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Original Article

Multi-Objective Optimization (MOO) of Machining Process Factors by Hybrid Taguchi Grey Relational Analysis (HGRA)

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Abstract *- An effort to optimize machining processes, such as turning operations, is made in this work. The following are adjustable process parameters: Cutting Environment (CE), Feed Rate (FR), Depth Of Cut (DOC), Nose Radius (NR), and Type of Tool (TT). The parameters of the response are Surface Roughness (SR), Material Removal Rate (MRR), Cutting Force (CF), Tool tip Temperature (Temp) and Tool Wear (TW). For experiments, the L27 Taguchi (OA) Orthogonal Array is employed. The CNC Spinner lathe was used for the experiment. The most recent coolant system, MQL, is employed in today's manufacturing setting. Taguchi method and Grey Relational Analysis (TGRA) are utilized for data analysis. GRA processes several output parameters and combines them into a single response parameter. Lastly, the ideal process parameters are determined using the traditional Taguchi approach. The contribution and ranking of input parameters are determined using ANOVA and Signal-to-Noise Ratio (SRN) in order to maximize the number of output parameters. The conformance test is used to formulate the results' hypothesis. The conformance test findings showed that both the experimental and projected values are acceptable*.

Keywords *- Taguchi method, Turning process, Multi-optimization, Grey Relational Analysis.*

1. Introduction

Consumer demands regarding product quality and production volume are rising these days. For manufacturers to keep a commanding position in the market, they must promptly meet this need. Process streamlining will make this possible. Optimizing machining settings is a common step in the manufacturing process to boost productivity and improve product quality.

In addition to fundamental characteristics of the cutting process, such as FR, DOC, NR, CE, and TT, these variables significantly impact the quality qualities that perform well in the turning process. Optimization of machining operations is an imperative zone of research in production engineering, aiming to increase output, reduce costs, and improve the quality of final goods.

Numerous recent studies have examined multi-objective optimization techniques to determine the ideal operating parameters for various milling operations. The literature review presents methodologies and findings of five outstanding studies that applied Grey Relational Analysis, among other optimization tools, in the optimization of different machining processes.

In their assessment of monocrystalline silicon precision machining, Wang et al. (2025) put great concern on modeling and simulation tools like FEA and MD for cutting parameter optimization and surface integrity. Roy et al. (2025) explored other cooling-lubrication methods, highlighting the sustainability benefits and industrial challenges. Hussain et al. (2025) enhanced surface roughness and efficiency by optimizing GFRP composite turning parameters using TOPSIS. Collectively, these works enhance process optimization, sustainability, and machining accuracy. Nadikudi, 2024, utilized the strategy of Grey Relational Analysis and analyzed the parametric optimization of the turning operation for aluminum alloys. The performance variables underdetermination of the ideal setting in this work were SR, MRR, and TW. In this research, GRA had effectively combined several objectives into one composite performance index so that the turning process could be comprehensively and in-depth studied. Results indicated that GRA is a good tool for balancing goals to improve overall machining performance. Another landmark work by Zhujani et al. (2024) was carried out that was dedicated to the CNC turning of Inconel 718, with this material characterized by low machinability. The efforts of Taguchi's method, GRA and ANOVA, were combined with the intent to optimize many performance characteristics like SR, CF, and TW. These methods were combined to yield a solid optimization framework, and the machinability of the system was greatly enhanced and made more reliable. This work showed a nice example of using GRA and Taguchi together, especially for tough machining situations. Moi and Ranjan (2024) used the GRA for chip geometrical analysis and parametric optimization while spinning the AISI 202 stainless steel metal at high temperatures.

This research worked toward process parameter optimization intending to understand the effect of temperature on chip formation to improve machinability. GRA helped efficiently manage the multiple goals of surface finish and chip reduction coefficient. Research results also showed the importance of temperature control in the turning process and the efficiency of GRA in multi-objective optimization. Using the combination of Grey Relational-based Taguchi analysis, El-Deen (2024) conducted research on MOO in slot milling composites. Delamination and fiber pull-out represent two special issues usually attributed to CFRP composites; the current study targeted the elimination of these defects in addition to aims at achieving multi-objective optimization of machining effectiveness and surface finish.

