Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 14s (2025)
https://www.jneonatalsurg.com

Optimization Of Multiple Objectives in The Machining Process of SS304 Sheet Metal Components.

Nikhil Janardan Rathod [1], Praveen B. M. [2], Mayur Gitay[3], Sidhhant N. Patil[4], Mohan T. Patel[5]

[1]Post Doctorate Fellowship, Department of Mechanical Engineering, Srinivas University, Manglore, Karnataka, India,

[2]Professor, Department of Nanotechnology, srinivas university mangalore, Karnataka, India

[3]Lecturer, Department of Mechanical Engineering, Bivrabai Sawant Polytechnic, Pune, Maharashtra, India

[4]Assistant Professor, Department of Electrical Engineering, Shatabdi Institute of Engineering and Research, Nashik, Maharashtra, India

[5]Assistant Professor, Department of Electrical Engineering, Late G. N. Sapkal college of Engineering, Nashik, Maharashtra, India

***Corresponding Author:**

Email ID: rathodnikhil358@gmail.com

Cite this paper as: Nikhil Janardan Rathod , Praveen B. M. , Mayur Gitay, Sidhhant N. Patil, Mohan T. Patel, (2025) Optimization Of Multiple Objectives in The Machining Process of SS304 Sheet Metal Components.. *Journal of Neonatal Surgery*, 14 (14s), 801-809.

ABSTRACT

A comprehensive investigation has been conducted on the settings for the turning operation of SS 304. This study utilizes the Grey-Based Taguchi method to explore the multi-objective optimization of the turning process, aiming to determine the optimal combination of settings that results in the shortest production time and the longest tool life. The parameters examined include feed rate, cutting speed, and depth of cut. To address the multi-response optimization challenge, nine experimental runs were performed based on Taguchi's L9 orthogonal array, followed by a Grey relational analysis. The Grey relational grade value was employed to ascertain the most effective parameter levels. Additionally, the analysis of variance (ANOVA) will play a crucial role in identifying the key parameters among speed, feed, and cut depth.

Keywords: *SS 304, Grey relation analysis, Tool life, Production time*.

