Sigma J Eng Nat Sci, Vol. 44, No. 1, pp. 292–308, February, 2026

Sigma Journal of Engineering and Natural Sciences
Web page info: https://sigma.yildiz.edu.tr
DOI: 10.14744/sigma.2025.00101

Research Article

Optimization of precision machine part manufacturing by integration of Grey-Taguchi method with principal component analysis

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ARTICLE INFO

Article history
Received: 05 September 2024
Revised: 18 November 2024
Accepted: 14 January 2025

Keywords:
Confirmation Test; Grey Relational Analysis; Precision Machine Part Manufacturing; Principal Component Analysis; Sensitivity Analysis; Taguchi Method

ABSTRACT

Determining and optimizing the process parameters impacting the outputs at each production stage is necessary to reduce production costs. The Taguchi Method (TM) and the Grey Relational Analysis (GRA) are commonly utilized two techniques for process parameter optimization. In precision machine part manufacturing, Computer Numerical Control (CNC) production is the most critical process. In this study, the objective is to optimize CNC manufacturing parameters using TM, GRA and Principal Component Analysis (PCA) in metal sector. Process parameters like operator experience level (in years), CNC machine brand, CNC machine age, and CNC machine size were determined and optimized based on their degree of impact on the outputs. The experiments were carried out using a four-factor, four-level Taguchi orthogonal array (L16), and Analysis of Variance (ANOVA) was conducted aiming to determine the effects of these process parameters on production time, dimension conformity, and surface roughness performance factors. Selection of these input parameters and performance factors in the study is to provide a solution to a problem in the company from which the data are obtained with scientific methods and to contribute to the literature. Utilizing TM, the optimal values of process parameters are determined as ten years for operator experience, as Mazak for CNC machine brand, as two years for machine age, and as 500x550x550 for machine size. Utilizing the combination of GRA and PCA optimal parameter values are determined as ten years for operator experience, as Yuntes for CNC machine brand, as two years for machine age, and as 700x450x500 for machine size. A sensitivity analysis was performed using 21 different weight sets for performance factors (production time, dimension conformity, and surface roughness). Compared to the initial CNC production process parameters, 45%, 95%, and 504% improvements were obtained in production time, dimension conformity, and surface roughness process parameters. Companies, especially operating in the metal sector, can benefit from managerial practices by considering the ranking of parameters affecting CNC production according to the results obtained from this study.

Cite this article as: Erol K, Kapan Ulusoy S, Şenyiğit E. Optimization of precision machine part manufacturing by integration of Grey-Taguchi method with principal component analysis. Sigma J Eng Nat Sci 2026;44(1):292–308.

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This paper was recommended for publication in revised form by Editor-in-Chief Ahmet Selim Dalkilic

Published by Yıldız Technical University Press, İstanbul, Turkey

INTRODUCTION

Precision machine part manufacturing aims to produce machine parts that precisely fit the specified shapes and dimensions [1]. Computer Numerical Control (CNC) machines are often utilized for manufacturing precision parts. CNC is a machining process in which the machining tools are automatically controlled by a computer and operated on the workpiece to be shaped. It is the most critical process of an organization operating in the metal sector. A CNC machine follows the instructions programmed with codes to precisely machine a workpiece of a specific type of material (such as metal, plastic, ceramics, or composites) until the workpiece has the desired dimensions and shape [2]. To enhance quality and efficiency in CNC production, minimizing the variability caused by the uncontrollable process parameters is necessary. This may be achieved by optimizing the controllable process parameters of the CNC process. For this purpose, both Taguchi Method (TM) and the Grey Relational Analysis (GRA) methods are used commonly in the literature.

TM is a statistical experimental design technique that is utilized to make the products or processes more robust. Uncontrollable process parameters cause variation in the performance factors. TM minimizes this variation by optimizing the controllable process parameters [3]. In factorial or fractional experimental designs, as the quantity of independent variables and their levels increase, the quantity of experiments to be performed rises significantly. TM employs orthogonal arrays to decrease the quantity of experiments thus it provides more efficient experimentation for robust design [4]. The downside of the TM is that it can only optimize a product or a process for a single performance factor. When there are multiple performance factors TM can only find sub-optimal solutions. In such cases, TM in combination with GRA can be utilized to find the optimal solutions.

GRA is an approach to measure the degree of convergence between arrays using the grey relational degree [5]. GRA can transform a multi-objective problem into a single-objective problem through determining a Grey Relational Grade (GRG). The GRG estimates the impacts of parameters on the overall performance [6]. In the experimental design case, GRA is utilized to decrease multiple performance factors to an individual performance factor by combining them. Then using the combined performance factor TM is utilized to discover the optimal levels of process parameters.

Principal Component Analysis (PCA) is a statistical technique used for decreasing the dimensionality of a problem. This method considerably decreases the complexity of the solution by decreasing inter-related variables to independent principal components preserving the primary data with linear combinations [13]. PCA can be used to calculate the combination weights in GRA according to the relative importance of the factors. The literature review indicated that various studies have been carried out to optimize CNC process parameters utilized the Grey-Taguchi method. However, no studies use the Grey-Taguchi method in combination with PCA for the optimization of CNC manufacturing parameters [7]. PCA can be used to calculate the combination weights in GRA according to the relative importance of the factors.

Literature Review

TM in combination with GRA (Grey-Taguchi) has been used in many studies for multiple performance optimization in CNC manufacturing. E.g. Rao et al. [8] applied the Taguchi method to investigate the parameters sliding speed, load and sliding distance using the minimum number of tests possible. Kasman et al. [9] utilized the Taguchi method to establish an experimental installation to analyse the impacts of laser engraving on engraving depth and surface roughness. Swapna et al. [10] utilized the integration of PCA with GRA for optimizing the process parameters in sheet forming of Al6061-T6. Adar [11] used Taguchi method to analyse the influence of temperature, substrate/inoculation ratio and mixing speed parameters on the anaerobic digestion of cattle manure liquid fraction. Mola et al. [12] utilised the TM, and optimal levels of parameters were identified for flexural strength, toughness and strength. Singh et al. [13] intended to evaluate the impact of the parameters while milling on the material removal rate and surface roughness of AISI H11. Kumar et al. [14] employed Taguchi-based GRA to optimize corrosion rate, material removal rate and surface roughness for CNC milling of ZE41A Mg alloy. Esangbedo & Abifarin [15] used statistical approaches and GRA to optimize the surface roughness and cutting force of CNC machine to produce halloysite nanotube hybrid composite. Suresh Kumar et al. [16] used TM and GRA to measure the effect on the surface quality of Al-6063 regarding material removal rate and surface integrity. Prakash et al. [17] dealt with the optimization of machining parameters such as surface finish and material removal rate during production of Aluminium/Rock dust composite via Taguchi and GRA. Kouahla et al. [18] aimed to optimize the cutting force, tool vibration, material removal rate, power consumption and surface roughness under different cutting conditions such as feed rate, cutting speed, tool nose radius and depth of cut. Teja et al. [19] deals with on their study to optimize tool temperature, work temperature and surface roughness while producing Ti alloy CNC machining parameters like cutting depth, spindle speed and feed utilized TM. Raguraman et al. [20] analysed the CNC turning machining parameters of AA6061 alloy using TM, ANOVA and GRA. Zhujani et al. [21] aimed to utilized TM based GRA approach to optimize the parameters such as tool wear, surface roughness and machining time of Inconel 718 alloy. Zeydan [22] intended to optimize process factors of flexible polyurethane foam by TM. Sahare et al. [23] used GRA with Taguchi to propose an optimum milling process parameter set-up for multi performance factors. Mastan Rao et al. [24] examined the exploit of Taguchi and GRA to optimize the turning process parameters of a nickel-based alloy, taking into account surface roughness, tool wear rate and material removal rate. Summary of literature review that used TM-GRA for CNC parameter design is given in Table 1. The literature in Table 1 is also detailed by adding the input parameters and performance factors used in the papers.