The technique successfully eliminated the defects achieved with respect to multi-objective optimization of machining effectiveness and surface finish. The experiment results offered novel vital information regarding the efficient machining of composite materials. In the case of friction stir welding of A319 aluminum alloy, Marichamy and Chockalingam investigated the process parameters by means of a hybrid approach related to TOPSIS and GRA. Tensile strength and hardness were just two of the weld quality attributes this approach to multi-criteria decision-making sought to maximize. The study presented herein showed how applicable and effective it will be to combine TOPSIS with GRA in order to completely establish an approach to optimization and improvement of the mechanical properties of welded joints.

The author applied this hybrid methodology to predict tool wear in turning EN24 material using the Taguchi method with Artificial Neural Networks. The effectiveness of generating training data for the ANN models that can accurately predict tool wear is demonstrated with applying the Taguchi design of experiments. "The hybrid Taguchi-ANN research approach heightened the applicability of the findings by optimizing the turning parameters whilst deriving a predictive model for tool wear. In additional work, Alaba et al. (2023) examined the use of palm kernel oil in turning AISI 1039. The Taguchi-grey relational optimization theory is emphasized by increasing the surface smoothness, decreasing cutting pressures, and causing a downturn in tool wear". The results also established that AISI 1039 steel could be conveniently machined with palm kernel oil as a cutting fluid substitute that is more eco-friendly. It was feasible to simultaneously consider many performance parameters in a comprehensive optimization process using the incorporated Taguchi and GRA. Agebo et al. (2023) used a TGRA to probe the effects of misty and green cryogenic turning on steel. The research work has focused on optimizing a few selected reactions, such as TEM, TW and SR.

The cryogenic turning method, using liquid nitrogen for the cutting process, is proven to gain much improvement in machining efficiency and environmental sustainability. With the optimization of tagging-based GRA, it is possible to handle several objectives, hence resulting in the comprehensive optimization of the turning process. Sutisna and Nowoasto also worked on optimizing operation settings and cutting angles to improve the SR. The work aimed to find the best parameters set, which in combination could provide the highest possible surface finish using GRA with Taguchi.

It also identified the proper control of process parameters for excellent surface quality and depicted the application of GRA in difficult optimization settings.

There remain challenges regarding the generalization of Grey Relational Analysis (GRA), and Taguchi approaches to machining process optimization across a range of materials, complex multi-objective problems, and varying machining conditions, regardless of immense research in this field. Existing studies have no rigorous, dependable, and adaptive optimization framework and focus on specific materials and objectives. In addition, limited research on environmental sustainability in machining optimization remains. Our study aims to bridge these gaps through enhanced multi-objective optimisation methods and ensure greater sustainability, reliability, and applicability in machining processes. Developing a more advanced optimization approach will enhance machining productivity, reduce its adverse impact on the environment, and provide a more versatile industrial application method.

By bridging the gaps in existing research, the current study outlines a new and flexible optimization scheme for machining processes. While GRA, Taguchi methods, and hybrids like TOPSIS-GRA and Taguchi-ANN have been employed in previous studies, they are often only valid in specific materials and objectives. This study, however, generalizes approaches across different materials, enhancing generalizability. It has more parameters to enhance multi-objective optimization as a whole and ensure safe results under different conditions. In this work, machining sustainability—which is often overlooked—is applied to enhance eco-friendly processes. This research goes beyond existing methods by filling these gaps and enhancing machining efficiency, sustainability, and industrial usability.

This approach provides flexibility and reliability while promoting machining process optimization for modern production challenges.

