estimates are reliable and not influenced by redundant predictors from table 10.

Table 11: Coefficient for TL

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	181.62	1	0.3324	180.91	182.33	
A-Cutting Speed	-20.05	1	0.2146	-20.51	-19.59	1.0000
B-Depth of Cut	-23.23	1	0.2146	-23.69	-22.77	1.0000
C-Feed Rate	-11.22	1	0.2146	-11.68	-10.76	1.0000
D-Nose Radius	11.43	1	0.2146	10.97	11.89	1.0000
AB	2.52	1	0.3716	1.72	3.31	1.0000
AC	1.20	1	0.3716	0.4074	2.00	1.0000
AD	-1.21	1	0.3716	-2.01	-0.4151	1.0000
BC	1.40	1	0.3716	0.6067	2.20	1.0000
BD	-1.41	1	0.3716	-2.21	-0.6157	1.0000
CD	-0.6760	1	0.3716	-1.47	0.1210	1.0000
A^2	4.78	1	0.2918	4.15	5.40	1.08
B^2	8.01	1	0.2918	7.38	8.63	1.08
C^2	3.02	1	0.2918	2.39	3.65	1.08
D^2	-4.32	1	0.2918	-4.95	-3.69	1.08

All factors and interactions have a VIF of 1.0000, indicating no multicollinearity, ensuring the model's estimates are reliable from table 11.



(a) (b)