This study focuses on applying Grey-Taguchi method in combination with PCA techniques to optimize selected

Table 1. Summary of literature review

Author(s)	Input Parameters	Performance factors	Author(s)	Input Parameters	Performance factors
Ficko et al. [36]	Feed rate, cutting speed and cutting depth	Material removal rate and surface roughness	Rao et al. [8]	Sliding speed, load, distance	Wear, coefficient of friction
Mola et al. [12]	Water/binder ratio, silica fume, kevlar fiber and steel fiber	Compressive strength, flexural strength, and toughness	Swapna et al. [10]	Die speed, temperature, type of lubricant and sheet thickness	Punch force, thickness variation
Singh et al. [13]	Feed rate, cutting speed and cutting depth	Material removal rate and surface roughness	Zeydan [22]	TDI (Toluene Diisocyanate) index, polyol, water, air amount	Hardness
Adar [11]	Temperature, Mixing speed and substrate/ inoculation ratio	Methane yield	Kumar et al. [14]	Tool rotation, feed rate, cutting speed and cutting depth	Metal removal rate, corrosion rate and surface roughness
Esangbedo & Abifarin [15]	Spindle speed, cutting depth and feed rate	Cutting force and surface roughness	Zade & Meshram [37]	Feed load, cutting speed and reduction depth	Roundness and surface roughness
Suresh Kumar & Senthil Kumar [16]	Feed rate, spindle speed, cutting depth	Metal removal rate and surface roughness	Dhanalakshmi & Rameshbabu [34]	Feed rate, cutting speed, depth of cut, and cutting fluid flow rate	Metal removal rate, cost analysis and surface roughness
Prakash et al. [17]	Particle size, particle weight, feed, speed and cutting depth	Surface roughness and metal removal rate	Sundara Bharathi et al. [38]	Feed rate, cutting speed and cutting depth	Metal removal rate and surface
Kouahla et al. [18]	Feed rate, cutting speed, tool nose radius and cutting depth	Surface roughness, tool vibration, power consumption, cutting force, and material removal rate	Azim et al. [35]	Spindle speed, depth of cut, feed rate	Surface roughness
Teja et al. [19]	Spindle speed, feed, cutting depth	Tool temperature, surface roughness and work temperature	Sahare et al. [23]	Feed, spindle speed, tool diameter, and tool type	Material removal rate, surface roughness, cutting force and tool wear
Kumar Yadav et al. [39]	Spindle speed, depth of cut, tool diameter and feed rate	Surface roughness and material removal rate	Mastan Rao et al. [24]	Speed, feed rate, cutting depth	Tool wear rate, surface roughness and material removal rate
Raguraman et al. [20]	Rotational speed, feed, depth of cut	Metal removal rate and surface roughness	Rathod et al. [33]	Cutting speed, cutting depth and feed rate	Tool life, surface roughness, and production time
Zhujani et al. [21]	Cutting speed, feed rate and cutting depth	Maximum roughness, average roughness and roundness	Kasman et al. [9]	Scan speed, scan direction, and fill spacing	Surface roughness and engraving depth

Table 2. Process parameters and levels for CNC production

Parameters	Symbol	Level 1	Level 2	Level 3	Level 4
Operator Experience Year	A	2.00	3.00	10.00	14.00
CNC Machine Brand	B	Mazak	Okuma	Taksan	Yuntes
CNC Machine Age	C	2.00	11.00	15.00	17.00
Workbench Size (mm)	D	500x550x550	700x450x500	1000x500x500	1600x3000x800

parameters in CNC manufacturing considering multiple performance factors. The proposed TM-GRA-PCA method is applied to the CNC process of a metal industry company. Input parameters and performance factors chosen for this study were determined in line with the opinions of expert engineers in the company. Firstly, TM is used to optimize selected CNC input parameters for each performance factor separately. The experiments used a Taguchi orthogonal array (L16) with four factors and four levels. This analysis could result in only a sub-optimal solution since for each performance factor different levels of input parameters were optimal. Secondly, a TM-GRA approach is utilized in which the combination weights of the performance factors are taken equally. Again this analysis is sub-optimal since it is not considered the relative importance of the performance factors. As the final method, a TM-GRA-PCA technique is used in which the combination weights of the performance factors are calculated using PCA reflecting the relative importance of the performance factors. A sensitivity analysis was performed as risks, and uncertainties could potentially affect the study. As a result of the confirmation experiments conducted in the study, the compatibility of the estimated S/N values of the CNC manufacturing parameters with the actual S/N values was determined and an improvement level was obtained compared to the initial CNC manufacturing process parameters.

When the open literature on TM and GRA for multiple performance optimization of CNC production in the metal sector is reviewed, it is seen that primarily input parameters such as cutting speed, depth of cut and feed rate and their short-term impacts on production results [13,15–17,19–21] are studied and it is noted that the input parameters and dimension conformity performance factors used in this study have yet to be researched. Selection of these input parameters and performance factors in the study is to provide a solution to a problem in the company from which the data are obtained with scientific methods and to contribute to the literature. Moreover, in this study, besides the TM and GRA, PCA was conducted to weigh the performance factors, and sensitivity analysis was carried out to identify the risks or uncertainties that may potentially affect the study. In these aspects, this study is unique and contributes to the literature.

MATERIALS AND METHODS

The data used in the study were obtained from a company operating in the metal sector in Kayseri, Turkey. Production engineers have identified the CNC production process parameters and their levels and this information is shown in Table 2.

In the study, TM, GRA, and PCA are used to optimize the process parameters that affect CNC production outputs, such as operator experience level (in years), CNC machine brand, CNC machine age, and CNC machine size. To determine the influences of process parameters on production time, dimension conformity, and surface roughness performance factors, sensitivity analysis and Analysis of Variance (ANOVA) were also conducted. Last but not least, confirmation experiments were conducted to verify if predicted S/N ratios are consistent with the actual values. Details of the analysis are given below.