2. Grey Relational Analysis (GRA)

First, the investigational information of the dependent variable is mapped within the 0–1 range before doing the grey relational analysis. It is known as the “generation of grey relational." Next, GR coefficients are generated after normalization in order to indicate the association between the anticipated and the real investigational data. Finally, the overall GR grade is computed by taking the mean of the GR coefficient of the output answers. A determined GR grade portrays the overall quality feature of a multi-objective procedure.

2.1. Grey Relational Coefficient (GRC)

To calculate the GRC, utilize the formula below.

$$\gamma_i = \frac{\Delta\, min + \varsigma \Delta max}{\Delta_{oi}(k) + \varsigma \Delta max} \qquad (1)$$

2.2. GR Grade (GRG)

The GRCs related to the individual trial are aggregated to decide the GRD. The GRD helps as the basis for various enactment quality's whole response. This permits the conversion of optimization of complex multiple-objective features addicted to optimization of a solo GR grade. One might achieve the GR grade as

$$\alpha_i = \frac{1}{n} \sum_{k=1}^{n} Y_i\,(k) \qquad (2)$$

3. Methodology

As shown in Figure 1, the real experiment was carried out on a CNC lathe. Cutting test parts of 50 millimeter by 80 millimeter was made. This work had five independent factors: CE, FR, NR, DOC, and TT. A CNC Spinner lathe, a high-precision machine often employed in turning operations for industrial machining, was employed in the experimental investigation. To provide precise and reproducible machining performance, the CNC Spinner lathe utilized in this research has a solid structure that maintains low vibration while in operation. The high-precision linear guides and variable spindle speed control system of the lathe allow precise regulation of the Feed Rate (FR), Depth of Cut (DOC), and Nose Radius (NR). The lubrication and cooling method was a Minimum Quantity Lubrication (MQL) system. By injecting a small mist of lubrication mixed with compressed air directly into the cutting area, the MQL technology significantly reduces heat production and friction. This setup enhances tool life and surface finish by minimizing coolant usage and ensuring effective lubrication. The MQL system parameters—flow rate, pressure, and nozzle location—were optimized to provide consistent cooling under different machining conditions.

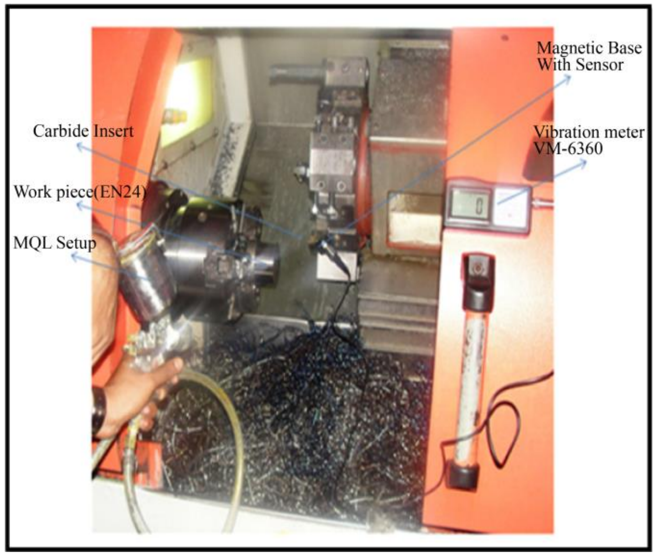

Fig. 1 Experimental setup

Cutting Environment (CE), Feed Rate (FR), Depth Of Cut (DOC), Nose Radius (NR), and Tool Type (TT) were varied systematically in the study with the help of an L27 Taguchi Orthogonal Array (OA). Surface Roughness (SR), material removal rate (MRR), Cutting Force (CF), tool tip temperature (Temp), and Tool Wear (TW) are some of the responses monitored.

High-accuracy equipment, such as a contact-type surface roughness tester, cutting force dynamometer, and infrared thermometer for tool temperature monitoring, was employed to ensure precise data collection.

This comprehensive setup validates the effectiveness of the Hybrid Taguchi Grey Relational Analysis (HGRA) approach for multi-objective optimization by ensuring precise evaluation of machining performance under different conditions.