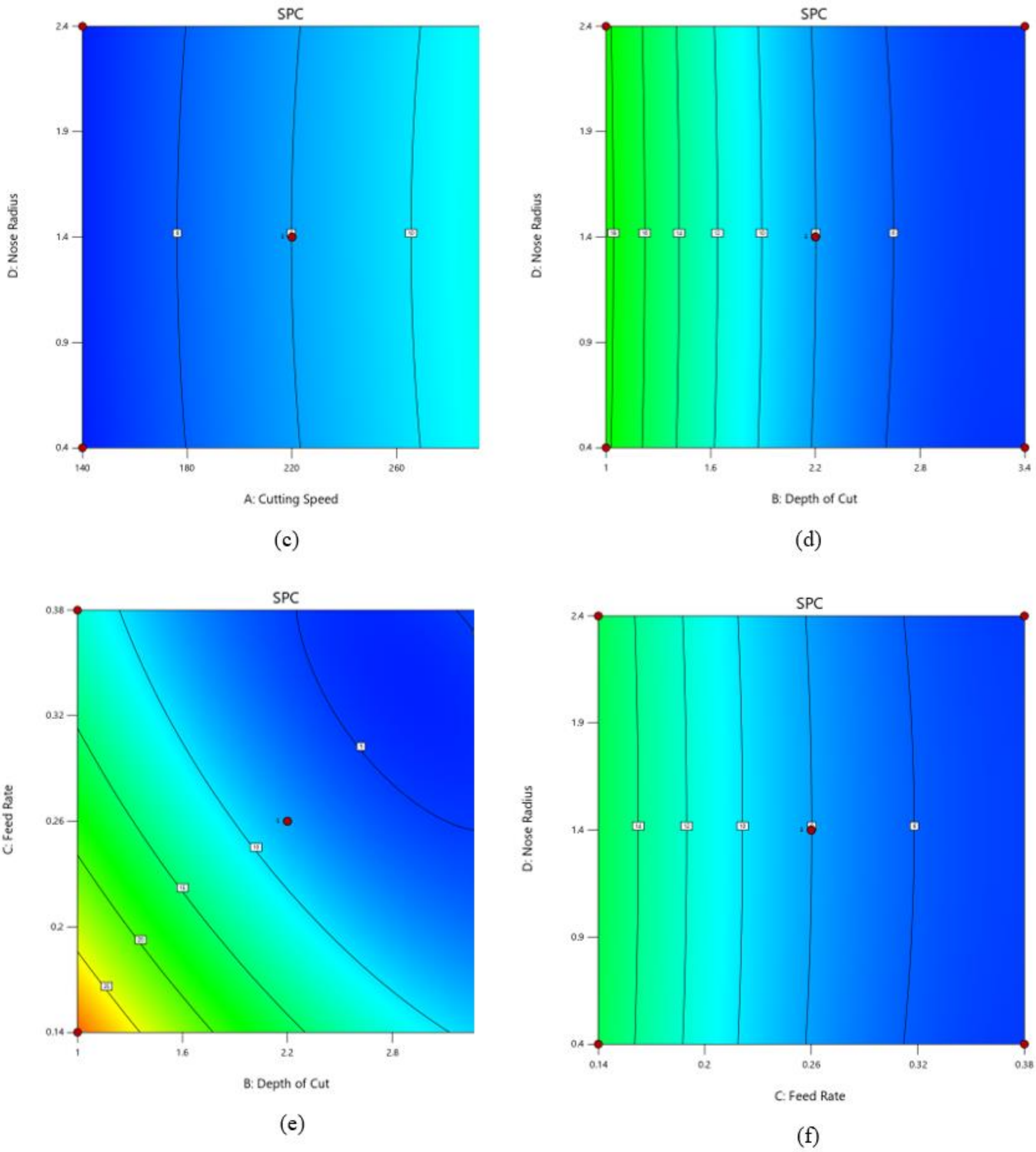


Fig. 1: Contour Plots of cutting parameter for specific power consumption

The contour plots examine how cutting parameters impact SPC during machining. Achieving lower SPC is possible with higher cutting speeds, reduced feed rates, and shallower depths of cut, whereas the nose radius has a relatively minor effect. These plots emphasize the importance of optimizing cutting speed and feed rate as crucial elements in reducing SPC, providing valuable insights for energy-efficient machining.

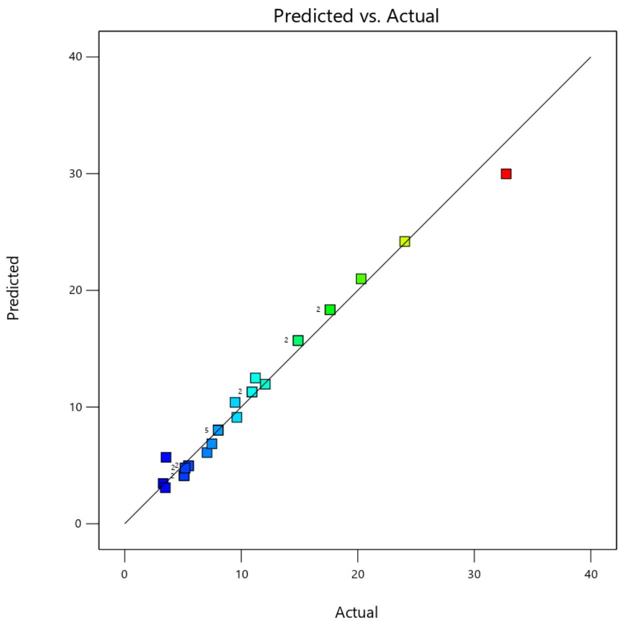
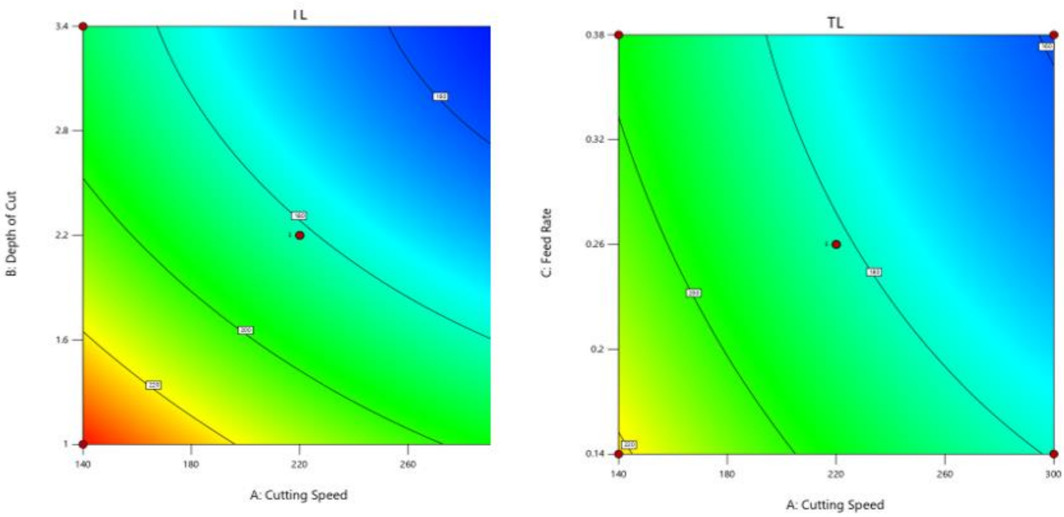