Taguchi Method

TM was used as the initial method to optimize the process parameters. A four-factor and four-level orthogonal design L16 was selected for the study. Operator experience year, CNC machine brand, CNC machine age, and workbench size were used as control parameters. The TM, based on the orthogonal array, facilitates the design of experiments and evaluates process performance using the signal-to-noise (S/N) ratio, which is resistant to the effects of noise factors and acts as an objective function for optimization, guiding the selection of control levels that best compensate for the impact of noise factors on performance [10], [22]. Noise factors are uncontrollable variables that can impact the product or process. The highest S/N ratio was taken into account to identify the optimum levels for each parameter. The S/N ratio for each response variable (output factor) was identified by transforming the response variable into a fixed value (decibels, dB) utilizing the "Smaller the better" or "Larger the better" criteria. S/N ratios for the response of production time, dimension conformity, and surface roughness were calculated utilizing the "Smaller the better," "Larger the better," and "Smaller the better" criteria, respectively. The smaller the better, and larger the better, calculations for input parameters were performed successively according to Equation 1 and Equation 2 [25].

$$\frac{S}{N} = -10\,log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{1}$$

$$\frac{S}{N} = -10\,log\left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right] \tag{2}$$

where i is the experiment order, y_i is the experimental result, and n is the total number of experiments.

Grey Relational Analysis- Principal Component Analysis

GRA-PCA was utilized to optimize the process parameter levels corresponding to each output factor, considering their weighting in CNC machining. GRA was applied to analyse the relations in a multi-factor system. At the same time, PCA was performed to identify the corresponding weight value indicating the relative significance of each response in GRA. In this context, the following steps of GRA in combined with PCA were applied to optimize multiple responses:

1. Normalization of S/N results for each response: Normalization of the S/N values obtained from Taguchi analysis, the "Smaller the Better", and "Larger the Better" calculations were performed using Equation 3 and Equation 4, respectively.

$$N_{rp} = \frac{\left[maxe_{rp} - e_{rp}\right]}{\left[maxe_{rp} - mine_{rp}\right]} \tag{3}$$

$$N_{rp} = \frac{\left[e_{rp} - mine_{rp}\right]}{\left[maxe_{rp} - mine_{rp}\right]} \tag{4}$$

N_{rp} represents the normalized experimental data of e_{rp}, which is the experimental result of the r^{th} response variable before the normalization process is applied. Min_{erp} is the smallest value of e_{rp}, while max_{erp} is the largest value of e_{rp} [26].

2. Identification of grey correlation coefficient (GRC) and GRG: GRCs are calculated using Equation 5 to states the relationship between optimal and actual test results. The coefficient value (φ) is taken as 0.5 in this equation. In the literature, it has been found that this coefficient does not efficiently change the grey relational ranking [25]. Δ_{0i} is the difference between the reference ($y_0(k)$) and comparison ($y_i(k)$) values (Equation 6). Δ_{min} (Equation 7) and Δ_{max} (Equation 8) indicate the min and max values of Δ_{0i}, respectively.

$$GRC\big(X_0(k)X_i(k)\big) = \frac{\Delta_{min} + \varphi\Delta_{max}}{\Delta_{0i} + \varphi\Delta_{max}} \tag{5}$$

$$\Delta_{0i}(k) = \left|X_0(k) - X_j(k)\right| \tag{6}$$

$$\Delta_{min} = min_j min_k \left|X_0(k) - X_j(k)\right| \tag{7}$$

$$\Delta_{max} = max_j max_k \left|X_0(k) - X_j(k)\right| \tag{8}$$

The weighted PCA-GRG was identified using the different weighted factors in Equation 9.

$$GRG(X_0X_i) = \frac{1}{n}\sum_{k=1}^{n} w_k \varphi_i(k) \tag{9}$$

where n is the quantity of experiments and w_k is the weight for the k^{th} performance [26]. The w_k value of each response was identified by PCA. PCA method was performed using MINITAB, in this study.

3. PCA: In GRA, weighting values for multiple responses are objectively defined utilizing PCA [27]. This multi-variate data analysis aims to decrease the dimensionality of the study as much as practicable [28]. PCA is an orthogonal transformation method that transforms observations of potentially correlated factors into uncorrelated factor (PCs) values [29]. The following equation was utilized to assess the targeted PCs.
   (i) The variance-covariance sequence X is formulated by GRCs, as given in Equation 10.

$$X = \begin{bmatrix} X_1(1) & \cdots & X_1(n) \\ \vdots & \ddots & \vdots \\ X_m(1) & \cdots & X_m(n) \end{bmatrix} \tag{10}$$

where X is the GRC for each response, m is the quantity of experiments, and n is the quantity of responses.

   (ii) The set of correlation coefficients was predicted utilizing Equation 11.

$$R_{jl}\left(\frac{cov\big(x_i(j)x_i(l)\big)}{\sigma_{xi}(j)\sigma_{xi}(l)}\right), j = 1,2,3,\dots,n \; l = 1,2,3,\dots,n \tag{11}$$

$cov(x_i(j)\ x_i(l))$ is the covariance of $x_i(j)$ and $x_i(l)$; $\sigma_{xi}(j)$ and $\sigma_{xi}(l)$ are the standard deviation of $x_i(j)$ and $x_i(l)$, respectively.

   (iii) The eigenvectors and eigenvalues attained by employing the correlation coefficient array are given in Equation 12.

$$(R - \lambda_k\, l_m)V_{ik} = 0 \tag{12}$$

where λ_k are the eigenvalues; $V_{ik} = [\alpha_{k1}\alpha_{k2}\dots\alpha_{km}]^T$ are the eigenvectors related to the eigenvalues λ_k and $\sum_{k=1}^{n}\lambda_k = n, k = 1,2,\dots,n.$

   (iv) The PCs of the model responses are predicted using Equation 13.

$$Y_{mk} = \sum_{i=1}^{n} Y_m(i)V_{ik} \tag{13}$$

where Y_{m1}, Y_{m2}, ..., Y_{mn} are referred to as the first PC, second PC, etc. (decreasing order of variance).

Sensitivity Analysis

A sensitivity analysis was applied to analyse the potential effect of risks and uncertainties on the study. In this study, twenty-one different importance (weight) levels were determined for the responses besides TM, GRA, and GRA-PCA methods, and it was researched to which extent the weights affect the results obtained.

Analysis of Variance (ANOVA)

ANOVA is an effective statistical tool for evaluating the relative influence of different process parameters and for evaluating experimental errors. ANOVA ensures a countable measure of the contribution of each factor, providing a better understanding of the comparative impacts on output variables. This technique is crucial for identifying any error variability in factor impact and the disparity in estimation errors. The main objective of ANOVA is to determine which design parameters substantially affect quality characteristics [30]. ANOVA determined the influence ratio of input parameters on performance factors. With this statistical approach, differences in input parameters can be demonstrated in terms of output values, in this study. The most efficient parameter for the process characteristics can be identified, and that factor can be controlled to improve the process [31].

