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Optimization of Vertical Machining Parameters of DIN 1.0038 Steels Using Hybrid Taguchi Based Grey-Fuzzy Algorithm in CNC Pocket Milling Process

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ABSTRACT

In CNC pocket milling, surface quality, material removal rate and production time are critical parameters. However, setting the optimum parameters related to the process is problematic due to the presence of many factors. In this study, a hybrid grey-based fuzzy algorithm with a Taguchi L16 orthogonal array experimental design was used to determine the optimum results by combining factors such as cutting speed, feed rate, cutting depth and cutting path strategy. The optimum results were found as 0.36 µm surface roughness, 10 s machining time and 120 mm³/min material removal rate. These results were achieved by using 1500 rpm cutting speed, 2.0 mm/rev feed rate, 1.25 mm cutting depth and zigzag cutting path strategy. In the analysis made using the Analysis of Variance (ANOVA), it was concluded that the process was affected by feed rate, cutting depth, cutting speed and cutting path strategy, respectively.

CNC Cep Frezeleme Prosesinde Hibrit Taguchi Tabanlı Gri-Bulanık Algoritma Kullanılarak DIN 1.0038 Çeliklerinin Dikey İşleme Parametrelerinin Optimizasyonu

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Sorumlu Yazar

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Anahtar Kelimeler

CNC işleme
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ÖZ

CNC cep frezelemede, yüzey kalitesi, talaş kaldırma oranı ve üretim süresi kritik parametrelerdir. Ancak prosese ilişkin optimum parametrelerin ayarlanması, çok sayıda faktörün bir arada bulunması nedeniyle sorun teşkil etmektedir. Bu çalışmada; kesme hızı, ilerleme oranı, kesme derinliği ve kesme yolu stratejisi gibi faktörler birleştirilerek optimum sonuçları belirlemek için bir Taguchi L16 ortogonal dizi deneysel tasarımına sahip hibrit gri tabanlı bulanık algoritma kullanılmıştır. Optimum sonuçlar 0,36 µm yüzey pürüzlülüğü, 10 sn işleme süresi ve 120 mm³/dk talaş kaldırma oranı şeklinde bulunmuştur. Bu sonuçlara 1500 rpm kesme hızı, 2,0 mm/dev ilerleme oranı, 1,25 mm kesme derinliği ve zikzak kesme yolu stratejisi kullanılarak ulaşılmıştır. Varyans Analizi (ANOVA) yöntemi kullanılarak yapılan analizlerde prosesin sırasıyla ilerleme oranı, kesme derinliği, kesme hızı ve kesme yolu stratejisinden etkilendiği sonucuna ulaşılmıştır.

1. INTRODUCTION

CNC milling is often regarded as a highly favored process in the field of industrial applications. However, improper selection of cutting settings may result in issues such as diminished surface quality and reduced production speed. Given the capabilities of CNC milling machines, it is essential to ensure a superior surface finish in CNC milling operations. The assessment of the manufactured components' quality is contingent upon the presence of form defects and the efficacy of surface finishing procedures used throughout the milling processes [1,2]. Surface quality considerations during milling processes are a critical requirement that must not be disregarded. Additionally, it has a substantial influence on several characteristics, including the product's resistance to wear, ductility, and fatigue resistance in the final fabrication of components. Material resistance to friction, temperature, corrosion, and stress is substantially influenced by the surface properties of machined components [1,3-7].

Advancements in industries such as automotive, aviation, and die manufacturing have heightened the need for goods with improved specifications. To enhance their competitiveness within their respective sectors, manufacturers need to simultaneously improve surface quality, reduce manufacturing time, increase production rates and efficiency [4,5,8-10]. Numerous studies indicate that the control of surface roughness of the manufactured workpiece is a crucial aspect that directly influences the overall quality. The fatigue life of manufactured components is diminished because of substantial surface roughness [4,5,10-12]. Manufacturing time and material removal rate (MRR) are additional parameter outputs that should be considered in addition to surface roughness. The rapidness and efficiency of the process are affected by these parameters. Manufacturers have an incentive to get top-notch products at the lowest possible cost for a certain production method [13].

The task of determining the optimal settings in milling processes is multifaceted and determined by a variety of variables, such as the cutting parameters, workpiece material, and the properties of the cutting tool. [4,5,14]. While the workpiece material characteristics and the properties of the cutting tool are significant, cutting parameters exert a predominant influence, encompassing numerous sub-parameters that directly impact the overall cutting quality in the milling process. These include the conditions during cutting (wet or dry), cutting fluid, machine vibrations, feed rate, depth of cut, cutting speed, and cutting path strategy. Among these cutting parameters, cutting depth, cutting path strategy, feed rate and speed of cutting have the most dominant effects on the roughness of the workpiece surface [3,4,15]. Therefore, choosing the cutting parameters to optimize cutting performance, reduce energy and time consumption, and implement the milling process to achieve the highest possible surface quality is a necessity [16]. General approaches to selecting accurate cutting parameters are usually determined through practical experience or by referencing catalogs or handbooks [17]. Conversely, when optimization approaches are necessary, mathematical models using neural computing and statistical regression analysis are often applied to delineate the link between performance and machining parameters [18]. Achieving the optimal parameters then requires the formulation of a constrained objective function utilizing optimization techniques. In addition, an adequate number of cutting experiments must be conducted to construct mathematical models precisely. As a result, the process of constructing the necessary model requires significant expenses in terms of both labor and resources.