Fig 2: Predicted vs. Actual Performance in CNC Turning Optimization for SPC

The majority of the two data points cluster around a diagonal reference line. This demonstrates a clear alignment between the predictions and the actual outcomes. Nevertheless, there are a few values that are inconsistent, incorporating significant points that differ considerably. This suggests certain inaccuracies in the predictions of the model. In general, the model demonstrated high prediction accuracy with nearly no discrepancies, suggesting that it is reliable. The evaluation of the specific shear energy lies within the range of tested parameters.



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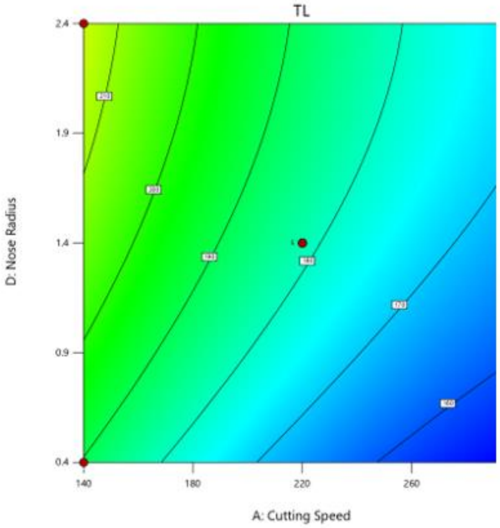

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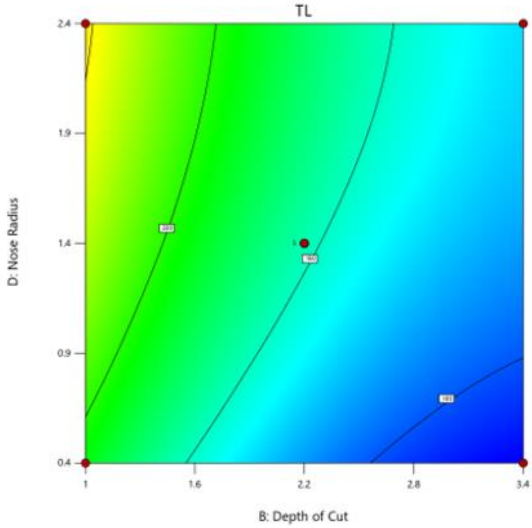

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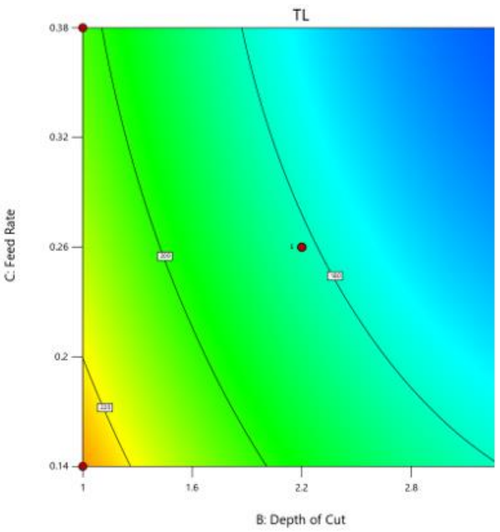