Table 1. Factors and levels

Process Parameters	Level 1	Level 2	Level 3
CE	1	2	3
NR (mm)	1	2	3
FR (m/rev)	1	2	3
DOC (mm)	1	2	3
TT	1	2	3
Spindle vibration (m/s^2)	1.7	4.3	6.9

The analysis of GRA data is done as indicated below.

1. The L27 OA states that trials are conceded out and outcomes are dignified. Then, the respective response's S/N is computed (Table 2).
2. First, experimental data were normalized (Table 3), a process called "grey relational generation."

3. Calculating the gray relational coefficients and assessing Δ0i (K) for each response in every experimental run (Table 4).
4. The overall average GR grade is calculated. This represents MPCI_GRA.
5. The Taguchi idea has been implemented to boost the MPCI_GRA (Table 4). After analyzing the main effect graph (Figure 2), the anticipated greatest combination was strongly considered $A_3B_3C_3D_1E_3$.
6. A confirmatory test has confirmed the optimal configuration.

Table 2. S/N ratio of SR, MRR, CF, TEMP and TW

SR	MRR	CF	TEMP	TW
-18.3834	11.1542	-52.3805	-32.9020	16.5912
-15.8636	19.9882	-52.6923	-33.3713	19.7259
-13.7044	21.9188	-55.5364	-33.5137	16.2009
-16.9452	18.2117	-51.9243	-32.8795	18.3176
-14.2887	20.0430	-55.1365	-34.1024	15.5590
-9.9410	14.9812	-52.3325	-33.0580	22.9192
-14.1991	18.3614	-54.5012	-33.7747	15.2281
-11.6875	12.4501	-51.5305	-32.9613	24.2507
-6.9513	20.6060	-52.1626	-34.5106	22.1032
-17.0969	10.7866	-52.3054	-32.3119	15.4207
-14.9780	19.5924	-52.7029	-32.8785	18.1235
-12.1633	21.4740	-55.7018	-33.2122	15.1231
-14.7814	17.8727	-52.0006	-32.4261	16.9645
-12.6739	19.6681	-55.2970	-33.6077	14.5329
-7.8905	14.5231	-52.4415	-32.5644	20.6475
-13.3826	18.0378	-54.7439	-33.3087	14.2181
-9.8784	12.0711	-51.7168	-32.2014	21.7015
-3.8945	20.2009	-52.3148	-34.0231	20.0913
-15.4989	10.4699	-52.3497	-32.2428	17.3603
-13.1956	19.2538	-52.6964	-32.5787	20.8517
-10.6198	21.0942	-55.6033	-33.0033	16.9347
-14.6686	17.5815	-51.9556	-32.3383	19.2653
-11.7326	19.3467	-55.2002	-33.5104	16.2385
-5.2012	14.1326	-52.3761	-32.2772	24.5961
-12.6813	17.7594	-54.6001	-33.0803	15.8569
-9.2782	11.7453	-51.6049	-32.1543	26.1409
-0.2554	19.8536	-52.2235	-33.9879	23.6159

Table 3. Grey relational generation

SR	MRR	CF	TEMP	TW
1.00	0.94	0.20	0.32	0.80
0.86	0.17	0.28	0.52	0.54
0.74	0.00	0.96	0.58	0.83
0.92	0.32	0.09	0.31	0.66
0.77	0.16	0.86	0.83	0.89
0.53	0.61	0.19	0.38	0.27
0.77	0.31	0.71	0.69	0.92
0.63	0.83	0.00	0.34	0.16
0.37	0.11	0.15	1.00	0.34
0.93	0.97	0.19	0.07	0.90
0.81	0.20	0.28	0.31	0.67
0.66	0.04	1.00	0.45	0.92
0.80	0.35	0.11	0.12	0.77
0.69	0.20	0.90	0.62	0.97
0.42	0.65	0.22	0.17	0.46
0.72	0.34	0.77	0.49	1.00
0.53	0.86	0.04	0.02	0.37
0.20	0.15	0.19	0.79	0.51
0.84	1.00	0.20	0.04	0.74
0.71	0.23	0.28	0.18	0.44
0.57	0.07	0.98	0.36	0.77
0.80	0.38	0.10	0.08	0.58
0.63	0.22	0.88	0.58	0.83
0.27	0.68	0.20	0.05	0.13
0.69	0.36	0.74	0.39	0.86
0.50	0.89	0.02	0.00	0.00
0.00	0.18	0.17	0.78	0.21