Confirmation Experiment

The final stage of optimization is to confirm the outcomes. After the optimum process parameters have been defined, the predicted values of the optimal factor levels obtained from the S/N ratios and the experimental values are utilized to confirm the accuracy of the optimization process. The experimental findings under optimum conditions were used to determine the progress in performance factors. The estimated S/N ratios and the optimum levels of the process parameters were calculated using Equation 14.

$$n_o = n_m + \sum_{i=1}^{j} (n_i - n_m) \tag{14}$$

where η_m is the overall average of the S/N ratio, η_i is the average of the S/N ratio corresponds to the optimal levels, and j is the number of process parameters.

RESULTS AND DISCUSSION

Taguchi Optimization

In the study, as an initial method, TM was conducted to determine the optimum process parameters for each performance factor separately since TM could handle only one performance factor at a time. The findings of the TM are shown in Table 3 and Table 4.

Table 3 shows the L16 orthogonal array, the average values, and the S/N ratios of the performance factors. Table 4 shows the S/N ratios of each process parameter for performance factors. As can be seen in Table 4, S/N ratios for production time, dimension conformity, and surface roughness

Table 3. Taguchi L16 orthogonal array for CNC manufacturing, average values, and S/N ratios

	Process Parameters				Average Values			S/N Ratios, dB		
No.	A	B	C	D	Production Time (min)	Dimension Conformity (ratio)	Surface Roughness (µm)	Production Time (min)	Dimension Conformity (ratio)	Surface Roughness (µm)
1	1	1	1	1	282.00	0.36	1.49	-49.00	-8.87	-3.46
2	1	2	2	2	220.00	0.50	0.28	-46.85	-5.98	10.91
3	1	3	3	3	377.00	0.35	1.22	-51.53	-9.16	-1.73
4	1	4	4	4	464.00	0.07	0.37	-53.33	-23.53	8.70
5	2	1	2	3	265.00	0.82	0.21	-48.46	-1.68	13.62
6	2	2	1	4	48.00	0.42	0.68	-33.62	-7.52	3.41
7	2	3	4	1	223.00	0.10	1.34	-46.97	-19.96	-2.54
8	2	4	3	2	257.00	0.97	1.41	-48.20	-0.26	-2.98
9	3	1	3	4	434.00	0.86	0.80	-52.75	-1.27	1.94
10	3	2	4	3	349.00	0.72	1.37	-50.86	-2.85	-2.73
11	3	3	1	2	106.00	1.00	0.25	-40.51	0.00	12.02
12	3	4	2	1	37.00	0.40	1.19	-31.36	-7.93	-1.51
13	4	1	4	2	255.00	0.87	0.17	-48.13	-1.18	15.28
14	4	2	3	1	272.00	0.19	0.45	-48.69	-14.43	7.03
15	4	3	2	4	527.00	0.14	1.09	-54.44	-16.88	-0.75
16	4	4	1	3	388.00	0.95	0.10	-51.78	-0.43	20.12

Table 4. S/N for production time, dimension conformity, and surface roughness responses*

	Production Time (min)				Dimension Conformity (ratio)				Surface Roughness (μm)			
Levels	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
1	-50.18	-49.59	**-43.73**	**-44.01**	- 11.89	**-3.25**	**-4.20**	-12.80	3.60	**6.84**	**8.02**	-0.12
2	-44.31	**-45.01**	-45.28	-45.92	- 7.35	-7.69	-8.12	**-1.85**	2.88	4.65	5.57	**8.81**
3	**-43.87**	-48.36	-50.29	-50.66	**- 3.01**	-11.50	-6.28	-3.53	2.43	1.75	1.06	7.32
4	-50.76	-46.17	-49.82	-48.54	- 8.23	-8.04	- 11.88	-12.30	**10.42**	6.08	4.68	3.32
Delta**	6.89	4.58	6.56	6.65	8.87	8.25	7.67	10.94	7.99	5.09	6.96	8.93
Rank***	1	4	3	2	2	3	4	1	2	4	3	1

Optimum values of the process parameters are given in bold, ** Delta represents the absolute value of the difference between the max and min S/N ratio* [40], * Rank is determined by the order of the delta value and indicates the relative importance of the parameters according to their influence* [40].

responses vary between -43.73-50.76, -1.85-12.80, and -0.12-10.42 dB, respectively. According to the Delta results, the process parameters affecting the production time are operator experience level (Δ=6.89), machine size (Δ=6.65), CNC machine age (Δ=6.56), and CNC machine brand (Δ=4.58). The parameters influencing the dimension conformity factor are machine size (Δ=10.94), operator experience level (Δ=8.87), CNC machine brand (Δ=8.25), and CNC machine age (Δ=7.67). The responses affecting surface roughness are machine size (Δ=8,93), operator experience level (Δ=7,99), CNC machine age (Δ=6,96), and CNC machine brand (Δ=5,09), respectively.

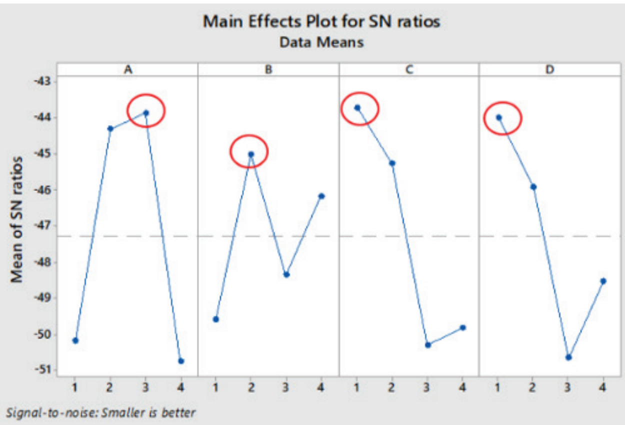

Figure 1. Mean effects plot of production time for S/N ratios.

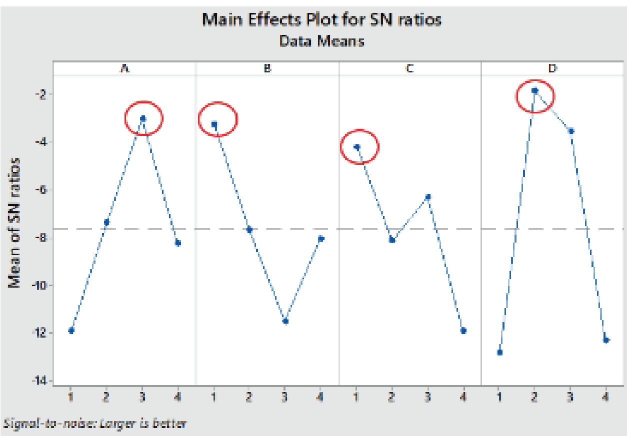

Figure 2. Mean effects plot of dimension conformity for S/N ratios.

Fig. 1, Fig. 2, Fig. 3, and Table 5 present the optimum values of the process parameters for S/N ratios.