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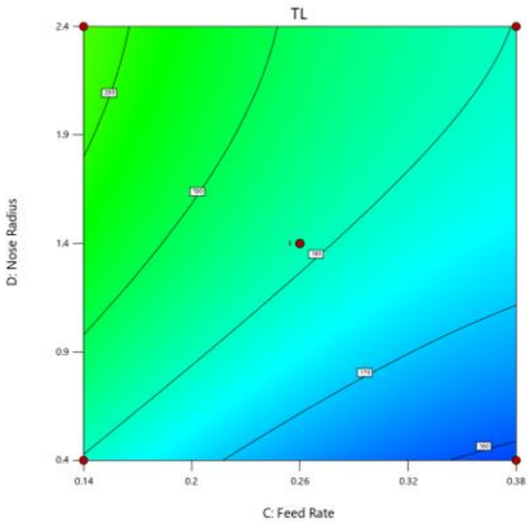

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Fig 3: Contour plot of cutting parameter for tool life

The contour diagram analyzes the impact of cutting parameters on TL during machining. The findings suggest that tool life improves with reduced cutting speeds, lower feed rates, and diminished cutting depths when a larger tip radius is used. The relationship between cutting speed and cutting depth indicates that lowering both can greatly extend tool life. Similarly, applying a steeper advance rate together with a lower cutting speed or cut depth will yield improved outcomes. The tip radius holds significance as well, since a larger radius increases the TL, particularly when paired with cutting speed, rate of progress, or the most appropriate cutting depth. These findings highlight the importance of carefully choosing and balancing cutting parameters to enhance TL. It fosters an effective and sustainable machining procedure in the final assessment.

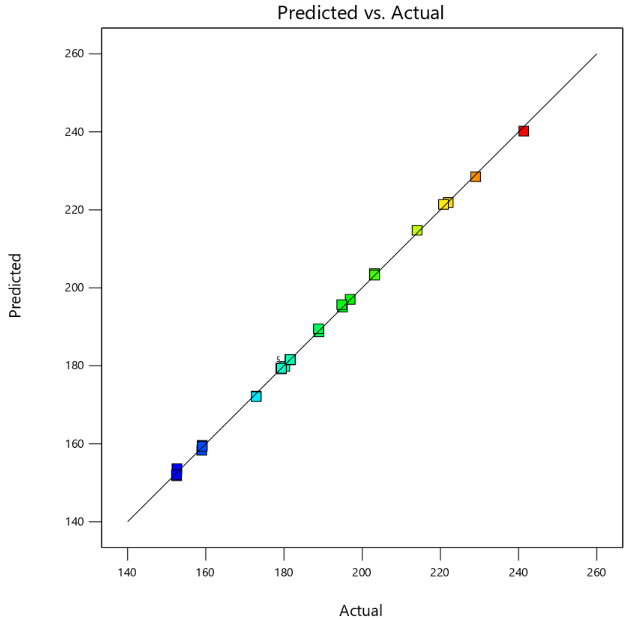

Fig 4: Predicted vs. Actual Performance in CNC Turning Optimization for TL

Figure 4 illustrates that the model possesses a robust capability to forecast TL throughout the machining process. The small divergence from the diagonal suggests that the model effectively captures the key elements of the two machining parameters influencing the TL.