The Taguchi method is a systematic approach used across multiple processes to enhance performance, efficiency, quality, and cost-effectiveness of experimental designs by reducing the number of necessary runs while applying a simple but efficient methodology [19,20]. The Taguchi method has been extensively employed in numerous applications [18,21].

A comprehensive examination of the relevant literature indicates that several studies have been conducted to examine the cutting parameters in CNC milling. These studies have used many cutting settings, materials, and cutting instruments, as well as experimental and optimization methodologies. Mantle et al. [22] performed a study using a Taguchi orthogonal array to assess the surface properties created by the end milling tool. Benardos and Vosniakos [23] employed the Taguchi experimental design approach to estimate the roughness of workpieces through CNC face milling. Ertekin et al. [24] put forward the prevalent and useful sensory characteristics to measure roughness of the surface and dimensional accurateness during CNC milling.

Paris et al. examined the effect of vibration during the process of cutting on the surface roughness of the manufactured components. [25]. Franco et al. [26] proposed a model to approximate a surface's textural characteristic and roughness during the process of surface milling utilizing round-tipped cutting tools. Ozcelik and Bayramoglu [15] put forth a model of statistics in order estimate the surface roughness occurrence under wet cutting conditions in high-speed end milling. The researchers used several values of feed rate, cut depth, spindle speed and step over. The determination of optimal conditions of cutting DIN 1.2738 die steel was determined by a series of studies conducted by Gologlu and Sakarya. [7] utilizing end mills made of high-speed steel. Shamsuddin et al. [27] utilized visual charts for comparing diverse machining strategies to identify more effective cutting path strategies for end milling process of aluminum alloy components with thin walls. Using three distinct materials, Ali et al. [28] examined the various cutting tool path strategies on face milling through the implementation of optimization studies utilizing Taguchi grey relational analysis. In addition, they noted that the strategy for the tool path has a substantial effect on face milling. Allocating population-based meta-heuristic learning to an adaptive neuro-fuzzy inference system (ANFIS) and interval type 2 neuro-fuzzy network, Asadi et al. [29] assessed the average level of surface roughness and the cutting force that was created in surface milling process of aluminum alloys.

The process parameters that impact rapidness directly influence the total time of the manufacturing, and the generation of roughness generated during the CNC milling of the insole rubber foam used in the soles of the shoes worn by diabetic patients were optimized by Bawono et al. [30] using Taguchi's method. The Taguchi method was used by Daniel et al. [31] to examine the impact of individual control factors on response variables during the milling process of Al5059/SiC/MoS_2 material. In the study conducted by Kar et al. [17] a fuzzy-based desirability function was used to optimize several responses in the context of CNC milling of the Inconel 718 alloy. These responses included the MRR, the generated axial force, and the surface roughness obtained. Machinability of austenitic stainless steel AISI 316 under dry circumstances was studied by Mashinini et al. [32] using the Taguchi and grey entropy methods to examine the impacts of cut depth and speed along with feed rate.

The literature study indicates that there are studies investigating the parameters of the CNC milling process using various experimental and computational methodologies. However, there is a scarcity of research employing grey fuzzy algorithm and Taguchi method in CNC pocket milling process. This work aims to integrate the grey fuzzy algorithm with the Taguchi method in the CNC pocket milling process to identify the most critical parameters and address a gap in the existing literature.

For this purpose, the study employed the Taguchi L16 orthogonal array to design experiments for the CNC pocket milling of DIN 1.0038 medium carbon steel. The experimental design was constructed by taking into account the following control factors: depth of cut (d, mm), feed rate (f, mm / rev), cutting speed (V, rpm), and cutting path strategy (p). Then, grey-based fuzzy algorithm combined with Taguchi experimental design was employed to acquire optimal vertical CNC pocket milling parameters for minimum surface roughness (R_a, µm), lowest machining time (t, s), and highest material removal rate (MRR, mm^3/min). Subsequently, the study performed analysis of variance (ANOVA) and confirmation tests in the final phase to evaluate the most significant cutting values, validate the findings, and compare the optimal results with the expected outcomes.

2. EXPERIMENTAL PROCEDURE AND ANALYTICAL METHOD

2.1. Material and Equipment

The workpiece material was a 180x320x20 mm piece of DIN 1.0038 medium carbon steel plate. Table 1 shows the workpiece's mechanical properties and chemical content (wt.%). Figure 1 illustrates the C-TEK brand CNC vertical machining center that was employed to conduct pocket milling experiments in accordance with the selected parameters. The cutting path strategy is an essential parameter in the manufacture of workpieces that meet specified tolerances and surface quality. As illustrated in Figure 2, two distinct cutting path strategies—zigzag and spiral—were chosen and simulated by the MASTERCAM software. After verifying the simulation results, the experimental phase was accomplished in accordance with the selected parameters.

A surface roughness analyzer (Phynix TR-100) was employed to calculate six surface roughness measurements. Then, the average of these six values was calculated.