As seen in Figure 1, the best value of the parameter operator experience level is obtained as level 3 (10,00),

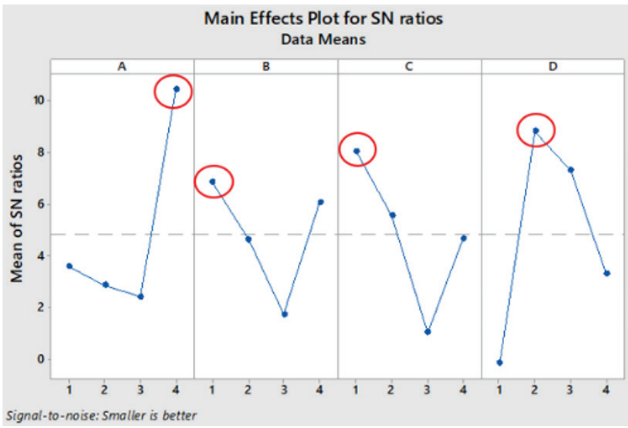

Figure 3. Mean effects plot of surface roughness for S/N ratios.

Table 5. Optimum values of the process parameters according to S/N ratios

Performance factors	A	B	C	D
Production Time (min)	3	2	1	1
Dimension Conformity (ratio)	3	1	1	2
Surface Roughness (μm)	4	1	1	2
Combination	3	1	1	2

the best value of the CNC machine brand is obtained as level 2 (Okuma), the best value of the CNC machine age is obtained as level 1 (2,00) and the best value of machine size is obtained as level 1 (500x550x550) for production time. As can be seen in Figure 2, the best value of the operator experience level parameter was found as level 3 (10,00), the best value of the CNC machine brand was found as level 1 (Mazak), the best value of the CNC machine age was found as level 1 (2,00) and the best value of machine size was found as level 2 (700x450x500) for dimension conformity. Lastly, as seen in Figure 3, the best value of the operator experience level parameter was found as level 4 (14,00), the best value of the CNC machine brand was found as level 1 (Mazak), the best value of CNC machine age was found as level 1 (2,00) and the best value of machine size was found as level 2 (700x450x500) for surface roughness. When the responses are combined according to the levels' frequency of occurrence, the best value of the operator experience level parameter is level 3 (10,00), the best value of the CNC machine brand is level 1 (Mazak), the best value of the CNC machine age is level 1 (2,00) and the best value of machine size is level 2 (700x450x500).

When the optimal input levels of performance factors are compared in light of the results obtained with TM, it is concluded that TM is insufficient for the simultaneous optimization of multiple performances for CNC production. The GRA method was utilized following TM, and the resulting data was analysed.

Grey Relational Analysis Optimization

As a second method GRA with equal weights are utilized in combination with TM. Table 6 shows the results obtained with GRA for the responses. S/N ratio values were first normalized and then converted to normalization values. The distance matrix and weightings of the test samples were calculated, and then GRGs were estimated using GRA.

The average GRG values and the optimal values of the input parameters according to the parameters and GRGs are given in Table 7 and Table 8, respectively.

Table 7. Average GRG values and parameters

Levels	A	B	C	D
1	0.48	0.60	0.68	0.49
2	0.60	0.56	0.57	0.71
3	0.63	0.52	0.52	0.59
4	0.60	0.61	0.53	0.51
Delta	0.15	0.10	0.16	0.22
Rank	3	4	2	1

Table 8. Optimum values of input parameters by GRGs

Method	A	B	C	D
GRA	3	4	1	2

Table 6. GRA results for CNC production

	Normalization			Distance Matrix			Weighting				
No.	Production Time (min)	Dimension Conformity (ratio)	Surface Roughness (μm)	Production Time (min)	Dimension Conformity (ratio)	Surface Roughness (μm)	Production Time (min)	Dimension Conformity (ratio)	Surface Roughness (μm)	GRG	Rank
1	0.50	0.29	-0.06	0.50	0.71	1.06	0.50	0.41	0.32	0.41	14
2	0.63	0.45	0.86	0.37	0.55	0.14	0.57	0.47	0.78	0.61	6
3	0.31	0.28	0.14	0.69	0.72	0.86	0.42	0.41	0.37	0.40	15
4	0.13	-0.04	0.80	0.87	1.04	0.20	0.36	0.33	0.71	0.47	11
5	0.53	0.80	0.92	0.47	0.20	0.08	0.52	0.72	0.86	0.70	3
6	0.98	0.36	0.56	0.02	0.64	0.44	0.96	0.44	0.53	0.64	5
7	0.62	0.00	0.05	0.38	1.00	0.95	0.57	0.33	0.35	0.42	13
8	0.55	0.97	0.00	0.45	0.03	1.00	0.53	0.94	0.33	0.60	8
9	0.19	0.85	0.46	0.81	0.15	0.54	0.38	0.77	0.48	0.54	9
10	0.36	0.69	0.03	0.64	0.31	0.97	0.44	0.62	0.34	0.47	12
11	0.86	1.00	0.88	0.14	0.00	0.12	0.78	1.00	0.81	0.86	1
12	1.00	0.33	0.17	0.00	0.67	0.83	1.00	0.43	0.38	0.60	7
13	0.56	0.86	0.94	0.44	0.14	0.06	0.53	0.78	0.90	0.74	3
14	0.52	0.10	0.74	0.48	0.90	0.26	0.51	0.36	0.65	0.51	10
15	0.00	0.05	0.24	1.00	0.95	0.76	0.33	0.34	0.40	0.36	16
16	0.28	0.95	1.00	0.72	0.05	0.00	0.41	0.90	1.00	0.77	2

The optimal values of the input parameters for the responses with the GRA method are as follows: operator experience level is level 3 (10,00), CNC machine brand is level 4 (Yuntes), CNC machine age is level 1 (2,00), and machine size is level 2 (700x450x500).

The results show that the optimum values of input parameters according to TM and GRA are slightly different. This reveals this study's inadequate use of TM and GRA for multiple performance optimization of CNC machining. Hence, GRGs are computed using GRA-PCA in the following subsection of this study.

Grey Relational Analysis- Principal Component Analysis Optimization

The GRA-PCA method was applied after the GRA method for multiple performance optimization. The correlation coefficient matrix generated utilizing the variance-covariance matrix was also utilized to identify the eigenvalues and associated eigenvectors for each response of the model. The eigenvectors corresponding to the PCs and the weight contribution of each process parameter predicted for the first PC are represented in Table 9.

As seen in Table 9, the weight contribution of production time, dimension conformity, and surface roughness responses are 45.3%, 32.3%, and 22.4%, respectively. Based on this, it is seen that the weight contribution of production time is the most significant for CNC production.

After conducting GRA-PCA, GRCs for responses were recalculated based on the weighted factors. Lastly, each response was combined into a single response as a GRG value (Table 10).

According to GRG values obtained with GRA-PCA, the optimal values of the input parameters are as follows: operator experience level is level 3 (10,00), CNC machine brand is level 4 (Yuntes), CNC machine age is level 1 (2,00) and machine size is level 2 (700x450x500). While the most significant parameter for CNC production is machine size, the least effective parameter for CNC production is the CNC machine brand. The efficiency levels of the parameters are as follows in order from highest to lowest: machine size, operator experience level, CNC machine age, and CNC machine brand. After the GRA-PCA method was applied, sensitivity analysis was applied, and twenty-one different alternatives were analysed according to the weight levels that the perfomance factors could be weighted.