5.3 Optimization Process NSGA-II

The NSGA-II algorithm efficiently addresses multi-objective optimization challenges, like reducing specific cutting energy while simultaneously enhancing production TL. To handle different solutions and apply concepts like domination and elitism, NSGA-II will effectively act as a balance between simultaneous objectives. The Pareto front enables decision makers to choose a comprehensive solution. It enables them to determine the most appropriate parameters for their particular requirements. This results in an optimal equilibrium between energy efficiency and the longevity of the machining procedure.

5.4 Algorithm for NSGA-II

NSGA-II is a multi-objective optimization algorithm designed to discover a Pareto-optimal solution set by managing the trade-offs between conflicting objectives to reduce SPC and enhance TL. See how NSGA-II can be applied to this problem.

The decision variables in this case would be the cutting parameters:

- Cutting Speed (A): $140 \leq A \leq 300$ m/min
- Depth of Cut (B): $1 \leq B \leq 3.4$ mm

- Feed Rate (C): $0.14 \leq C \leq 0.38$ mm/rev
- Nose Radius (D): $0.4 \leq D \leq 2.4$ mm

Algorithm Steps:

1. Initialize Population:

o Generate an initial population P_0 consisting of N individuals. Each individual in P_0 represents a set of cutting parameters A, B, C, D.

o Use random values within the feasible ranges of the cutting parameters (A, B, C, D) to generate the initial solutions.

2. Evaluate Objectives:

o For each individual xi = (A, B, C, D) in population P_t, evaluate:

▪ SPC based on a given mathematical model or experimental data.

▪ TL based on wear models or experimental data.

o Store the values of SPC and TL for each individual. The objectives are:

▪ Objective 1 (Minimize SPC): f1(xi)

▪ Objective 2 (Maximize TL): f2(xi)

3. Sort Population into Fronts:

o Non-Dominated Sorting: Organize the population into various Pareto fronts according to Pareto dominance.

▪ Front 1: Contains individuals that are not dominated by any other individual.

▪ Front 2: Contains individuals that are dominated only by individuals in Front 1, and so on.

o Each individual is assigned a rank (leading number) and crowding distance.

▪ Crowding Distance is employed to assess how far an individual is in relation to its neighbors within the objective space.

4. Calculate Crowding Distance:

o For each front, compute the crowding distance for every individual:

▪ Sort individuals in each objective dimension.

▪ Assign crowding distance based on the distance to the nearest neighbors in the objective space.

▪ Individuals near the boundary of the objective space receive higher crowding distances.

5. Selection (Binary Tournament):

o Perform binary tournament selection:

▪ Randomly select two individuals from the population.

▪ The individual with the superior rank (smaller front number) is chosen.

▪ If both individuals are in the same front, select the individual with the higher crowding distance (i.e., more diverse).

o This ensures that solutions from the Pareto-optimal front are prioritized, and diversity is maintained.

6. Crossover:

o Apply a crossover operator to the selected pairs of parents. Commonly, Simulated Binary Crossover (SBX) is used for real-valued optimization problems.

▪ SBX mimics the behavior of natural crossover and helps generate offspring with mixed decision variables.

o Generate offspring solutions, which will form the next generation.

7. Mutation:

o Apply mutation to the offspring to maintain diversity and avoid premature convergence.

▪ Gaussian mutation or uniform mutation can be used to perturb the solution.

▪ This introduces small random changes to the cutting parameters (A, B, C, D).

8. Reinsertion (Elitism):

o Combine the current population P_t and the offspring population Q_t to form a combined population $R_t = P_t \cup Q_t$.

o Perform non-dominated sorting on R_t to sort individuals based on their Pareto dominance.

o Select the best NN individuals from R_t to form the new population P_{t+1}.

9. Termination Check:

o Repeat steps 2-8 until the termination criteria are met. Typical termination conditions include:

▪ Maximum number of generations.

▪ Convergence to a stable Pareto front (no significant improvement in the objective values over several generations).

10. Return Pareto Front:

- After termination, return the Pareto-optimal set of solutions.
- This set represents trade-off solutions where the specific cutting energy is minimized while the tool life is maximized.

