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Optimization of CNC Turning Operation Parameters for H-13 Tool Steel Towards Sustainable Manufacturing

B. G. Marlapalle[1], P. K. Ambadekar[2], J. S. Gawande[3], B. K. Suryatal[4], M. J. Sable[5], K. A. Mahajan[6], S. H. Gawande[6*]

[1] Department of Mechanical Engineering, Deogiri Institute of Engineering and Management Studies, Chh. Sambhajinagar 431005, India
[2] Department of Mechanical Engineering, SIES Graduate School of Technology, Mumbai 400706, India
[3] Department of Mechanical Engineering, PES Modern College of Engineering, Pune, S.P. Pune University, Pune 411005, India
[4] Department of Mechanical Engineering, PDEA's College Engineering, Manjari (Bk), Pune 412307, Maharashtra, India
[5] Department of Mechanical Engineering, COEP Technological University, Pune 411005, Maharashtra, India
[6] Industrial Tribology Laboratory, Department of Mechanical Engineering, M.E.S. College of Engineering, Pune, S.P. Pune University, Pune 411001, India

Corresponding Author Email: shgawande@mescoepune.org

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ABSTRACT

In this study, the multi-criteria decision-making (MCDM) method was applied for the optimum parameter selection in CNC turning operations. The aim of this paper is to optimize the process parameters for the H-13 tool steel. In this study, the TOPSIS ranking method is used for the selection of process parameters. However, the three levels of parameters were considered for optimization, which are cutting speed, feed rate, and depth of cut. H-13 tool steel material has wide applications in bulk as well as in sheet metal forming industries for the manufacturing of rolling, extrusion, bending, and forging dies. Due to the wide application of this material, there is a need to develop the optimum process parameter for an effective machining process. In this work, the combination of the parameters was planned in the Taguchi ANOVA L18 array for experimentation on a CNC machine. However, the Taguchi technique is applied for efficient and reliable product design and development so that variations in machining processes can be minimized. Furthermore, the ANOVA is used to study the relationship between the variables. According to the combinations of the parameters, the experiments were conducted, and the output parameters were measured, which are material removal rate (MRR), surface roughness (Ra), tool tip temperature, and emissions produced during the machining process for a sustainable solution. The main objectives of this study are to maximize the material removal rate and to get the minimum surface roughness (Ra). In this work, the optimum parameters are observed to be: cutting speed of 200 m/min, feed rate of 0.15rev/mm, and depth of cut of 0.6mm, which give the best combinations to achieve high MRR and low Ra values.

1. INTRODUCTION

Nickel-based H-13 tool steel is renowned for its heat resistance, particularly during the machining process. Optimizing turning parameters is crucial for enhancing efficiency, reducing waste, and minimizing environmental impacts across various industries. Many researchers have focused on Al6061 alloy, noting that speed and feed are the major influencing parameters in turning operations. The Taguchi experimental design has proven helpful in achieving a good surface finish at high cutting speeds [1]. Rao et al. [2] investigated Al6315 alloy, performing operations on a CNC machine by varying cutting velocity, feed, and depth of cut. They recorded responses such as machining rate and surface roughness, utilizing multi-objective optimization TOPSIS. Al7075 grade aluminum alloy was also studied to optimize material removal rate and machining time. Using a carbide tool for the turning operation, it was observed that speed is the most influential parameter compared to feed and depth of cut [3].

Sustainable machining practices, which consider the lifecycle implications of parameter choices, enable manufacturers to improve productivity and quality while maintaining environmental responsibility [4]. Turning operations are integral to manufacturing and prevalent in the automotive, aerospace, and agriculture industries. With evolving technologies and market requirements, it is imperative to optimize input parameters in turning operations to meet these demands. Sustainability in machining involves improvements in production rate, coolant consumption, tool life, power consumption, and emissions, along with achieving quality surface finish and dimensional accuracy. Optimized parameters are key to enhancing manufacturing performance and reducing emissions [5].