Sensitivity Analysis

At this subsection of this study, a sensitivity analysis was performed as it was expected that the risks and uncertainties that may arise from the results obtained with the previously applied methods could potentially affect the study. Twenty-one alternative weight levels were defined for the responses of production time, dimension conformity, and surface roughness. The weight values are shown in Table 11. The weighted GRG values and parameters for the alternatives are shown in Table 12 - Table 32.

The results attained in the sensitivity analysis performed are as follows: In the seven different alternatives (alternative no. 4, 5, 6, 7, 8, 9, and 15), level 3 of parameter A (10.00), the level 4 of parameter B (Yuntes); the level 1 of parameter C (2.00) and the level 2 of parameter D (700x450x500) are optimum. In the six different alternatives (alternative no. 16, 17, 18, 19, 20, and 21), level 4 of parameter A (14.00), level 1 of parameter B (Mazak), level 1 of parameter C (2.00) and level 2 of parameter D (700x450x500) are optimum. In the five different alternatives (alternative no. 10, 11, 12, 13, and 14), level 3 of parameter A (10.00); level 1 of parameter B (Mazak); level 1 of parameter C (2.00), and level 2 of parameter D (700x450x500) are optimum. In the two different alternatives (alternative no. 2 and 3), level 3 of parameter A (10.00), level 2 of parameter B (Okuma), level 1 of parameter C (2.00), and level 2 of parameter D (700x450x500) are obtained as optimum. Finally, among the twenty-one different alternatives, in the one alternative (alternative no. 1), level 3 of parameter A (10.00); level 2 of parameter B (Okuma); level 1 of parameter C (2.00); and level 1 of parameter D (500x550x550), are determined as optimum.

Table 10. Weighted GRG values and parameters according to GRA-PCA

Levels	A	B	C	D
1	0.469	0.583	**0.675**	0.517
2	0.608	0.568	0.574	**0.692**
3	**0.639**	0.519	0.516	0.564
4	0.564	**0.610**	0.515	0.507
Delta	0.17	0.09	0.16	0.19
Rank	2	4	3	1

Table 9. Eigenvectors for PCs and the contribution of each response

Responses	PC1	PC2	PC3	Weight contribution
Production Time (min)	0.361	0.895	-0.261	0.453
Dimension Conformity (ratio)	-0.69	0.068	-0.721	0.323
Surface Roughness (μm)	0.628	-0.44	-0.642	0.224

Table 11. Weight values of performance factors in sensitivity analysis

Alternative No.	Production Time (min)	Dimension Conformity (ratio)	Surface Roughness (μm)
1	1.00	0.00	0.00
2	0.90	0.10	0.00
3	0.80	0.10	0.10
4	0.70	0.20	0.10
5	0.60	0.20	0.20
6	0.50	0.30	0.20
7	0.40	0.30	0.30
8	0.30	0.40	0.30
9	0.20	0.50	0.30
10	0.10	0.60	0.30
11	0.10	0.70	0.20
12	0.10	0.80	0.10
13	0.00	0.90	0.10
14	0.00	1.00	0.00
15	0.30	0.30	0.40
16	0.20	0.30	0.50
17	0.20	0.20	0.60
18	0.10	0.20	0.70
19	0.10	0.10	0.80
20	0.00	0.10	0.90
21	0.00	0.00	1.00

Table 12. Weighted GRG values and parameters for Alternative-1

Levels	A	B	C	D
1	0.464	0.482	**0.662**	**0.645**
2	0.643	**0.620**	0.606	0.602
3	**0.650**	0.525	0.459	0.447
4	0.446	0.576	0.476	0.509
Delta	0.204	0.138	0.203	0.198
Rank	1	4	2	3

Table 13. Weighted GRG values and parameters for Alternative-2

Levels	A	B	C	D
1	0.459	0.502	**0.665**	0.619
2	0.640	**0.606**	0.595	**0.622**
3	**0.656**	0.525	0.476	0.469
4	0.462	0.584	0.480	0.506
Delta	0.197	0.104	0.189	0.153
Rank	1	4	2	3

Table 14. Weighted GRG values and parameters for Alternative-3

Levels	A	B	C	D
1	0.468	0.518	**0.667**	0.599
2	0.628	**0.603**	0.596	**0.634**
3	**0.643**	0.522	0.477	0.489
4	0.492	0.587	0.491	0.509
Delta	0.175	0.084	0.189	0.144
Rank	2	4	1	3

Table 15. Weighted GRG values and parameters for Alternative-4

Levels	A	B	C	D
1	0.463	0.538	**0.670**	0.573
2	0.625	0.589	0.586	**0.654**
3	**0.649**	0.523	0.494	0.512
4	0.507	**0.595**	0.496	0.506
Delta	0.185	0.073	0.176	0.147
Rank	1	4	2	3

Table 16. Weighted GRG values and parameters for Alternative-5

Levels	A	B	C	D
1	0.473	0.555	**0.671**	0.553
2	0.614	0.586	0.586	**0.665**
3	**0.635**	0.519	0.495	0.532
4	0.537	**0.599**	0.507	0.510
Delta	0.163	0.080	0.176	0.155
Rank	2	4	1	3

Table 17. Weighted GRG values and parameters for Alternative-6

Levels	A	B	C	D
1	0.468	0.574	**0.674**	0.527
2	0.611	0.572	0.576	**0.685**
3	**0.641**	0.520	0.512	0.554
4	0.553	**0.607**	0.511	0.506
Delta	0.174	0.087	0.163	0.178
Rank	2	4	3	1

Table 18. Weighted GRG values and parameters for Alternative-7

Levels	A	B	C	D
1	0.477	0.591	**0.676**	0.507
2	0.600	0.569	0.577	**0.696**
3	**0.628**	0.517	0.513	0.574
4	0.583	**0.611**	0.522	0.510
Delta	0.151	0.094	0.162	0.190
Rank	3	4	2	1

Table 19. Weighted GRG values and parameters for Alternative-8

Levels	A	B	C	D
1	0.472	0.610	**0.679**	0.481
2	0.597	0.555	0.566	**0.716**
3	**0.633**	0.517	0.530	0.597
4	0.599	**0.619**	0.527	0.507
Delta	0.162	0.102	0.152	0.235
Rank	2	4	3	1

Table 20. Weighted GRG values and parameters for Alternative-9

Levels	A	B	C	D
1	0.467	**0.630**	**0.682**	0.456
2	0.594	0.541	0.555	**0.736**
3	**0.639**	0.517	0.546	0.619
4	0.614	0.627	0.531	0.503
Delta	0.173	0.113	0.151	0.280
Rank	2	4	3	1