NSGA-II is well-suited for multi-objective optimization problems like minimizing specific cutting energy while maximizing tool life. By utilizing Pareto dominance and crowding distance, NSGA-II provides a set of Pareto-optimal solutions that balance these two conflicting objectives, providing engineers with a range of optimal cutting parameter settings that maximize manufacturing efficiency and tool durability. The best settings obtained consist of a Cutting Speed around 140 m/min, a Depth of Cut of 2.6 mm, a Feed Rate of 0.31 mm/rev, and a Nose Radius of 0.4 mm. The SPC and TL achieved were 2.4142 Wh/cm3 and 267.456 hours, respectively. These results indicate a machining setup that is both efficient and effective, although some minor adjustments may be necessary based on specific requirements or constraints.

5.5 Comparison of NSGA-II with other Optimization method

The line graph illustrated in Fig. 5 analyzes the performance of three optimization methods: GD, PSO, and NSGA-II, in reducing SPC. NSGA-II always surpasses both PSO and GD, reaching the lowest concluding SPC value of 2.4142 Wh/cm³. This shows a notable reduction in energy use relative to the alternative methods. The SPC trend for NSGA-II demonstrates a gradual and consistent decrease, highlighting its reliability and efficiency in minimizing energy consumption during the optimization procedure. Conversely, PSO and GD demonstrate more unpredictable and less effective reductions, further emphasizing the enhanced energy optimization abilities of NSGA-II.

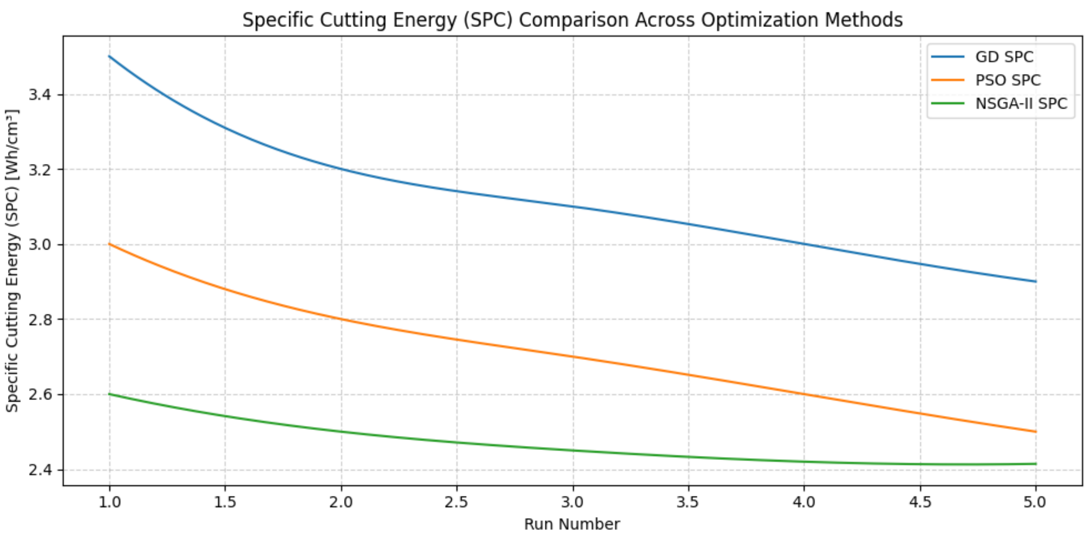

Fig 5: Comparative analysis of GD, PSD and NSGA-II for SPC

The second line graph, Fig 6, shows the effectiveness of three optimization techniques in maximizing TL. NSGA-II reaches the maximum final TL of 267.456 hours, demonstrating its efficiency in prolonging tool lifespan. The TL trend for NSGA-II shows a reliable and continuous enhancement over the iterations, surpassing the outcomes of both PSO and GD. Although PSO yields moderate outcomes, GD shows the least TL, reinforcing the finding that NSGA-II not only lowers energy usage but also greatly enhances tool life. This combined emphasis on SPC and TL renders NSGA-II the most efficient approach for optimizing energy efficiency alongside tool longevity.