Sustainable manufacturing has grown widely owing to recent environmental issues. This study aims to develop a multi-objective, multi-pass turning optimization model to determine the optimal cutting parameters, including spindle rotation speed, feed rate, depth of cut, and number of roughing passes. The optimization model considers several criteria in the key metrics of sustainable manufacturing, i.e., energy consumption, carbon emissions, production time, and production cost. A numerical example is provided to show the application of the model, including sensitivity analysis, to study the effects of several cutting parameters on the objective functions [5]. The model can be used by manufacturing industries to improve their manufacturing process efficiency and simultaneously produce products that support sustainable manufacturing [6]. Researchers have extensively studied various materials and machining conditions to optimize parameters. For instance, the Al6061 alloy showed that speed and feed significantly influence turning operations, achieving a good surface finish at high cutting speeds through the Taguchi experimental design. Rao et al. [2] optimized machining rate and surface roughness for Al6315 alloy using CNC machines and multi-objective optimization TOPSIS by varying cutting velocity, feed, and depth of cut. For the Al7075 alloy, speed was identified as the most influential parameter in optimizing material removal rate and machining time using a carbide tool. In the automotive industry, EN-45 spring steel's optimal parameters were determined using the Taguchi L9 method, and Kumar et al. [5] employed the Taguchi L16 orthogonal array and regression analysis for further optimization.

The aim of this research work is to optimize material removal process parameters using CNC turning operations to get the desired value of surface roughness. With an orthogonal array of L27, the Taguchi approach is used, where three levels of each parameter are taken into account, which are cutting speed, feed, and nose radius. The experiments were done on EN8D carbon steel, and a carbide insert was used for a total of 27 experiments. Using the surface roughness tester, the roughness values were obtained. An analysis of variance (ANOVA) was executed on Minitab software to recognize the impact of individual machining parameters on surface roughness. A regression model was developed from the experimental data to validate the findings of the random experiment [7]. The Taguchi technique minimizes manufacturing variations, while ANOVA studies relationships between variables. TOPSIS helps in decision-making in manufacturing processes. Palaniappan et al. [8] investigated optimal parameters for material removal rate (MRR) and surface roughness (Ra) in aluminum 6082 alloy, finding feed rate to be the dominant factor affecting surface roughness.

A novel method, TOPSIS, was recommended by Kumar and Singh [9] to optimize the turning operation parameters on GFRP composites due to the non-requirement of computing challenging modeling formulations or process simulations. The AHP and TOPSIS methods have been recommended for parameter optimization, aiding material selection decisions for hydroforming process experimentation. Turning machining deals with removing unwanted material from the workpiece in the form of chips to get the required dimension. Hence, industries face the inevitable challenge of reducing costs as well as optimizing the machining operation. The response characteristics, such as material removal rate (MRR), surface roughness (Ra), and tool tip temperature, are greatly influenced by the input cutting parameters like speed, feed rate, and depth of cut [10]. Industries must consider multiple performance characteristics simultaneously, as focusing on a single objective may appear as a loss for the rest of the objectives. Hence, multi-objective optimization techniques may be suitable for experimentation. H-13 is commonly used in industries to perform different types of work. Response surface methodology (RSM) was used to determine the optimal value of cutting parameters, and the significance of the cutting parameters was determined and calculated using analysis of variance (ANOVA) with Central Composite Design (CCD) [11].

Despite extensive research on parameter optimization for efficiency and productivity [12, 13], there's a notable gap in assessing sustainability implications. Our study aims to bridge this gap by systematically evaluating the interplay between optimized turning parameters and sustainability metrics. This involves considering material usage, energy consumption, waste generation, and environmental impact. By integrating these aspects, we provide actionable insights for sustainable machining practices.