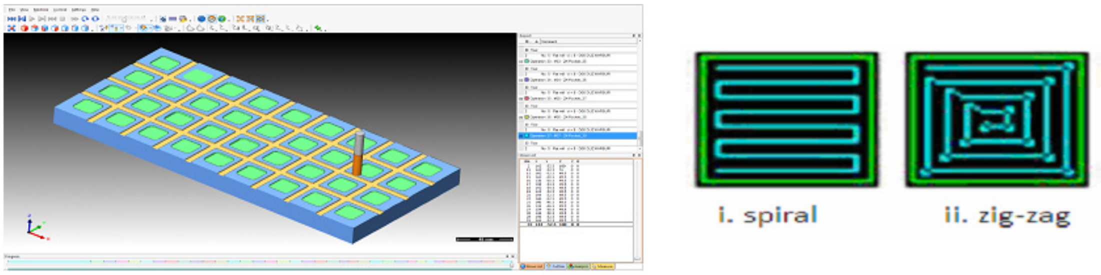
Table 1. Chemical composition (wt.%) and mechanical properties of DIN 1.0038 medium carbon steel

Chemical composition (wt. %)	**C**	**P**	**S**	**Mn**	**Cr**	**Al**	**Si**	**N**
	0.17	0.03	0.04	0.50	0.11	-	0.20	0.008

Mechanical properties	**Yield strength (Mpa)**	**Tensile strength (Mpa)**	**Elongation (%)**	**Vickers hardness (HV)**
	230	450	26	261

(a) (b)

Figure 1. (a) CNC vertical machining set-up used for experiments, (b) process of pocket milling



(a) (b)

Figure 2. Simulation images taken from MASTERCAM software, (b) employed cutting path strategies

2.2. Experimental Details and Process Parameters

The essential benefit of Taguchi experimental design is its ability to facilitate the design and execution of necessary experiments with minimal trial requirements [33]. This lowers the quantity of trials, their expenses, and the duration needed. The machining parameters for the CNC pocket milling process were organized using the four level L16 orthogonal design matrix, which comprised 16 sets of coded experimental data. Table 2 presented the input parameters and their respective levels.

Table 2. The variables used in CNC milling and their respective levels

Parameters	**Notation**	**Unit**	**Levels of factors**			
			1	**2**	**3**	**4**
Cutting speed	V	rpm	1000*	1500	2000	2500
Feed rate	f	mm/rev	0.5*	1.0	1.5	2.0
Depth of cut	d	mm	0.5*	0.75	1.0	1.25
Cutting path strategy	p	-	zig-zag*	spiral	-	-

*Initial settings for CNC pocket milling

The formula provided in Equation 1 was employed to calculate the material removal rate [34]:

$$MRR = \frac{f * d_{tool} * V * d * n}{1000} \tag{1}$$

where f: feed rate (mm/rev), d_{tool}: diameter of tool (mm), V: cutting speed (rpm), d: depth of cut (mm), n: flute number.

During the experiments an 8 mm High Speed Steel (HSS) end mill tool with four flutes was employed. To avert tool dullness resulting from elevated temperatures cutting tool was replaced after two successive rounds of each experiment. Compressed air was applied to cool the tool and to remove chips from the pocket milled area. The specified experimental conditions and experimental outcomes for MRR, t, and R_a responses were given in Table 3.

Table 3. Experimental conditions and results

Run no	Process parameters				Experimental results		
	V	f	d	p	R_a (μm)	t (s)	MRR (mm^3/min)
1	1	1	1	1	1.48	16	8
2	1	2	2	1	0.34	11	24
3	1	3	3	2	0.56	9	48
4	1	4	4	2	0.22	9	80
5	2	1	2	2	0.22	16	18
6	2	2	1	2	0.25	11	24
7	2	3	4	1	0.25	9	90
8	2	4	3	1	0.23	10	96
9	3	1	3	1	0.34	15	32
10	3	2	4	1	0.18	11	80
11	3	3	1	2	0.53	10	48
12	3	4	2	2	0.41	9	96
13	4	1	4	2	0.46	17	50
14	4	2	3	2	0.46	11	80
15	4	3	2	1	0.27	10	90
16	4	4	1	1	0.30	9	80

2.3. Grey-Based Fuzzy Method

2.3.1. Grey Relational Analysis

The Grey method theory, initially proposed by Chinese professor Julong Deng in 1989, posits a framework wherein a portion of knowledge remains unclear while the majority is known. In other words, the amount of detail between black and white is implied by the grey method. Although there is no data in the black region, the white region has all the information. One of the subtitles for grey modeling is Grey Relationship Analysis (GRA). Compared to the reference series, each factor in the method defines the degree of interaction between the factors [33].

The first step in this method is called normalization, which considers the translation of measured values from different units. In accordance with the parameters, experimental data is normalized from zero and one. Grey relation method utilizes three types of normalization criterions as follows: 1. Larger the better, 2. Smaller the better, 3. Ideal the better.

The current study demonstrated that the normalized responses of machining time and surface imperfection both adhered to the criterion of "smaller the better," as defined in Equation 2 as [33]:

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

Larger the better which was used for normalization calculation of material removal rate could be expressed in Equation 3 as:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{3}$$

Equation 4 was used to normalize the series where the aim value of the data sequence was "ideal the better":

$$x_i^*(k) = 1 - \frac{|x_i^0(k) - x_i^0|}{\max x_i^0(k) - x_i^0} \tag{4}$$

The grey relational coefficient (GRC) is calculated following the normalization phase to ascertain the relationship between the best and real normalized values. Equation 5 determines the Grey relational coefficient (GRC) as [33]:

$$\xi(x_0^{*}(k),\ x_i^{*}(k)) = \frac{\Delta_{\min} - \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \qquad 0 < \xi(x_0^{*}(k), x_i^{*}(k)) \leq 1 \tag{5}$$

The grey relational grade (GRG) quantifies the degree to which the reference and comparability sequences of each factor level are similar. After taking the average of Grey relational coefficients, the Grey relational grade (GRG) $\Gamma(x_0^{*}, x_i^{*})$ for each CNC pocket milling response can be calculated by using Equation 6 as [33]:

$$\Gamma(x_0^{*}, x_i^{*}) = \frac{1}{n}\sum_{k=1}^{n} \xi(x_0^{*}(k), x_i^{*}(k)) \tag{6}$$