1. INTRODUCTION

The endeavor to identify optimal machining parameters is a continuous engineering task focused on minimizing production time while maximizing tool longevity. Tool life is a critical performance indicator in the turning process, serving as a widely recognized quality metric and often a prerequisite for mechanical components. Concurrently, production time is a factor that significantly influences manufacturing costs and machining hourly rates. In the turning process, selecting cutting parameters that ensure high efficiency and quality for a specific machine and context is essential. To improve tool life and reduce production time, this study employed a multiple quality optimization approach, integrating Grey relational analysis with Taguchi methods to determine the most effective cutting settings. The Taguchi L9 orthogonal array, which encompasses three factors at three levels, was utilized to enhance various elements of a quality turning process while minimizing the number of trials needed to identify the optimal strategy. The three primary variables chosen for this analysis were cutting speed, depth of cut, and feed rate. To transform a multi-objective problem into a single objective, a Grey Relational Grade (GRG) is utilized. Grey Relational Analysis (GRA) was employed to identify the optimal combination of process parameters aimed at enhancing tool longevity while simultaneously reducing production time [1–4]. R. Viswanathan et al. [5] investigated cutting power, tool flank wear, material removal rate, and surface roughness during turning operations on magnesium alloy under dry conditions, utilizing a carbide insert coated through physical vapor deposition. The experiments were conducted using Taguchi's L27 Orthogonal Array. The optimal settings were determined by integrating principal component analysis with GRA. Variance analysis revealed that the depth of cut is the most significant factor influencing this stage of multiple output characteristics. P. Umamaheswarrao et al. [6] present a study that illustrates the application of multi-objective optimization to enhance surface quality, machining power, and surface temperature during the hard turning of AISI 52100 steel. The key input variables examined include feed rate, depth of cut, cutting speed, and nose radius. The research employs the L9 orthogonal Taguchi array for experimentation. Additionally, Grey Relational Analysis (GRA) and Principal Component Analysis are utilized for the optimization process. The findings indicate that the nose radius is the most influential factor on the outcomes, followed by cutting speed, feed rate, and depth of cut. R.A. Kazeem and colleagues [7] sought to assess the effectiveness of several lesser-known vegetable oils as machining cutting fluids. Their research focused on the surface roughness resulting from a jatropha oil blend, as well as cutting temperature and chip formation during the turning of Steel alloy AISI 1525 with a coated carbide tool. These results were compared to those obtained using mineral oil. The experimental approach employed was a Taguchi L9 orthogonal array, and they conducted multi-response optimization utilizing Grey Relational Analysis (GRA). The findings indicated that for both jatropha and mineral oil-based cutting fluids, the feed rate significantly influenced surface roughness, whereas cutting speed had the most substantial impact on cutting temperature. In their study, Muhammad Abas and colleagues [8] employ a combined desirability function approach to analyze and optimize the cutting process parameters for Aluminum alloy 6026-T9 using Minimum Quantity Lubrication (MQL), even under dry conditions. They emphasize the significance of various criteria through comparative analysis. The cutting parameters evaluated include surface roughness, tool life, and material removal rate, while the influencing factors consist of cutting speed, feed rate, cut depth, and positive rake angle. The research utilizes a specific Taguchi orthogonal array known as L16, which encompasses sixteen experimental trials. The analysis of variance reveals that the primary cutting parameters affecting surface roughness in both scenarios are cutting speed and feed rate. For tool life, the feed rate emerges as the predominant factor, whereas for material removal rate, the critical factors include feed rate, cutting speed, and cut depth. Abdullah Aslan and colleagues [9] investigated the influence of cutting parameters and tool geometry on various process factors through ANOVA in their research. The study involved the turning of AISI 5140, focusing on the relationship between cutting forces and both VB and Vb. Additionally, they conducted several optimizations utilizing Response Surface Methodology (RSM). The findings suggest that cutting force signals can effectively monitor VB, while VB signals provide critical insights into the machining process, as illustrated by the graphs. Sara Moghadaszadeh Bazaz and her team [10] aimed to identify an efficient machining process or a combination of techniques for evaluating tool life under various turning conditions and scenarios. The premise of this research is that integrating machine learning with mathematical modeling presents a viable approach to analyzing tool life in small-lot manufacturing, optimizing both cost and time. M. Durairaj and colleagues [11] employed a multi-objective genetic algorithm in their study to perform statistical modeling and optimize method parameters, aiming to determine the ideal cutting conditions for both tool wear and surface roughness. The coding was executed using a multi-objective genetic algorithm program. This approach was utilized to improve objectives such as surface roughness and flank wear, with the outcomes validated against experimental data. Wassila Bouzid and her team [12] concentrated on maximizing spindle speed and machine power as constraints in their research. Their methodology involved defining the feed rate based on surface roughness, which is affected by cutting speed. They identified the cutting speed that resulted in the shortest processing times and compared it to the permissible values established by the constraints. Ultimately, they determined the optimal feed rate. The findings indicate that the proposed system is capable of selecting the necessary conditions. Phengky Pangestu and colleagues [13] aim to create a model that enhances multi-objective multi-pass turning by identifying optimal cutting parameters, including feed rate, spindle speed, cutting speed, depth of cut, and the number of roughing passes. The optimization algorithm emphasizes key production metrics such as energy consumption, carbon emissions, production duration, and costs. An analytical example is included to demonstrate the model's functionality in assessing the influence of various factors on the parameters of the target functions, incorporating sensitivity analysis. Dau Majak and associates [14] investigated the efficacy of different natural vegetable oils as long-lasting lubricants in machining applications. The study utilized a Lathe Colechester Master 3250 to work with Stainless Steel AISI 304. Taguchi's experimental design methodology was employed in this research. To assess the performance of these oils in machining stainless steel AISI 304, input parameters such as feed rate, cutting speed, and depth of cut were examined, with results measured in terms of chip-compression ratio and surface roughness—two critical factors. The results indicated that sunflower oil outperformed the other oils as a cutting fluid. Ilhan Asiltürk and colleagues [15] present an innovative approach to determining optimal cutting conditions and developing mathematical models for surface roughness in CNC turning operations. Initially, the Taguchi method is employed to establish cutting parameters, including cutting speed, depth of cut, and feed rate. The findings indicate that the primary factor influencing surface roughness is its reduction when both the feed rate and depth of cut are minimized, while the cutting speed is maximized.