Table 4. GRA coefficients and grades with S/N ratio

SR	MR	CF	TEM	TW	GRAD	S/N
0.14	0.15	0.45	0.345	0.17	0.252	-
0.16	0.49	0.37	0.244	0.23	0.303	-
0.18	1.00	0.14	0.224	0.16	0.345	-
0.15	0.34	0.63	0.352	0.20	0.337	-
0.17	0.50	0.16	0.168	0.15	0.234	-
0.23	0.21	0.46	0.303	0.38	0.321	-
0.17	0.35	0.19	0.195	0.15	0.214	-
0.20	0.16	1.00	0.328	0.51	0.444	-
0.31	0.59	0.52	0.143	0.33	0.380	-
0.15	0.14	0.47	0.714	0.15	0.329	-
0.17	0.45	0.37	0.352	0.19	0.309	-
0.20	0.81	0.14	0.271	0.15	0.316	-
0.17	0.32	0.59	0.591	0.17	0.372	-
0.19	0.45	0.15	0.213	0.14	0.234	-
0.28	0.20	0.43	0.490	0.26	0.336	-
0.18	0.33	0.17	0.254	0.14	0.219	-
0.23	0.16	0.78	0.893	0.31	0.479	-

0.45	0.52	0.47	0.174	0.24	0.375	-
0.16	0.14	0.46	0.816	0.18	0.354	-
0.19	0.41	0.37	0.481	0.27	0.347	-
0.22	0.69	0.14	0.317	0.17	0.313	-
0.17	0.30	0.62	0.681	0.22	0.401	-
0.20	0.42	0.16	0.225	0.16	0.237	-
0.38	0.19	0.45	0.762	0.56	0.471	-
0.19	0.31	0.18	0.298	0.16	0.231	-
0.25	0.15	0.90	1.000	1.00	0.663	-
1.00	0.48	0.50	0.177	0.44	0.520	-

The S/N ratios of individual levels are averaged. Based on this, the ideal level and every parameter rank are found. Rank decides the parameter that works best for MPCI_GRA. It is shown in Figure 2. The highest S/N ratio for the Cutting environment, as shown in Figure 2, is -8.58 for the third level. This shows the ideal level for the CE. Similarly, the maximum S/N ratios for NR, DOC, FR, and TT are B3, C3, D1, and E3, respectively.

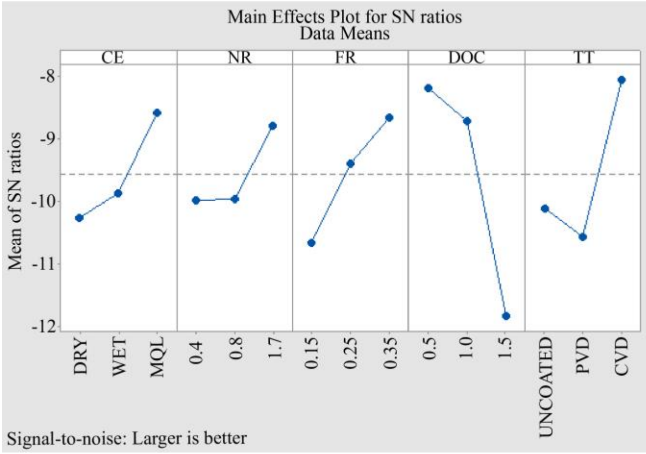

Fig. 2 Main effect graph

Table 5. ANOVA

Source	DF	Seq SS	Adj SS	Adj MS	F	P
CE	2	13.765	13.765	6.8824	8.93	0.002
NR	2	8.55	8.55	4.2752	5.55	0.015
FR	2	18.628	18.628	9.3138	12.09	0.001
DOC	2	69.922	69.922	34.961	45.39	0.000
TOOL TYPE	2	32.449	32.449	16.2243	21.06	0.000
Residual Error	16	12.325	12.325	0.7703		
Total	26	155.638				