In these equations, $x_i(k)$ denotes the actual value of the k-th response in experiment i, while $x_i^{*}(k)$represents the normalized value. x_0 is the ideal target value used in the "ideal-the-better" criterion. The deviation term $\Delta_i(k) = | x_0^{*}(k) - x_i^{*}(k) |$, and $\Delta_{\min}$ and $\Delta_{\max}$ denote the minimum and maximum deviation values observed among the experimental runs. The distinguishing coefficient ψ, used to control the closeness of the relational comparison, was assigned a constant value of 0.333 in this study. The parameter $n$represents the number of responses considered (R_a, t, and MRR). A higher GRG value indicates that the related experiment is closer to the optimal combination of machining parameters [35].

2.4. Fuzzy Inference System (FIS) Modeling

The utilization of normalization techniques based on response characteristic performance attributes, such as nominal-the-better, lower-the-better, and higher-the-better in GRA, indicates that the obtained results are subject to some degree of uncertainty. However, this uncertainty can be readily surmounted using fuzzy logic in modeling [36,37]. The grey-fuzzy method was initially developed and implemented by Lin [38]. Fuzzy principles are utilized in replacement of the conventional grey relational grade calculation for grey relational analysis. Two methodologies were utilized to assess the efficacy of the GRG estimation output. The first is the standard GRG function, and the second is the fuzzy inference system (FIS) [37]. To model the CNC milling process in this study, a fuzzy logic system with four inputs and one output was implemented. This system comprised a defuzzifier, inference engine, membership function, fuzzy rules and fuzzifier, as depicted in Figure 3.

As the first step, the membership function is used by the fuzzifier to fuzzify inputs obtained prior to GRG calculations of the responses X_1: GRC for R_a, X_2: GRC for t, X_3: GRC for MRR, and X_4: GRG).

The used membership functions determine how the calculated three GRC inputs (X_1, X_2, X_3 and X_4) and output (Y_0= grey fuzzy reasoning grade, GFRG) values are formed to a value that is between 0 and 1 [37]. In the subsequent phase of the computation, sixteen fuzzy rules for three inputs and one output were established using Equation 7, derived from the results of the inference tests.

Rule 1: if R_a is A_1; t is B_1;and MRR is C_1 then Y_0 is D_1; else

Rule 2: if R_a is A_2; t is B_2;and MRR is C_2 then Y_0 is D_2; else (7)

•
•
•

Rule n: if R_a is A_n; t is B_n;and MRR is C_n then Y_0 is D_n; else

A_i, B_i, C_i and D_i are the fuzzy subgroups specified by the related membership functions (low, medium, high etc.) such as μA_i, μB_i, μC_i and μD_i. The fuzzy reasoning process is carried out by the inference engine, which utilizes max-min inference, as described in Equation 8, on the selected fuzzy rules in order to get a fuzzified value [37].

$$\mu_{C_0}(Y_0) = \left(\mu_{A_1}(R_a) \wedge \mu_{B_1}(t) \wedge \mu_{C_1}(MRR) \wedge \mu_{D_1}(Y_0)\right) \ldots. \\ \mu_{A_n}(R_a) \wedge \mu_{B_n}(t) \wedge \mu_{C_n}(MRR) \wedge \mu_{D_n}(Y_0)) \tag{8}$$

where ∧ and ∨ is the minimum and maximum operations respectively. Finally, the centroid defuzzification method as presented in Equation 9, was used to transform the fuzzified values to obtain GFRG [37];

$$Y_0 = \frac{\sum Y \mu_{C_0}(Y)}{\sum \mu_{C_0}(Y)} \tag{9}$$

After the fuzzified output value (GFRG) is obtained using the centroid defuzzification method in Equation 9, the next step is to estimate how much improvement can be expected when the optimal machining parameters are applied. To achieve this, the Taguchi confirmation equation was used which was given in Equation 10 as [33];

$$\hat{\gamma} = \gamma_a + \sum_{i=1}^{p}(\bar{\gamma}_o - \bar{\gamma}_a) \tag{10}$$

where γ_a is the total average GFRG, $\bar{\gamma}_o$ is the average GFRG at the optimal level, and p is the design parameter number.

The flowchart of the hybrid Taguchi based grey-fuzzy inference system adopted for this work was illustrated in Figure 4.