The objective of the research outlined in this paper is to enhance tool longevity and decrease production time. The study details the application of Grey Relational Analysis (GRA) to optimize process parameters for high-speed machining of SS304. Consideration was given to cutting speed, feed rate, and depth of cut, with tool life and production time analyzed as response variables.

2. RESEARCH INITIATIVES

The study was carried out using SS 304 steel, a material commonly employed in water pumps and similar applications due to its favorable strength, ease of machining, and relatively low weight compared to alternative materials. The focus of this research is on SS 304, an austenitic steel that comprises 18% chromium, 8% nickel, and 0.08% carbon, often referred to as 18–8. As illustrated in Tables 1 and 2, the minimum chromium content of 18% is effective in preventing rust and oxidation-related damage. The 8% nickel content primarily influences the alloy's characteristics and enhances its resistance to corrosion from chemical agents. The carbon content is carefully regulated, remaining suitable for most applications with a maximum of 0.08%. Refer to Fig. 1 for further details. Machining was performed on a CNC turning machine, with the selected machining specifications detailed in Table 3. The Taguchi method employs a unique orthogonal array to explore all parameter variations while minimizing the number of tests conducted. This investigation utilized a Taguchi-based experimental design, specifically an L9 orthogonal array, incorporating three levels for three primary cutting parameters: feed rate, cutting speed, and depth of cut. The machining process varied across different cutting speeds, depths of cut, and feed rates. Tool life was assessed by counting the number of components produced per insert, while production time was tracked using a timer. The influence of design parameters on both tool life and production time was evaluated through ANOVA. The experimental findings were normalized and structured using Grey Relational Analysis (GRA). At the conclusion of the process, Grey relational generation was performed. The Grey Relational Coefficient (GRC) was computed from these normalized results, linking the actual trial outcomes to the anticipated results. The GRCs for each response were aggregated to form the overall Grey Relational Gradient (GRG), which signifies the total output characteristic of a process with multiple response parameters. The parameter combination yielding the highest GRG is deemed optimal and will be further analyzed. The Taguchi method will be employed to identify the set of parameters that produces the maximum GRG. For grey relation generation, the "Higher-the-better" criterion is applied to the normalized tool life, as indicated in "(1)", while the "Lower-the-better" criterion is utilized for the production time data, as shown in "(2)". Refer to Table 4 for additional details.

Figure 1 Machine Set Up

Table 1 Chemical composition of the work piece material (%)

C	**Mn**	**Si**	**Cr**	**Ni**	**P**	**S**
0.08	2.0	0.75	18-20	8-10.05	0.045	0.03

Table 2 Mechanical properties of carbon steel

Material	**Tensile strength**	**Yield strength (MPa)**	**Elongation**	**Hardness (Rockwell B)**	**Hardness (Brinell HB)**

	(MPa)				
SS304	515	205	40%	92	92

$$a^*(k) = \frac{\max a^i - a^i(k)}{\max a^i(k) - \min a^i(k)} \quad (1)$$

$$a^*(k) = \frac{a^i(k) - \min a^i(k)}{\max a^i(k) - \min a^i(k)} \quad (2)$$

$$\varepsilon(k) = \frac{\Delta_{min} + \gamma\,\Delta_{max}}{\Delta_o\,(k) + \gamma\,\Delta_{max}} \quad (3)$$

$$\Delta_i(k) = [x_o(l) - x_i(l)] \quad (4)$$

$$\Delta_{max} = \max max\,[x_o(l) - x_i(l)] \quad (5)$$

$$\Delta_{min} = \min min\,[x_o(l) - x_i(l)] \quad (6)$$

$$y_i = \frac{1}{n}\sum_{k=1}^{n} \epsilon_i\ (k) \quad (7)$$

3. RESULTS AND DISCUSSION

Table 5 displays the findings related to tool life and production time. The data in Tables 6–11 reveal that cutting speed is the most significant factor contributing to improved tool life and enhanced production time, as indicated by the ANOVA analysis. Table 6 outlines the percentage contributions of various machining factors, highlighting that cutting speed has a notable impact on both tool life and production time.