Surface finish [14] in manufacturing is critical for ensuring quality, avoiding secondary operations, and improving performance aspects like fatigue strength and corrosion resistance. Surface finish is influenced by input parameters such as speed, feed, and depth of cut. The heat generated during machining, primarily due to plastic deformation and friction, affects material properties and tool life. Quality machining products reduce manufacturing costs and enhance effectiveness. The cutting conditions, including speed, feed, and depth of cut, significantly impact performance characteristics. High production rates depend on optimized turning input parameters, with tools like PCD inserts achieving lower surface roughness [15]. Our study represents an advancement in sustainable machining by integrating parameter optimization with sustainability considerations. By addressing the often-overlooked relationship between temperature effects, parameter optimization, and sustainability, we empower manufacturers to make informed decisions balancing productivity with environmental responsibility. Temperature plays a crucial role, influencing material properties, tool life, and process performance. Excessive heat can degrade material integrity, increase tool wear, and necessitate frequent tool changes, thus raising production costs and environmental impact due to air and water pollution.

This work focuses on optimizing material removal process parameters for CNC turning operations, particularly studying surface roughness behavior. Multi-Criteria Decision Making (MCDM) methods, including the TOPSIS ranking method, are used for parameter selection. Employing an orthogonal L9 array with the Taguchi approach under wet conditions, we develop a regression model to validate findings through random experiments. This continuous need for parameter optimization in production departments enhances productivity and sustainability in manufacturing.

2. TOPSIS METHOD

The selection of the Taguchi L18 array for creating a decision matrix in this study is well-justified due to its orthogonality, efficiency, robustness, factor prioritization capabilities, and statistical rigor. The inherent orthogonality of Taguchi arrays ensures that each factor level combination appears equally with every other combination, allowing for independent estimation of factor effects and facilitating the identification of significant factors without confounding effects. The L18 array, in particular, provides a balanced design for experiments with up to 17 factors and requires only 18 experimental runs, striking a balance between the number of trials and the precision of estimates, thus reducing experimental costs and time while maintaining result quality [10, 16]. Furthermore, Taguchi methods emphasize robustness against variations and noise factors, making them suitable for experiments under imperfectly controlled conditions. This robustness, combined with the array's ability to prioritize influential factors and its grounding in statistical principles, allows for the efficient and reliable optimization of decision-making processes. The L18 array also enables the application of techniques like ANOVA to identify significant factors and interactions, assess their effects, and make data-driven decisions for process optimization or product improvement.

The MCDM method [17, 18] is widely used in the manufacturing sector to find optimum parameters in available alternatives. This method is powerful, widely used and efficient nowadays. In this method one of the TOPSIS methods is used to solve the multi model criteria problems. This is work on the best choice among the various alternatives. The following are the steps to choose the best choice:

Step-I Formulation of multi-objective**s** for experimental decision matrix (D_{ij}).

$$Dij = \begin{bmatrix} x11 & x1j & x1m \\ xi1 & xij & xim \\ xn1 & xnj & xnm \end{bmatrix}$$

where, i=1,2,3…n=number of experimental trials, j=1,2,….m=number of responses. The decision matrix is formulated by doing permutation and combinations of the variables by Taguchi L18 Array. The experimental analysis results are recorded and presented in Table 1.

Table 1. Experimental analysis

Experiment Nos.	V (m/min)	F (rev/min)	D (mm)	Ra	MRR	Workpiece Surface Temp
1	100	0.05	0.2	0.132	1	14.365
2	100	0.1	0.4	0.111	4	16.377
3	100	0.15	0.6	0.114	9	20.385
4	150	0.05	0.2	0.196	1.5	23.541
5	150	0.1	0.4	0.186	6	21.558
6	150	0.15	0.6	0.191	13.5	27.572
7	200	0.05	0.4	0.262	4	32.731
8	200	0.1	0.6	0.235	12	37.762
9	200	0.15	0.2	0.246	6	28.774
10	100	0.05	0.6	0.099	3	17.365
11	100	0.1	0.2	0.114	2	21.37
12	100	0.15	0.4	0.107	6	15.36
13	150	0.05	0.4	0.207	3	24.552
14	150	0.1	0.6	0.192	9	32.565
15	150	0.15	0.2	0.186	4.5	36.556
16	200	0.05	0.6	0.097	6	33.732
17	200	0.1	0.2	0.109	4	40.72
18	200	0.15	0.4	0.117	12	47.727