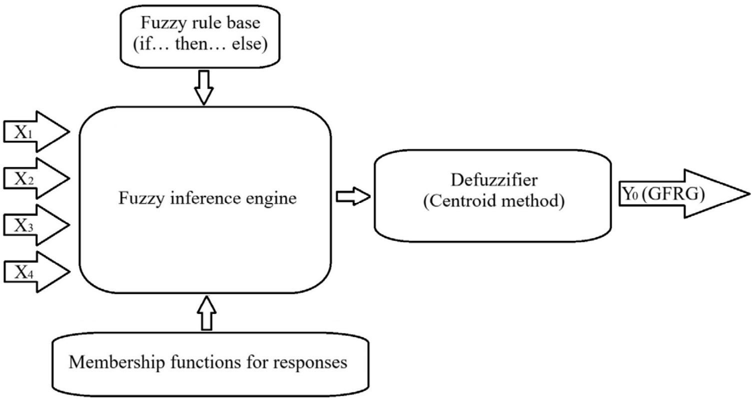


Figure 3. Fuzzy logic system comprised of four-inputs and 1-output

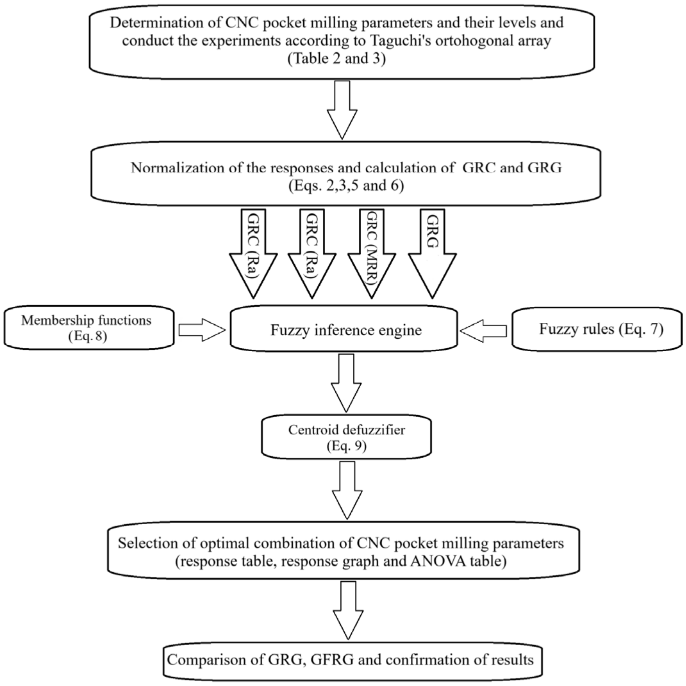


Figure 4. Flowchart illustrating the hybrid Taguchi based grey-fuzzy inference system

3. RESULTS AND DISCUSSION

Table 4 presents the cumulative grey relational grade and grey relational coefficients for each parameter set, as determined by the normalized responses. This table allows identifying which parameter combinations perform better in terms of multi-objective output. A higher GRG value indicates a machining condition closer to the optimal solution. Similar interpretations were reported in recent CNC milling optimization studies [33,37]. In addition, Pinarbasi et al. [39], demonstrated that machining parameters substantially alter surface roughness behavior in milling, supporting the findings of the study.

Table 4. Grey analysis for obtaining GRC and GRG.

Exp. no	Normalization of responses			Δ			Grey relation coefficients (GRC)			Grey relational grade (GRG)
	R_a	t	MRR	R_a	t	MRR	R_a	t	MRR	
1	0.000	0.125	0.000	1.000	0.875	1.000	0.248	0.274	0.248	0.256
2	0.877	0.750	0.182	0.123	0.250	0.818	0.728	0.569	0.287	0.527
3	0.708	1.000	0.455	0.292	0.000	0.545	0.530	1.000	0.377	0.635
4	0.969	1.000	0.818	0.031	0.000	0.182	0.915	1.000	0.645	0.852
5	0.969	0.125	0.114	0.031	0.875	0.886	0.915	0.274	0.271	0.486
6	0.946	0.750	0.182	0.054	0.250	0.818	0.860	0.569	0.287	0.571
7	0.946	1.000	0.932	0.054	0.000	0.068	0.860	1.000	0.829	0.895
8	0.962	0.875	1.000	0.038	0.125	0.000	0.896	0.725	1.000	0.872
9	0.877	0.250	0.273	0.123	0.750	0.727	0.728	0.306	0.312	0.448
10	1.000	0.750	0.818	0.000	0.250	0.182	1.000	0.569	0.645	0.737
11	0.731	0.875	0.455	0.269	0.125	0.545	0.551	0.725	0.377	0.550
12	0.823	1.000	1.000	0.177	0.000	0.000	0.651	1.000	1.000	0.882
13	0.785	0.000	0.477	0.215	1.000	0.523	0.605	0.248	0.387	0.413
14	0.785	0.750	0.818	0.215	0.250	0.182	0.605	0.569	0.645	0.605
15	0.931	0.875	0.932	0.069	0.125	0.068	0.827	0.725	0.829	0.792
16	0.908	1.000	0.818	0.092	0.000	0.182	0.781	1.000	0.645	0.807

The computations for the grey-fuzzy inference system were conducted using the fuzzy logic toolbox in MATLAB. Grey relation coefficients of the responses (X_1: R_a, X_2: t, X_3: MRR and X_4: GRG) create the input part of the grey-fuzzy inference system while Y_0 corresponds GFRG.

Using GRCs as input values allows the fuzzy inference system to evaluate multi-response machining performance instead of considering each output independently. This enables handling contradictory responses (for example, minimizing R_a and t while maximizing MRR), which is not achievable by conventional Taguchi analysis alone [37].

For fuzzy modeling of input and output data, the triangular shaped membership functions (six for R_a, four for t, five for MRR and six for output GFRG), shown in Figure 5, were used. Lowest, low, medium, high, higher and highest linguistic parameters were also used to indicate input and output parameters.