Table 3 Process Parameters and Levels

Level	Cutting Speed m/min	Feed Rate mm/Rev	Depth of Cut Mm
1	350	0.1	0.25
2	450	0.12	0.30
3	550	0.14	0.35

Table 4 Experimental layouts using an L9 orthogonal array

Exp No.	Cutting Parameter Level		
	A	B	C
	Cutting Speed	Feed Rate	Depth of Cut
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	3
5	2	2	1

6	2	3	2
7	3	1	2
8	3	2	3
9	3	3	1

Table 5 Experimental results for tool life and S/N ratio

Exp No.	Cutting Parameter Level				
	A	B	C	Tool Life	Production Time
	Cutting Speed	Feed Rate	Depth of Cut		
1	350	0.1	0.25	134	99
2	350	0.12	0.3	120	93
3	350	0.14	0.35	116	84
4	450	0.1	0.35	138	92
5	450	0.12	0.25	126	98
6	450	0.14	0.3	132	95
7	550	0.1	0.3	143	88
8	550	0.12	0.35	137	86
9	550	0.14	0.25	133	79

Table 6 ANOVA for S/N ratio of Tool Life

FACTORS	D.O.F. (n -1)	Sum of Square	Mean Square.	% Contribution of factor	Rank
Cutting Speed	2	1.43206	0.716029	51.08 %	1
Feed Rate	2	1.07416	0.537078	38.31 %	2
Depth of Cut	2	0.28288	0.141439	10.09 %	3
Error	2	0.01407	0.007035		
Total	8	2.80316			

Table 7 ANOVA for S/N ratio of Production Time

FACTORS	D.O.F. (n-1)	Sum of Square	Mean Square.	% Contribution of factor	Rank
Cutting Speed	2	1.7262	0.8631	50.74%	1
Feed Rate	2	0.8850	0.4425	26.01%	2
Depth of Cut	2	0.4122	0.2061	12.11%	3
Error	2	0.3784	0.1892		
Total	8	3.4018			

Table 8 Normalized values

Exp. No.	Normalized values of responses		
	Tool Life	Production Time	Surface Roughness
	Larger-the better	Smaller-the-better	Smaller-the-better
1	0.689	1.000	0.769
2	0.162	0.723	0.197
3	0.000	0.272	0.458
4	0.830	0.675	0.027
5	0.395	0.955	1.000
6	0.617	0.817	0.567
7	1.000	0.478	0.951
8	0.795	0.376	0.000
9	0.654	0.000	0.727

Table 9 Deviation sequences of responses

Exp. No.	Deviation sequences		
	Tool Life	Production Time	Surface Roughness
1	0.311	0.000	0.231
2	0.838	0.277	0.803
3	1.000	0.728	0.542
4	0.170	0.325	0.973
5	0.605	0.045	0.000
6	0.383	0.183	0.433
7	0.000	0.522	0.049
8	0.205	0.624	1.000
9	0.346	1.000	0.273

Table 10 Grey relational coefficients

Exp. No.	Grey relational coefficients		
	Tool Life	Production Time	Surface Roughness
1	0.617	1.000	0.684
2	0.374	0.643	0.384
3	0.333	0.407	0.480
4	0.746	0.606	0.339
5	0.453	0.917	1.000
6	0.567	0.732	0.536
7	1.000	0.489	0.911
8	0.709	0.445	0.333
9	0.591	0.333	0.647

Table 11 Grey relational grade

Exp. No.	Grey relational grade	Rank
1	0.767	3
2	0.467	8

3	0.407	9
4	0.564	5
5	0.790	2
6	0.612	4
7	0.800	1
8	0.496	7
9	0.524	6

In Fig. 2, the average initially declines before rising again as cutting speed increases. The average for feed rate consistently increases, while the depth of cut shows an initial rise followed by a decline. Similarly, Fig. 3 illustrates that the average first decreases and then increases again with rising cutting speed. In contrast, the average for feed rate continues to rise, and the depth of cut initially increases before experiencing a decrease.

Grey relational analysis

This study emphasizes the importance of tool life and production time. Ideally, tool life should be maximized, while production time should be minimized. In the context of Grey Relation Analysis, tool life is categorized as "Higher-the-better," whereas production time is classified as "Lower-the-better." The analysis of all sequences is conducted using equations “(1)”, “(2)”, and “(3)”, with the findings presented in tables IX and VIII. In this context, xo( )l denotes the reference point, and xi( )l signifies the sequence being compared. To calculate the Grey relational coefficient, the distinguishing coefficient 2 is incorporated into equation “(4)”. The Grey relational grade for each experiment, as well as for each L9 OA experiment, is evaluated using equations “(4)”, “(5)”, “(6)”, and “(7)”. The multi-objective optimization challenge addressed through GRA is streamlined into the optimization of a single comparable objective function. As a result, by focusing on the highest Grey relational grade, the Taguchi method is employed to identify the optimal combination of process parameters.