Table 2. Normalized responses

Experiment No.	Cutting Speed (v)	Feed Rate (f)	Depth of Cut (d)	Surface Roughness (Ra)	MRR	Workpiece Surface Temp
1	100	0.05	0.2	0.183024	0.033908	0.117048
2	100	0.1	0.4	0.153907	0.135632	0.133442
3	100	0.15	0.6	0.158066	0.305172	0.166099
4	150	0.05	0.2	0.271763	0.050862	0.191815
5	150	0.1	0.4	0.257898	0.203448	0.175657
6	150	0.15	0.6	0.26483	0.457759	0.22466
7	200	0.05	0.4	0.363275	0.135632	0.266696
8	200	0.1	0.6	0.325838	0.406897	0.307689
9	200	0.15	0.2	0.34109	0.203448	0.234454
10	100	0.05	0.6	0.137268	0.101724	0.141492
11	100	0.1	0.2	0.158066	0.067816	0.174125
12	100	0.15	0.4	0.14836	0.203448	0.125155
13	150	0.05	0.4	0.287015	0.101724	0.200053
14	150	0.1	0.6	0.266217	0.305172	0.265344
15	150	0.15	0.2	0.257898	0.152586	0.297863
16	200	0.05	0.6	0.134495	0.203448	0.274852
17	200	0.1	0.2	0.151134	0.135632	0.331792
18	200	0.15	0.4	0.162226	0.406897	0.388885

Table 3. Weighted normalized matrix

Experiment No.	v	f	d	Ra	MRR	Workpiece Surface Temp
1	100	0.05	0.2	0.036605	0.010172	0.029262
2	100	0.1	0.4	0.030781	0.04069	0.03336
3	100	0.15	0.6	0.031613	0.091552	0.041525
4	150	0.05	0.2	0.054353	0.015259	0.047954
5	150	0.1	0.4	0.05158	0.061034	0.043914
6	150	0.15	0.6	0.052966	0.137328	0.056165
7	200	0.05	0.4	0.072655	0.04069	0.066674
8	200	0.1	0.6	0.065168	0.122069	0.076922
9	200	0.15	0.2	0.068218	0.061034	0.058614
10	100	0.05	0.6	0.027454	0.030517	0.035373
11	100	0.1	0.2	0.031613	0.020345	0.043531
12	100	0.15	0.4	0.029672	0.061034	0.031289
13	150	0.05	0.4	0.057403	0.030517	0.050013
14	150	0.1	0.6	0.053243	0.091552	0.066336
15	150	0.15	0.2	0.05158	0.045776	0.074466
16	200	0.05	0.6	0.026899	0.061034	0.068713
17	200	0.1	0.2	0.030227	0.04069	0.082948
18	200	0.15	0.4	0.032445	0.122069	0.097221

Table 4. Ideal+ve and -ve

P+	1	100	0.05	0.2	0.026899	0.010172	0.029262
P-	18	200	0.15	0.6	0.072655	0.137328	0.097221

Table 5. Separation measures

Experiment No.	S+	S-
1	0.009706	0.148615
2	0.031035	0.123169
3	0.082433	0.082958
4	0.0336	0.132903
5	0.058402	0.095428
6	0.132558	0.045533
7	0.066518	0.101351
8	0.127502	0.026475
9	0.071803	0.085621
10	0.02125	0.131441
11	0.018147	0.1351
12	0.050978	0.109614
13	0.042131	0.11777
14	0.093226	0.058533
15	0.062611	0.096663
16	0.064369	0.093418
17	0.061843	0.106503
18	0.131035	0.043008

Step-II Normalize the responses (Nij) is given as,

$$Nij = \frac{xij}{\sqrt{\sum_{i=1}^{n} x2ij}}$$

The responses are normalized to eliminate the difference in measuring units and bring them on the same scale in the range of 0 and 1 as shown in Table 2. Table 3 shows the weighted normalized matrix.

Step-III Ideal positive (P+) and negative (P-)

$$P+=Max(Wij)\ ,\ P-=Max(Wij)$$

whereas, P+=Larger is the better, P-=Smaller is the better.