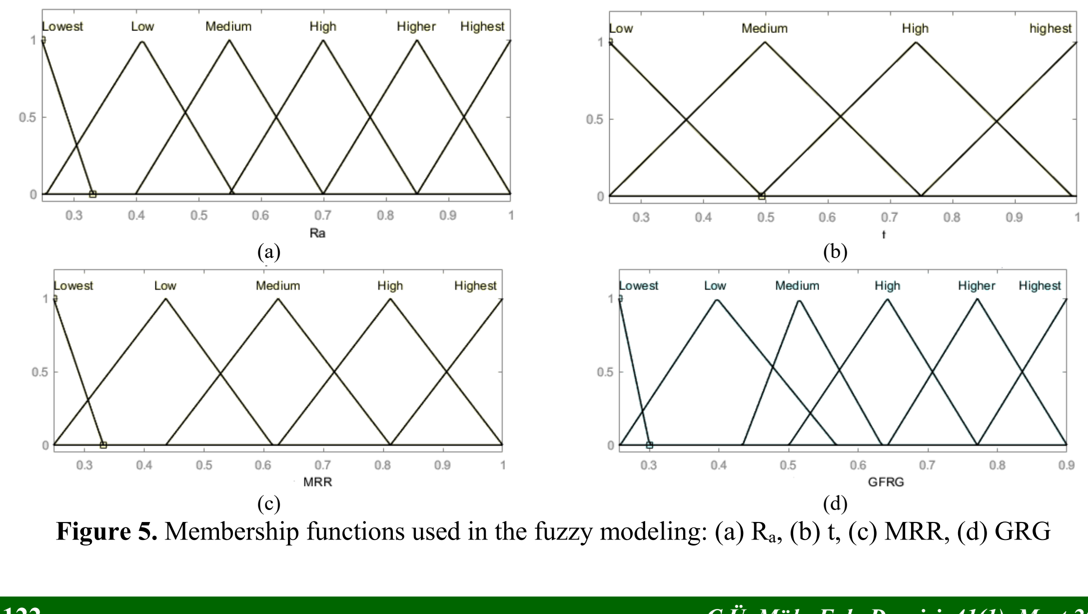


Figure 5. Membership functions used in the fuzzy modeling: (a) R_a, (b) t, (c) MRR, (d) GRG

The grey-fuzzy reasoning and rule display which has GRG of three inputs and GFRG output can be seen in Figure 6 graphically.

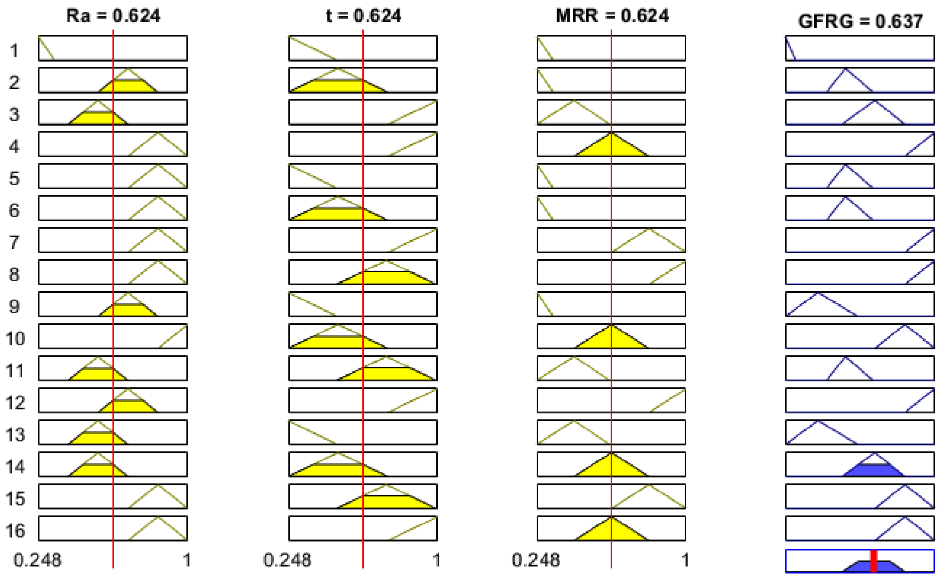


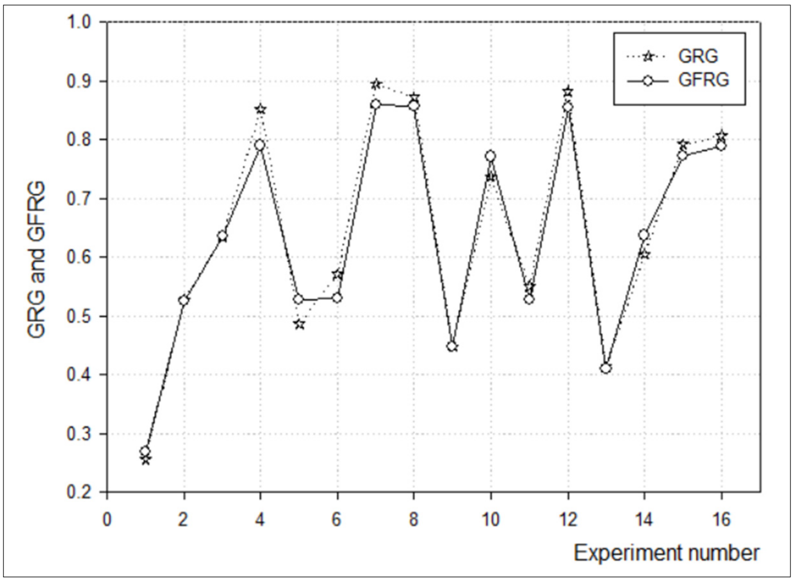
Figure 6. Schematic representation of the grey-fuzzy logic rules

Sixteen rows correspond to sixteen rules and their distribution according to the experiment number. Table 5 displays the GRG and GFRG values calculated for sixteen experiments. Experiment numbers 7 and 8 showed the best multiple output characteristics for CNC milling process with the maximum GFRG. The gray-fuzzy computations yielded a total average percentage error of 3.63 percent between the GRG and GFRG. Pandey and Panda [37] reported that hybrid fuzzy-based grey analysis typically produces a prediction error of 4–6%. This low error confirms the consistency of the grey-fuzzy inference predictions.