Table 6. Comparative effectiveness in machining process optimization

Criterion	Taguchi Method	Grey Relational Analysis (GRA)
Optimization Type	Single-objective	Multi-objective
Experimental Efficiency	High (Uses OA)	Moderate (Normalization Required)
Parameter Interaction	Limited	Captures Non-Linear Effects
Robustness	High	High
Ease of Implementation	Simple	Moderate
Computational Complexity	Low	High
Application in MOO	Limited	Highly Effective

The impact of input factors on a response variable is analyzed in the ANOVA table. F-statistic (F), which quantifies factor influence, Mean Square (MS), which is a measure of variance, and Sum of Squares (SS), which is a measure of variation, are important measures. A statistically significant effect is identified with a p-value less than 0.05. Depth of Cut (DOC) ($p = 0.000$, $F = 45.39$) is the one with the most impact on the results, followed by Feed Rate (FR) and Tool Type. The capability of the model to analyze machining parameters is confirmed by the fact that all of the factors significantly influence the response and that residual error explains variation that cannot be explained.

4. Comparative analysis of Taguchi and Grey Relational Analysis

Grey Relational Analysis (GRA) and the Taguchi method are two popular engineering optimization methods, particularly for welding and machining process parameter optimization. By utilizing orthogonal arrays and Signal-to-Noise (S/N) ratios to identify optimal parameters, the Taguchi method, founded on the Design of Experiments (DOE), seeks to minimize variability and enhance quality. It is very effective for robust design and single-response optimization problems. However, its inability to effectively solve multi-response optimization is its greatest weakness.

GRA, however, is a powerful multi-criteria decision-making tool that compares the grey relational grades of process parameters to rank them. When the parameter relationship is missing or uncertain, it is very useful.

5. Results and Discussion

The findings of the MPCI ANOVA, supposedly a performance index, suggest that among all machining parameters, depth of cut significantly impacts the highest number of performance characteristics. The CE, NR, FR, and TT come afterwards, in order of importance, after the depth of cut. The optimum set of machining parameters is: Level 3 cutting environment, A3 = MQL presumably for Minimum Quantity Lubrication; level 3 nose radius. The best combination is represented by the acronym A3B3C3D1E3. The acronym thus refers to the levels of each parameter that the analysis considers optimal.

Strengthened Discussion on ANOVA Results: - Depth of Cut (DOC) has the greatest effect on the optimization process, as its highest F-value (45.39), as shown in ANOVA results indicates, and its P-value is 0.000. Because it directly affects material removal rate, cutting forces, and heat conditions, all of which influence tool wear, surface roughness, and machining efficiency as a whole, this kind of great influence is expected. Increased DOC is a controlling parameter in optimization since it will create more cutting forces, which will cause increased tool wear and heat generation. Because cutting tools of mixed hardness, coating, and geometry affect machine force and temperature resistance, tool geometry also plays a significant role (P=0.000, F=21.06, P=0.000).

Feed Rate (FR), which also affects tool wear and surface integrity, is significant (F=12.09, P=0.001). Higher feed rates cause greater material removal, but machining stability will be affected by increased cutting forces and vibration. Cutting Environment (CE) (F=8.93, P=0.002 F=8.93, P=0.002) and Nose Radius (NR) (F=5.55, P=0.015 F=5.55, P=0.015) are statistically significant but exert lesser impacts than DOC. CE, i.e., dry machining compared to machining with lubricant, has impacts on-chip cooling and chip removal and may decrease the tool wear but perhaps lacks as much direct impact on machining efficiency as the situation for DOC. Similarly, NR impacts tool life and surface roughness but is, to some extent, affected by parameters that consist of DOC and FR.