The i^{th} criteria were considered during evaluation of the alternative solutions and positive indicates the best alternative and negative sign indicates the worst alternative and the predictions are shown in Table 4.

Step-IV Separations the measure as,

$$S^{+} = \sqrt{\sum_{i=1}^{n} (W_{ij} - P^{+})^{2}}$$

$$S^{-} = \sqrt{\sum_{i=1}^{n} (W_{ij} - P^{-})^{2}}$$

Step-V Multi-response index (MRI) or closeness coefficient

In the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, the Multi-response Index (MRI) or Closeness Coefficient is a measure used to assess the relative proximity of alternatives to the ideal solution. It helps in determining the overall performance of each alternative based on its distance to the ideal solution and the ideal negative solution.The Multi-response Index (MRI) or Closeness Coefficient for a particular alternative is calculated as the ratio of the distance from the ideal solution to the sum of the distances from both the ideal solution and the ideal negative solution.

$$MRI = \frac{S^{-}}{S^{+} + S^{-}}$$

The rationale behind the chosen weights (wj) in STEP-III is grounded in an extensive review of existing literature. These weights were determined by analyzing numerous studies that have addressed similar problems and employed comparable methodologies. By synthesizing the findings from these sources, we identified a consistent set of weights (Table 3) that have been validated in previous research.

In TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), the separation measure (Table 5) evaluates the relative performance of alternatives by their proximity to the ideal and negative ideal solutions. First, we defined the evaluation criteria such as cost-effectiveness and efficiency, then normalized these values to ensure comparability. We assigned weights to each criterion based on their importance, grounded in extensive literature review. The ideal solution (P+) was identified as the highest values for beneficial criteria and lowest for non-beneficial, while the negative ideal solution

(P-) was the lowest values for beneficial criteria and highest for non-beneficial criteria. We calculated the Euclidean distances of each alternative to these ideal solutions, then computed the separation measure by dividing the distance to the ideal solution by the sum of the distances to both ideal and negative ideal solutions [10, 11]. Finally, we ranked the alternatives based on these separation measures, identifying Experiment X as the best due to its highest separation measure, which was consistent with expectations and offered a balanced, objective assessment compared to methods like AHP, ensuring a robust decision-making process.

The use of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method in the manufacturing sector is well-documented in the literature, showcasing its relevance and applicability in various decision-making processes. Several studies have utilized TOPSIS for tasks such as supplier selection, process optimization, product design, and quality management [18]. These studies collectively demonstrate the versatility and effectiveness of TOPSIS in addressing diverse decision-making challenges in the manufacturing sector, providing a systematic framework for informed decision-making and helping organizations enhance operational efficiency, quality, and competitiveness [19, 20].

One notable study that applied the TOPSIS method in the manufacturing sector. In their research, they utilized TOPSIS for the optimization of machining parameters in computer numerical control (CNC) machining processes. By identifying optimal machining parameters, they achieved improved efficiency and productivity in CNC machining operations [21]. This study serves as a valuable reference for understanding how TOPSIS can be effectively used in process optimization within the manufacturing domain.

3. EXPERIMENTAL SETUP

The selection of specific input and output parameters, as well as their ranges, for this study was guided by an extensive review of relevant literature. The input parameters were chosen based on their significant impact on the manufacturing process, as identified in previous research. For instance, studies have shown that parameters such as cutting speed, feed rate, and depth of cut are critical in influencing the quality and efficiency of machining operations.In Table 6, the 'Machining Condition' category, specifically 'Wet,' refers to the use of coolant during the cutting operation. The application of coolant is crucial for achieving a good surface finish, as it helps to reduce the temperature and friction between the cutting tool and the workpiece. This categorization ensures clarity and emphasizes the role of coolant in enhancing the machining process's effectiveness and outcome quality.