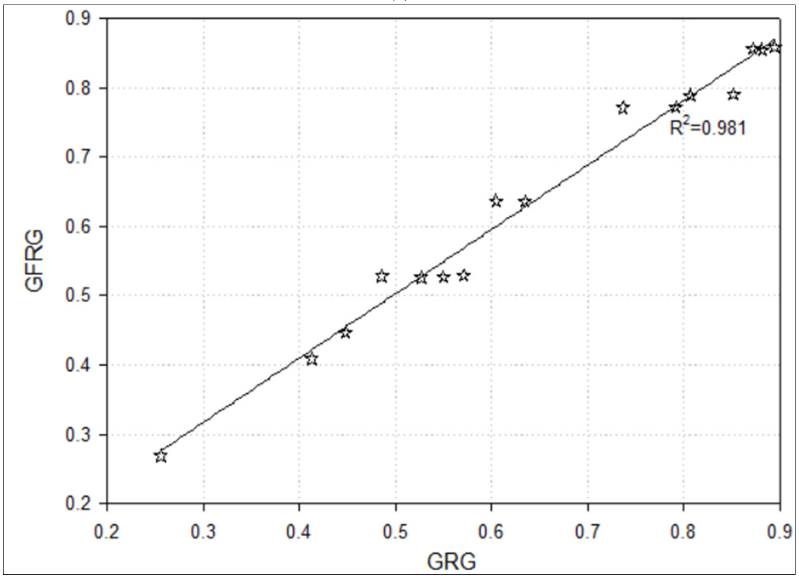
Table 5. GRG and GFRG comparison

Experiment no	Grey relational grade (GRG)	Grey-fuzzy reasoning grade (GFRG)	Rank	Absolute error (%)
1	0.256	0.269	16	5.084
2	0.527	0.526	13	0.472
3	0.635	0.636	9	0.389
4	0.852	0.790	4	7.297
5	0.486	0.528	11	8.902
6	0.571	0.529	10	7.270
7	0.895	0.859	1	4.053
8	0.872	0.856	2	1.867
9	0.448	0.447	14	0.258
10	0.737	0.771	7	4.640
11	0.550	0.527	12	3.899
12	0.882	0.855	3	3.005
13	0.413	0.409	15	0.986
14	0.605	0.637	8	5.349
15	0.792	0.772	6	2.520
16	0.807	0.789	5	2.190
Average percentage error=3.63 %				

The robust association between GRG and GFRG was shown by a high correlation value of R^2=0.981, as seen in Figures 7 (a) and (b). This also proved the constructed hybrid grey-fuzzy model well suited to the process. The strong linear correlation verifies that the fuzzy-enhanced GRG does not distort the decision ranking; instead, it refines it. High R^2 values were likewise observed by Pinarbaşı et al. [39], confirming that fuzzy-infused grey methods effectively model machining performance.



(a)



(b)

Figure 7. Correlation of; (a) GRG and GFRG vs experiment number and (b) GRG vs GFRG

In addition, Table 6 displayed the response table for the average GFRG of each parameter, indicating that higher GFRG values are associated with optimum parameter combination [35,37].

Delta statistics, which are defined as the disparity between the highest and lowest values, quantify the relative size of each effect. The feed rate had the highest delta value at rank 1, followed by the depth of cut at rank 2, which had the second highest delta factor, as determined by delta values. Cutting speed and cutting path strategy were ranked 3 and 4, respectively. This means that feed rate has the strongest contribution to overall process performance, A similar dominance of feed rate on surface roughness was also reported by Demirdogen et al. [40].

In Figure 8, the parameter's graphical response was visually represented. The correlations between the parameter and response of the output were seen to be directly proportional to the slope of the response graph [35,37]. As previously stated, the optimum process condition pertained to the cutting speed of level 2, feed rate of level 4, depth of cut of level 4, and cutting path strategy of level 1, as shown by the maximum value of the GFRG above the dashed line ($V_2f_4d_4p_1$). The optimum parameter set not only yielded minimum Ra (0.36 µm) but also increased productivity (MRR = 120 mm³/min) and reduced machining time (10 s), thereby improving machining economics.

To assess the important factors and the impact they had on the GFRG, ANOVA was carried out. The Fisher's F ratio was employed during the analysis to evaluate the parameter's influence on the output responses [33,35,37]. The ANOVA summary was given in Table 7. The feed rate was determined to have the greatest impact on the multi output characteristics, accounting for 70.00% of the overall effect. Following that, the depth of cut, cutting speed, and cutting path strategy ranked as the second, third, and fourth most influential factors, respectively, on the surface roughness, machining time, and material removal rate of CNC pocket milling. Furthermore, the F test ratio in Table 7 yielded the same contribution order. This factor ranking is consistent with recent studies, which showed that increased feed rate significantly increases material removal due to a direct rise in chip thickness and tool-workpiece engagement [39,40].