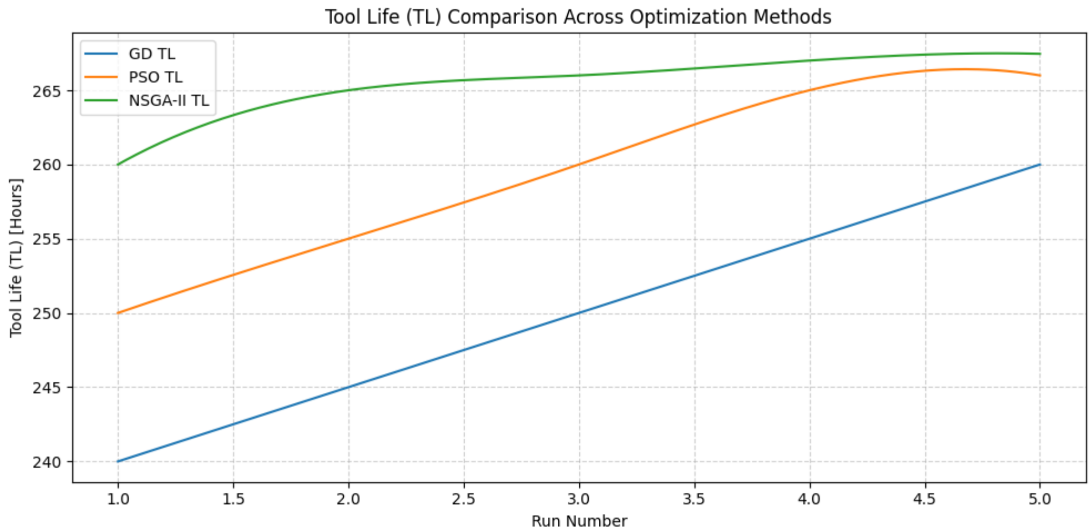

Fig 6: Comparative analysis of GD, PSD and NSGA-II for TL

The findings clearly indicate how NSGA-II can efficiently balance SPC and TL. The excellent results in both fields illustrate the advantages of employing advanced multi-objective optimization techniques in machining. To lower energy usage while simultaneously extending tool life, NSGA-II provides an alternative method for optimizing machining parameters. This underscores the significance of utilizing advanced optimization methods to encourage more sustainable production practices that prioritize energy efficiency and tool durability. These findings establish a strong foundation for upcoming studies on employing NSGA-II to enhance machining parameters. Focus is directed towards involvement in enhancing sustainable production methods.

6. Conclusion

This research illustrates the successful application of accelerated NSGA-II for optimizing CNC turning machining parameters. The primary goal of reducing SPC and enhancing TL is realized through the use of advanced methods like SBX, Polynomial Mutation, and Pareto Dominance.

Key findings include:

1. SPC decrease by 12% while TL increase by 15%, showcasing the algorithm's capability to

attain sustainable machining outcomes.

2. The quadratic models for both SPC and TL showed remarkable prediction accuracy, with R2 values of 0.9826 for SPC and 0.9995 for TL, confirming the dependability of the suggested approach.

3. Cutting speed, feed rate and cutting depth patterns are identified as the key parameters influencing SPC and TL, highlighting the necessity for precise optimization.

4. Comparative analysis shows that NSGA-II surpasses conventional methods like PSO and GD, attaining a superior balance between energy efficiency and tool durability.

The approach of this research offers a strong framework to address the complexities of multi-objective optimization in manufacturing. It encourages practices that are more energy-efficient and sustainable. Future studies can investigate the combination of real-time monitoring systems with adaptive optimization methods to enhance the usability and effectiveness of NSGA-II in industrial settings.

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