The TNMG 160404 carbide cutting insert and the PTGRNR-25-25 M16 050 tool holder were chosen for their versatility, geometry, chip control, stability, and material compatibility. The TNMG 160404 insert is widely used for both roughing and finishing operations across various materials, including steel, stainless steel, and cast iron, thanks to its neutral rake angle and effective chipbreaker design, which enhance chip formation and evacuation. Its specific carbide grade and coating improve wear resistance for tougher materials. The PTGRNR-25-25 M16 050 tool holder provides excellent rigidity and stability, reducing vibration and chatter during machining, and accommodates various inserts, allowing for quick changes and flexible tooling options. Its potential coolant-through capability aids in effective chip evacuation and cooling, especially with heat-resistant materials. This tool holder's compatibility with the TNMG insert style and the machining requirements ensures precise and efficient turning operations, resulting in consistent performance and extended tool life.

Table 6. Selection of input and output parameters

Machining Condition	Notation	Description
Cutting speed, mm/min	v	100, 150, 200
Feed, mm/rev	f	0.05, 0.1, 0.15
Depth of cut, mm	d	0.2, 0.4, 0.6
Cutting condition		Wet
Cutting insert		TNMG 160404
Tool holder		PTGRNR-25-25 M16 050
Workpiece dimensions, mm		Diameter 20mm, length 100 mm
Material		H-13 tool steel
Voltage, volt		415±10%
Power, kW		20
Spindle power, kW		5 to 7
Working temperature, °C		10 to 500
Spindle speed, rpm		20 to 4000
Machine type		CNC
MRR, mm^3/s		
Surface roughness, μm	Ra	Taylor Hobson Surtronic-3 Ra Tester
Workpiece surface temp, °C	T	K-Type Digital Thermocouple

Each input parameter in Table 6 is selected to predict the output measures, Material Removal Rate (MRR) and Surface Roughness (Ra), based on their established effects in machining processes. Cutting speed typically influences both MRR and Ra; higher cutting speeds can increase MRR but may also lead to higher Ra if not optimized. Feed rate is another critical parameter, where an increase generally boosts MRR but can negatively impact Ra by causing rougher surfaces. Depth of cut directly affects MRR, with deeper cuts removing more material per pass, but it can also increase Ra due to greater tool engagement and potential vibrations. The use of coolant ('Wet' condition) is expected to improve Ra by reducing heat and friction, leading to a smoother surface finish. These input parameters were chosen based on extensive literature review and their known impact on machining efficiency and surface quality, and their effects are demonstrated in the results section.

The workpiece specimens were prepared with 20mm diameter and 100mm long as shown in Figure 1. The range for the spindle speed (20 to 4000 rpm) is based on the capabilities of the CNC machine used in the experiments, which allows for a broad spectrum of speeds to accommodate various machining conditions and material types. The spindle speed was precisely controlled and monitored through CNC programming to ensure accurate and consistent application during each machining operation. For the temperature range (10 to 500°C), this wide range reflects the potential temperatures that could be encountered during different machining scenarios. The temperature of the workpiece surface was measured immediately after machining using a high-precision infrared thermometer to capture accurate temperature readings, ensuring the consistency and reliability of the data collected.

Figure 1. Workpiece specimens

The Taylor Hobson Surtronic-3 is a highly accurate and portable surface roughness tester used for measuring surface texture and roughness parameters such as Ra, Rz, and Rt, making it ideal for quality control in various industries. The device is cleaned and calibrated before use, and the surface is prepared to ensure accurate measurements. During operation, the probe scans the surface, displaying roughness parameters that can be further analyzed or documented. The K-Type Digital Thermocouple is employed for measuring the workpiece surface temperature immediately after machining, known for its wide temperature range and rapid response time. This thermocouple provides precise temperature readings by converting thermal potential differences into digital signals. Using these high-accuracy instruments ensures the reliability and consistency of the experimental data, enhancing the overall quality and credibility of the study's findings.