Table 6. Response table representation for GFRG

Parameters	Grey relational grade					
	Level 1	Level 2	Level 3	Level 4	Delta=max-min	Rank
V	0.555	0.693	0.650	0.651	0.137	3
f	0.413	0.615	0.698	0.822	0.409	1
d	0.528	0.670	0.644	0.707	0.178	2
p	0.661	0.613	-	-	0.047	4
Total mean Grey relational grade= 0.637						

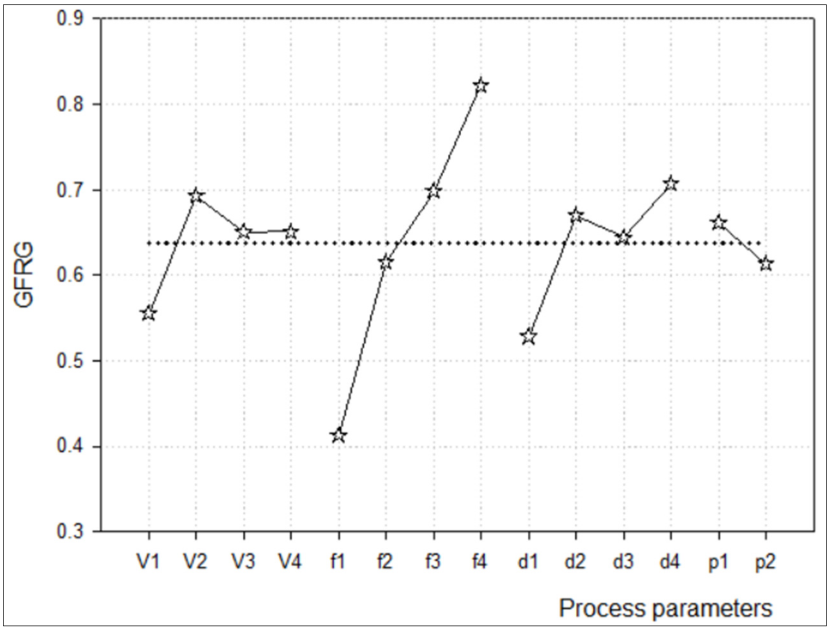


Figure 8. GFRG response plot of CNC parameters

Table 7. ANOVA for GFRG

Parameters	Degree of freedom	Sum of square	Mean Square	F	Contribution (%)
V	3	0.0408	0.0136	2.97	8.051
F	3	0.3548	0.1182	25.81	70.008
D	3	0.0714	0.0238	5.20	14.088
P	1	0.0089	0.0089	1.95	1.756
Residual	5	0.0309	0.0045	-	6.097
Total	15	0.5068	-	-	100
S=0.0676 R-Sq=95.41% R-Sq (adj)=86.22%					

The concluding phase of this study was conducting a confirmation test at the optimal parameter combination level ($V_2f_4d_4p_1$) to validate the improvement in process responses and the success of the best CNC pocket milling condition. The confirmation test results were given in Table 8.

The confirmatory test indicated that the anticipated GFRG at the optimal configuration ($V_2f_4d_4p_1$) was 0.97, while the GFRG obtained from the experimental analysis was 0.85. Both values exceeded the GFRG obtained at the initial factor configuration of 0.26. Therefore, the fact that the hybrid grey-fuzzy logic yielded a benefit of 0.59 in GFRG indicated that it may be efficiently used to optimize multiple variables in the CNC milling, aligning with the findings of Pandey and Panda [37].

Table 8. Confirmatory test results

	Initial factor settings	Optimal process condition	
		Prediction	**Experiment**
Parameter levels	$V_1f_1d_1p_1$	$V_2f_4d_4p_1$	$V_2f_4d_4p_1$
R_a (µm)	1.48		0.36
t (s)	16		10
MRR (mm^3/min)	8		120
Grey-fuzzy reasoning grade (GFRG)	0.26	0.97	0.85
Improvement in GFRG=0.59			

4. CONCLUSIONS

In this study, a hybrid Taguchi–Grey–Fuzzy optimization approach was applied to the CNC pocket milling of DIN 1.0038 medium-carbon steel to improve surface quality, reduce machining time, and increase material removal rate. Taguchi's structured experimental design was integrated with Grey Relational Analysis and fuzzy inference. This integration provided to handle multiple different responses simultaneously. Furthermore, it enabled the identification of the most effective machining parameter combination with fewer experimental trials. Based on the analysis that has been completed, it is possible to derive the conclusions that follow;

i. Hybrid Taguchi-based grey-fuzzy logic algorithm and its utilization has the potential to significantly improve machining time, material removal rate and surface roughness of the CNC pocket milling process. The study revealed a clear improvement in multi-response performance, simultaneously minimizing surface roughness and machining time while maximizing material removal rate. This situation is an important outcome that conventional single-objective optimization methods cannot provide.

ii. ANOVA revealed that feed rate was the most dominant parameter, contributing ≈70% to performance variation, followed by depth of cut, cutting speed, and cutting path strategy. This ranking aligns with previous machining studies emphasizing that feed rate has the strongest effect on chip load, productivity, and generated surface finish.

iii. The optimum cutting parameter combination was determined as V_2–f_4–d_4–p_1, corresponding to 1500 rpm cutting speed, 2.0 mm/rev feed rate, 1.25 mm depth of cut, and zig-zag toolpath strategy. Under these conditions, the process achieved a surface roughness of 0.36 µm, machining time of 10 s, and material removal rate of 120 mm^3/min, representing a substantial improvement from the initial setup.

The confirmation test validated the improvement achieved by the hybrid optimization strategy, increasing the grey-fuzzy reasoning grade from 0.26 (initial condition) to 0.85 (optimal condition), with a predicted value of 0.97, demonstrating the robustness and predictability of the developed approach.

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