4. CONCLUSION

ANOVA and Grey Relational Analysis were employed to investigate the impact of cutting parameters on the turning of SS 304. The primary objectives were to achieve the maximum tool life and the minimum production time.

- Grey Relational Analysis (GRA) is a highly efficient technique for enhancing machining processes that involve multiple responses.

- For optimal turning of SS 304, the recommended cutting parameters include a speed of 550 m/min, a feed rate of 0.1 mm/rev, and a depth of cut of 0.30 mm, utilizing a coated carbide insert.

REFERENCES

[1] K. Soorya Prakash, P.M. Gopal, S. Karthik, Multi-objective optimization using Taguchi based grey relational analysis in turning of Rock dust reinforced Aluminum MMC, Measurement 157 (2020) 107664.

[2] R. Viswanathan, S. Rameshb, V. Subburam, Measurement and optimization of performance characteristics in turning of Mg alloy under dry and MQL conditions, Measurement 120 (2018) 107–113.

[3] S.J. Raykara, D.M. D’Addonab, A.M. Mane, Multi-objective optimization of high speed turning of Al 7075 using grey relational analysis, Procedia CIRP 33 (2015) 293–298.

[4] P. Sivaiah, D. Chakradhar, Performance improvement of cryogenic turning process during machining of 17–4 PH stainless steel using multi objective optimization techniques, Measurement 136 (2019) 326–336.

[5] R. Viswanathan, S. Ramesh, S. Maniraj, V. Subburam, Measurement and multiresponse optimization of turning parameters for magnesium alloy using hybrid combination of Taguchi-GRA-PCA technique, Measurement 159 (2020) 107800.

[6] P. Umamaheswarrao, D. Ranga Raju, K.N.S. Suman, B. Ravi Sankar, Multi objective optimization of Process parameters for hard turning of AISI 52100 steel using Hybrid GRA-PCA, Procedia Comput. Sci. 133 (2018) 703–710.

[7] R.A. Kazeem, D.A. Fadare, J. Abutu, S.A. Lawal, O.S. Adesina, Performance evaluation of jatropha oil-based cutting fluid in turning AISI 1525 steel alloy, CIRP J. Manufact. Sci. Technol. 31 (2020) 418–430.

[8] M. Abas, L. Sayd, R. Akhtar, Q.S. Khalid, Aqib Mashood Khan and Catalin Iulian Pruncu. Optimization of machining parameters of aluminum alloy 6026–T9 under MQL-assisted turning process, J. Mater. Res. Technol. 9 (5) (2020) 10916–10940.

[9] A. Aslan, Optimization and analysis of process parameters for flank wear, cutting forces and vibration in turning of AISI 5140: A comprehensive study, Measurement 163 (2020) 107959.

[10] S.M. Bazaz, M. Lohtander, J.h. Varis, The prediction method of tool life on small lot turning process – Development of Digital Twin for production, Procedia Manuf. 51 (2020) 288–295.

[11] M. Durairaj, S. Gowri, Parametric Optimization for Improved Tool Life and Surface Finish in Micro Turning using Genetic Algorithm, Procedia Eng. 64 (2013) 878–887.

[12] W. Bouzid, Cutting parameter optimization to minimize production time in high speed turning, J. Mater. Process. Technol. 161 (3) (2005) 388–395.

[13] P. Pangestu, Eko Pujiyanto and Cucuk Nur Rosyidi. Multi-objective cutting parameter optimization model of multi-pass turning in CNC machines for sustainable manufacturing, Heliyon. 7 (2021) e06043.

[14] D.u. Maja, Ezutah Udoncy Olugu and Sunday Albert Lawal. Analysis of the effect of sustainable lubricants in the turning of AISI 304 stainless steel, Procedia Manuf. 43 (2020) 495–502.

[15] I. Asiltürk, S. Neseli, Multi response optimisation of CNC turning parameters via Taguchi method-based response surface analysis, Measurement 45 (2012) 785–794

....