The chemical composition as presented in Table 7 of H-13 material is highly relevant to the study as each element plays a crucial role in its machining properties and the quality of the final product. H-13 steel is widely used in industries due to its excellent combination of toughness, hardness, and resistance to thermal fatigue. Elements such as carbon contribute to hardness and strength, while chromium increases hardenability and corrosion resistance. Molybdenum and vanadium enhance toughness and high-temperature strength, and silicon improves the steel's strength and resistance to oxidation. The precise balance of these elements affects the material's machinability, wear resistance, and surface finish quality, making H-13 an ideal choice for applications requiring durable and reliable components. Understanding the chemical composition helps in optimizing machining parameters to achieve superior performance and product quality.

Table 7. Chemical composition of H-13 tool steel

Elements	C	Mn	Cr	NI	Mo	S	P	Si	V
Contents (%)	0.43	0.38	5.23	0.42	1.25	0.007	0.02	0.91	0.87

A Macpower CNC machine was used for the experimentation, providing precise control over machining parameters to ensure accurate and reproducible results. The workpieces, specifically H-13 material specimens, were prepared using a Trob machine to achieve the required dimensions. These specimens were then securely mounted in the CNC machine's jaws, ensuring stability and alignment before initiating the cutting process. This setup and preparation process is crucial for maintaining consistency and reliability in the machining operations, allowing for the reproducibility of the study. Each experimental condition was repeated three times to ensure statistical validity and to account for variability in the machining process. During the experiments, errors were carefully monitored and handled by conducting multiple trials and averaging the results to minimize the impact of any outliers or fluctuations. If any outlier results were identified, they were scrutinized to determine their cause, and if necessary, additional experiments were conducted to verify their validity. Ultimately, outlier results were treated with caution, and efforts were made to understand the underlying reasons for their occurrence to ensure the accuracy and reliability of the experimental data.

4. RESULTS AND DISCUSSION

The maximization of MRR and minimization of Surface roughness and tool tip temperature were optimized. The priority given to output parameters and weight criteria were considered as 0.2, 0.3 and 0.5 respectively. The weight criteria were multiplied for normalizing the weighted matrix and from this best and worst performances were predicted. The response factors were taken to check the higher is better the performance for the turning operations. The significant parameters were cutting speed, feed and depth of cut i.e. 200m/min, 0.15mm/rev and 0.4mm.

The response accuracy was predicted in between 95 to 97% for MRR, Ra and Tool Tip temperature. The experimental numbers, respective closeness coefficients, Input and output parameters comparative were shown in Figure 2.

The experimental table was used for normalizing the data, and this same table was used for creating the weighted normalized matrix. The measured values were predicted, recorded in Excel, and displayed in Figure 2. The machining parameters affect the quality of the finished components, as shown in the interpreted data presented in the Figure 2. In summary, the relationship between cutting speed, Material Removal Rate (MRR), and surface roughness is complex and influenced by various factors such as material properties, tool geometry, cutting conditions, and machine rigidity. Optimal cutting speeds must be determined empirically through experimentation, considering the balance between achieving desired MRR and obtaining acceptable surface finish quality [22].

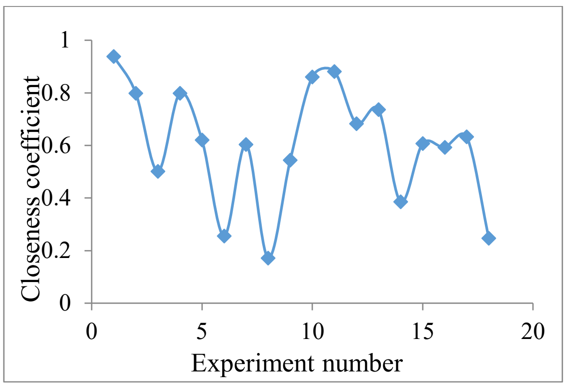

Figure 2. Variation of closeness coefficient

In CNC turning operations, several input parameters (process parameters) can affect output parameters (machining performance characteristics) [23]. The closeness coefficient, often referred to as the correlation coefficient or coefficient of determination, quantifies the degree of linear relationship between these input and output parameters. It indicates how well the output parameters can be predicted based on the input parameters. In CNC turning, the term "patterns" can refer to various aspects of the machining process, including toolpath patterns, machining strategies, or cutting patterns. Each of these contributes to how the material is removed and the final shape of the workpiece is achieved [24].