Table 21. Weighted GRG values and parameters for Alternative-10

Levels	A	B	C	D
1	0.462	**0.649**	**0.685**	0.431
2	0.591	0.527	0.545	**0.756**
3	**0.645**	0.517	0.563	0.641
4	0.630	0.635	0.536	0.500
Delta	0.183	0.132	0.149	0.326
Rank	2	4	3	1

Table 22. Weighted GRG values and parameters for Alternative-11

Levels	A	B	C	D
1	0.448	**0.652**	**0.687**	0.426
2	0.600	0.516	0.533	**0.765**
3	**0.665**	0.521	0.578	0.643
4	0.616	0.639	0.530	0.493
Delta	0.217	0.136	0.157	0.339
Rank	2	4	3	1

Table 23. Weighted GRG values and parameters for Alternative-12

Levels	A	B	C	D
1	0.433	**0.655**	**0.689**	0.422
2	0.608	0.505	0.522	**0.774**
3	**0.684**	0.524	0.593	0.645
4	0.601	0.643	0.523	0.487
Delta	0.251	0.150	0.167	0.352
Rank	2	4	3	1

Table 24. Weighted GRG values and parameters for Alternative-13

Levels	A	B	C	D
1	0.428	**0.674**	**0.692**	0.396
2	0.605	0.491	0.512	**0.794**
3	**0.690**	0.524	0.609	0.667
4	0.617	0.651	0.528	0.483
Delta	0.262	0.183	0.180	0.398
Rank	2	3	4	1

Table 25. Weighted GRG values and parameters for Alternative-14

Levels	A	B	C	D
1	0.414	**0.677**	**0.694**	0.392
2	0.614	0.480	0.500	**0.803**
3	**0.709**	0.528	0.624	0.669
4	0.603	0.655	0.522	0.476
Delta	0.295	0.197	0.194	0.411
Rank	2	3	4	1

Table 26. Weighted GRG values and parameters for Alternative-15

Levels	A	B	C	D
1	0.486	0.608	**0.677**	0.486
2	0.588	0.566	0.577	**0.707**
3	**0.614**	0.513	0.515	0.595
4	0.613	**0.615**	0.533	0.514
Delta	0.128	0.101	0.162	0.222
Rank	3	4	2	1

Table 27. Weighted GRG values and parameters for Alternative-16

Levels	A	B	C	D
1	0.495	**0.624**	**0.678**	0.465
2	0.577	0.563	0.578	**0.719**
3	**0.601**	0.510	0.516	0.615
4	0.643	0.619	0.544	0.517
Delta	0.148	0.114	0.162	0.254
Rank	3	4	2	1

Table 28. Weighted GRG values and parameters for Alternative-17

Levels	A	B	C	D
1	0.510	**0.622**	**0.676**	0.470
2	0.569	0.574	0.589	**0.710**
3	0.581	0.507	0.501	0.613
4	**0.657**	0.615	0.550	0.524
Delta	0.148	0.115	0.175	0.240
Rank	3	4	2	1

Table 29. Weighted GRG values and parameters for Alternative-18

Levels	A	B	C	D
1	0.519	**0.638**	**0.678**	0.449
2	0.557	0.570	0.590	**0.721**
3	0.568	0.504	0.502	0.634
4	**0.687**	0.619	0.561	0.527
Delta	0.169	0.135	0.175	0.272
Rank	3	4	2	1

Table 30. Weighted GRG values and parameters for Alternative-19

Levels	A	B	C	D
1	0.533	0.636	0.676	0.453
2	0.549	0.581	0.601	0.713
3	0.548	0.500	0.487	0.632
4	0.702	0.615	0.567	0.534
Delta	0.169	0.135	0.188	0.259
Rank	3	4	2	1

Table 31. Weighted GRG values and parameters for Alternative-20

Levels	A	B	C	D
1	0.542	0.653	0.677	0.433
2	0.537	0.578	0.602	0.724
3	0.535	0.497	0.489	0.652
4	0.732	0.618	0.578	0.538
Delta	0.197	0.155	0.188	0.291
Rank	2	4	3	1

Table 32. Weighted GRG values and parameters for Alternative-21

Levels	A	B	C	D
1	0.557	0.650	0.675	0.437
2	0.529	0.589	0.614	0.715
3	0.515	0.494	0.474	0.650
4	0.746	0.614	0.585	0.545
Delta	0.231	0.156	0.201	0.278
Rank	2	4	3	1

The ranking of parameters in terms of their influence on the performance factors (responses) is as follows:

- In the eight different alternatives (alternative no. 6, 8, 9, 10, 11, 12, 20, and 21): D > A > C > B,
- In the six different alternatives (alternative no. 7, 15, 16, 17, 18, and 19): D > C > A > B,
- In the three different alternatives (alternative no. 1, 2, and 4): A > C > D > B,
- In the two different alternatives (Alternative No. 3 and 5): C > A > D > B,
- In the two different alternatives (Alternative No. 13 and 14): D > A > B > C.

Based on the results obtained, it has been observed that the impact ranking of parameters on responses has converged into five different clusters for the various alternatives. Table 33 shows the optimal levels of input parameters for all problem solutions.

From the 24 different solutions, in 18 of them, the best level of parameter A was 3 (10,00), and in 6 of them, the best level was 4 (14,00). In 12 solutions, the best level of parameter B was 1 (Mazak); in 9 solutions, the best level was 4 (Yuntes), and in 3 solutions, the best level was 2 (Okuma). The best level of parameter C was found to be 1 (2.00) in all solutions. Lastly, the best level of parameter D was 2 (700x450x500) in 23 solutions and level 1 (500x550x550) in 1 solution. After the obtained results, the ANOVA method was applied based on the S/N ratios of CNC production in the next stage of this study.

Analysis of Variance

ANOVA, which is a statistical approach was applied according to the S/N ratios; the obtained results are given in Table 34.

SS represents the total variability between and within groups, while MS is the value obtained by dividing SS by the degrees of freedom (df). The F-value is the ratio of the variance between groups to the variance within groups. This value is used to test whether there is a significant difference between groups. The p-value indicates the probability that the observed difference between groups occurred by chance based on the calculated F-value. If $p<0.05$, the difference between groups is statistically significant, whereas if $p\geq0.05$, the difference is not statistically significant [32].

Table 33. Optimum values according to all applied methods

Methods	A	B	C	D
TM	3	1	1	2
GRA	3	4	1	2
GRA-PCA	3	4	1	2
Alt. 1	3	2	1	2
Alt. 2	3	2	1	2
Alt. 3	3	2	1	2
Alt. 4	3	4	1	2
Alt. 5	3	4	1	2
Alt. 6	3	4	1	2
Alt. 7	3	4	1	2
Alt. 8	3	4	1	2
Alt. 9	3	4	1	2
Alt. 10	3	1	1	2
Alt. 11	3	1	1	2
Alt. 12	3	1	1	2
Alt. 13	3	1	1	2
Alt. 14	3	1	1	2
Alt. 15	3	4	1	2
Alt. 16	4	1	1	2
Alt. 17	4	1	1	2
Alt. 18	4	1	1	2
Alt. 19	4	1	1	2
Alt. 20	4	1	1	2
Alt. 21	4	1	1	2

According to the ANOVA, the contributions of the process parameters and their influence ranking on the performance factors according to the F-values are given below.

i) For production time: A (24.71%) > C (19.40%) > D (15.41%) > B (7.79%).
ii) For dimension conformity: D (46.56%) > A (18.80%) > B (16.18%) > C (15.02%).
iii) For surface roughness response is as follows: D (18.11%) > A (14.31%) > C (6.71%) > B (5.82%).