Interaction Insights: Additional research on the interactions between such parameters would be feasible. For instance, the proper tool type and greater DOC will enhance productivity and continue to maintain tool life. Similarly, surface finish can be optimized through interaction between feed rate and nose radius, where a larger nose radius can offset rough finishes at higher feeds. Interactions between the cutting environment and the tool type are also of utmost importance; for certain tool materials, using coolant will be more effective, reducing wear and increasing tool life. In short, Tool Type and FR are significant parameters in machining surface smoothness and stability, but DOC prevails as it directly impacts cutting forces and material removal. Formulating an optimum machining plan balancing product quality, tool life, and productivity can be facilitated with these relationships.

6. Conclusion

The Taguchi approach has been effectively applied to identify the ideal parameters in this work. Outcomes and conclusions are expounded upon in the ensuing points:

- Utilization of Taguchi and Grey Relational Analysis in a MOO Problem: In this work, a fusion of Taguchi Analysis with GRA is employed to elucidate a MOO problem. This technique can simultaneously optimise numerous performance criteria by incorporating them into a single Grey Relational Grade. This approach is very effective, especially in cases with complex engineering challenges and when more quality criteria must be optimized simultaneously.
- Optimised Qualitative Features: Several vital quality characteristics were effectively optimized in the study for the turning process. Surface roughness: optimum value 0.958 μm Material Removal Rate: it describes effective removal of material and has been optimized to a value of 5.13 mm^3/Sec Cutting force: optimised to a value of 393.877 N, which influences the workpiece quality and tool wear. Temperature, or temp: The temperature reached a very good value of 58.966°C, something very critical to control the dissimilar effects of heat on the tool and workpiece. Tool wear reduced to 0.0401 mm is very important for maintaining machining accuracy and the tool's life.

These ideal values are called A3B3C3D1E3, representing the specific values for each factor.

6.1. Implications for Future Research and Industrial Applications

The research findings offer new and significant information about machining parameters optimization towards improved efficiency and effectiveness. Future work must explore complex adaptive control systems in machining processes where real-time monitoring and AI-based optimization can adaptively adjust these parameters towards increased productivity with the key influence of Depth of Cut (DOC), Tool Type, and Feed Rate (FR). Additionally, machining processes could be further optimized by exploring the synergistic impact of parameter interaction through machine learning models and multi-objective optimization.

These results indicate the need to achieve optimal cutting conditions from the industrial point of view that minimizes tool wear, improves the surface finish, and improves the material removal rate. Industries can utilize sensor-based condition monitoring and predictive analytics in smart manufacturing and CNC environments to achieve stable and high-quality machined products. To optimize the tool life and maintain the machining operations, there could be opportunities in future studies to address the effect of the coolant strategy, tool coating, and hybrid machining strategies.

6.2. Limitations and Future Work

While providing useful information through this research, some limitations must be mentioned. One of the major limitations is the sample size, which could restrict the generalizability of the results. Expanding the data set with a range of machining settings and material types would increase the statistical strength of the results. The research did not consider other important variables such as spindle speed, coolant approach, or tool coatings to its full potential because it focused mainly on three machining parameters: feed rate, depth of cut, and tool type. These parameters must be taken into account in future research to determine the interaction between them and the impact on the machining performance. One of the limitations is the absence of adaptive control systems and on-line monitoring in the test phase.

There is scope for future studies to improve precision and responsiveness in selecting machining parameters with sensor-based information acquisition and AI-based optimization. The results can be made more applicable to practical industrial problems if the studies are taken to multi-objective optimization methods, which can allow improved insight into productivity versus surface finish and tool life compromises.

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