From the results, it was found that the optimal parameters are crucial for obtaining correct values or good surface finish products. The feed rate is measured in mm/rev, and the cutting speed is measured in m/min.

The impact of the machining parameters patterns is shown in Figure 3. The machining parameters are dependent on each other to get good surface finish and MRR rate [25].

The impact of cutting speed on workpiece temperature and surface roughness pattern is shown in Figure 4. From Figure 4 it is observed that the cutting speed is a major contributing parameter to get better MRR rate and tool tip temperature affect the workpiece surface roughness and the pattern [26].

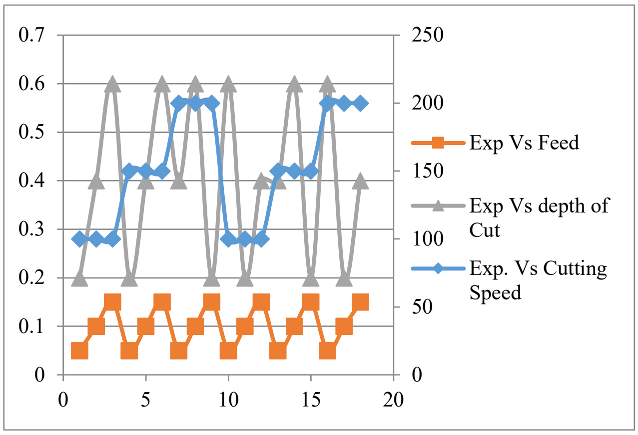

Figure 3. Variation of input parameters

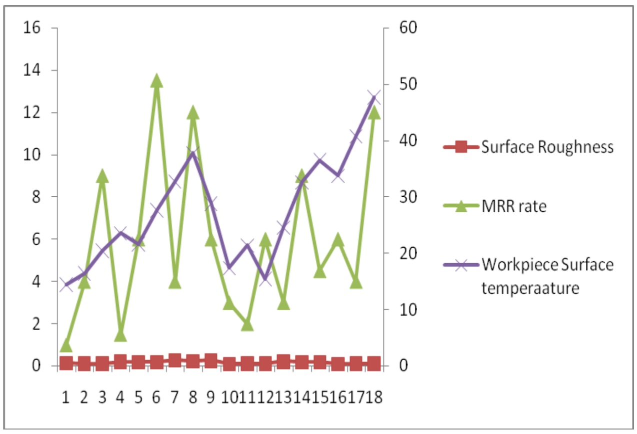

Figure 4. Variation of output parameters

5. CONCLUSION

The study highlights the critical importance of optimal input parameter selection during CNC turning operations, which not only extends the life of the cutting tool but also ensures the production of high-quality surfaces. This finding is significant within the broader field of manufacturing, emphasizing the necessity of precise control over machining parameters. In this study, the process parameters in the CNC turning process were optimized using the TOPSIS method. The researcher identified the best combination of turning parameters along with their levels to achieve the least surface roughness (Ra) value and a better Material Removal Rate (MRR). Based on the response noted from CCi values, the researcher found the optimum combination levels of input process parameters: cutting speed 200m/min, feed 0.15mm/rev, and depth of cut 0.6mm. The study employed the TOPSIS method due to its effectiveness in evaluating alternatives based on their closeness to an ideal solution, ensuring a robust selection process. The main research goal was to identify the optimal combination of CNC turning parameters to balance material removal rates and surface finish quality, and the findings directly address this goal, validating the research hypothesis. The practical implications are considerable; integrating these findings can enhance productivity and quality in CNC turning processes. For future research, exploring other optimization methods like the JAYA Algorithm and considering a wider range of materials and settings would be beneficial. While the results are specific to the materials and tooling used, they have the potential to be generalized to other turning operations. Industrial practitioners can integrate these optimized parameters into existing CNC turning processes to achieve significant improvements in productivity, quality, and competitiveness. By adopting these findings and pursuing continuous optimization and innovation, manufacturers can achieve superior results and maintain a competitive edge in the industry.

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