For input parameter production time, the ranking of the input parameters by applying Taguchi method was found as A (Δ=6.89) > D (Δ=6.65) > C (Δ=6.56) > B (Δ=4.58) (see Table 4), while the ranking in ANOVA was obtained as A (24.71%) > C (19.40%) > D (15.41%) > B (7.79%) (see Table 34). It is seen that the difference between the delta values of C (CNC Machine Age) and D (Workbench Size (mm)) parameters is quite low, while the percentage differences obtained by ANOVA are rather high. Additionally, with the expert feedback from the manufacturing company, it can be said that C is more important than D parameter in CNC production. When the results are observed, it can be

Table 34. ANOVA table for S/N ratios of CNC production

Responses	Parameters	df	SS	MS	F-value	P-value	Contribution (%)
Production Time (min)	A	3	163.7	54.58	1.31	0.316	24.71
	B	3	51.6	17.2	0.34	0.798	7.79
	C	3	128.6	42.86	0.96	0.442	19.4
	D	3	102.1	34.05	0.73	0.554	15.41
Dimension Conformity (ratio)	A	3	159.4	53.14	0.93	0.457	18.8
	B	3	137.2	45.74	0.77	0.531	16.18
	C	3	127.4	42.45	0.71	0.566	15.02
	D	3	394.8	131.59	3.48	0.05	46.56
Surface Roughness (μm)	A	3	0.5723	0.1908	0.67	0.588	14.31
	B	3	0.2329	0.07763	0.23	0.862	5.82
	C	3	0.2682	0.08941	0.29	0.834	6.71
	D	3	0.7245	0.2415	0.88	0.477	18.11

Abbreviations: df; degrees of freedom, SS; the sum of squares of errors, MS; the mean sum of squares of errors

concluded that the results of the ANOVA support the findings obtained in the other methods.

Confirmation Tests

Confirmation tests were carried out to verify the optimality of CNC process parameter levels found by the GRA-PCA-TM method and to confirm the improvement in the performance factors. The results are shown in Table 35. The experimental results of production time, dimension conformity, and surface roughness responses at the optimal parameter levels were utilized to predict the actual S/N ratio.

In the confirmation tests, it was observed that the estimated S/N values and the real S/N values were consistent. As a result, the actual S/N ratio for production time (-28.79) improved by 45% compared to the initial process parameter (-49.00), the actual S/N ratio for dimension conformity (-0.45) improved by 95% compared to the initial process parameter (-8.87) and lastly, the actual S/N ratio for surface roughness (13.98) improved by 504% compared to the initial process parameter (-3.46).

As previously stated in the study, no study using the input parameters used in this study has been found in the literature. While many studies in the literature have used surface roughness as a performance factor, one study has been encountered in which production time has been used [33], while no study has been found in which dimension conformity has been used. Although TM, GRA and PCA methods were used in this study, there is no other study in

Table 35. Results of confirmation tests for production time, dimension conformity, and surface roughness responses

			Optimum CNC production parameters	
Responses		Initial CNC production parameters	Prediction	Experiment
Production Time (min)	Levels	A1B1C1D1	A3B2C1D1	A3B2C1D1
	Average values	282.00		27.50
	S/N ratios	-49.00	-34.77	-28.79
	Improvement in S/N ratios			20.21 (%45)
Dimension Conformity (ratio)	Levels	A1B1C1D1	A3B1C1D2	
	Average values	0.36		
	S/N ratios	-8.87	10.54	-0.45
	Improvement in S/N ratios			8.42 (%95)
Surface Roughness (μm)	Levels	A1B1C1D1	A4B1C1D2	
	Average values	1.49		
	S/N ratios	-3.46	19.59	13.98
	Improvement in S/N ratios			17.44 (%504)

the literature that hybridises these methods. In this study, 45%, 95%, and 504% improvements were obtained in production time, dimension conformity and surface roughness, respectively, while it was observed that this level of improvement was not acquired earlier studies in the literature [14,17,21,24,34,35]. Since the input parameters used in the previous studies in the literature differ from those used in this study, it was not feasible to compare the findings obtained in terms of the parameters affecting CNC production with the appropriate studies in the literature.

CONCLUSION

This study focuses on multiple performance factor optimization of the process parameters of CNC production in metal sector, which is the most significant process of an organization operating in this sector, using TM, GRA, and GRA-PCA and performing sensitivity analysis. In this scope, the impacts of CNC production process parameters, which are operator experience level, CNC machine brand, CNC machine age, and machine size, on the performance factors of production time, dimension conformity, and surface roughness were searched and multiple performance optimization was conducted. The study revealed that the most influential parameter for CNC production was the machine size in TM, GRA, GRA-PCA, and sensitivity analysis in sixteen alternatives. The least affecting parameter for CNC production is the CNC machine brand in TM, GRA, GRA-PCA, and nineteen different alternative weightings made in the sensitivity analysis. The ANOVA application has supported these results and has been confirmed by the subsequent confirmation tests.

As a result of the confirmation tests, it was concluded that the estimated S/N values and the real S/N values are compatible. For production time, the actual S/N ratio (-28.79) improved by 45% compared to the initial process parameter (-49.00); for dimension conformity, the actual S/N ratio (-0.45) improved by 95% compared to the initial process parameter (-8.87) and finally for surface roughness the actual S/N ratio (13.98) improved by 504% in comparison to the initial process parameter (-3.46).

The optimum combination of CNC production parameters based on multiple response variables was obtained as A3B1C1D2, so the optimum values were determined as 10.00 for operator experience level, Mazak for CNC machine brand, 2.00 for CNC machine age and 700x450x500 for machine size.

From all the results obtained, this study has limitations that open a field of study for future research since the findings obtained from the data set received from the company operating in the metal sector are focused on a particular sector. Besides the TM and GRA, PCA was conducted to weigh the performance factors, and sensitivity analysis was performed to determine the risks or uncertainties that may potentially affect this study. In these aspects, this study is unique and contributes to the literature. Moreover, companies can benefit from managerial practices by considering the ranking of parameters affecting CNC production according to the results obtained from the study. For instance, companies can assign CNC operators to the appropriate machine especially in critical parts. In addition, in critical material production, the part can be assigned to the most proper machine. Additionally, the obtained results in this study provide managers a strategic perspective for future recruitment, machine investment decisions or long-term process planning.

In future studies, it is concluded that different multi-criteria decision-making methods can be used for multiple optimization of process parameters and the diversity of process parameters and response factors can be increased in CNC production.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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