The Scientific Temper
Vol. 13, No. 2, July-December, 2022:pp 1-13
ISSN 0976-8653, E-ISSN 2231-6396
A Web of Science Journal
DOI: https://doi.org/10.58414/SCIENTIFICTEMPER.13.2.2022.1-13
Doc ID: https://connectjournals.com/03960.2022.13.2.1

Multi-response Optimization of Machining Parameters in Inconel 718 End Milling Process Through RSM-MOGA

Gourav Kalra and Arun Kumar Gupta
Department of Mechanical Engineering, Maharishi Markandeshwar (Deemed to be University), Mullana, Haryana
Corresponding author: gkalra89@mail

ABSTRACT

Most of the time, thin walls may be developed during milling operations to manufacture complicated dies and moulds. In current high-speed machining, bending these thin walls is expected owing to thermal expansion, making it a common source of dimensional error. Workpiece temperature (WT) with a response Machine time has been considered output responses. By adopting a unique technique, the response surface methodology during 2.5 D milling of Inconel 718, an anti-corrosive material, we could reach the best process parameters combination for minimizing workpiece temperature. The workpiece's temperature was determined by three sets of combinations of k-type thermocouples while the surface tester measured surface quality. *Box–Behnken design* has been used to conduct 26 trials to determine the best combinations of parameters. Several process variables were examined, including cutting speed, feed per tooth, depth of cut, and tool nose radius, and ANOVA has been used to quantify the impact of these variables. A multi-objective genetic algorithm based on the regression model has been applied to optimize the parameters. Five structural experiments were also conducted to verify this optimized process parameters combination, which was proven more successful.

Keywords: W/p Temperature, RSM, BBD, k-type thermocouple, MOGA etc.

INTRODUCTION

Modern machining technologies are constantly under pressure to cut prices while improving quality. To remain competitive, firms are always seeking ways to reduce production costs without compromising product quality. It will be essential to improve the overall performance of cutting operations in order to achieve these goals. End milling is a very versatile machining process that is employed in a wide range of industrial applications.. End milling activities typically include the removal of metal from a work item using a multiple point cutting tool. End milling is a procedure that is used in the aerospace and automotive sectors to create deep slots, Sheet metal works, profile recesses, and steps. (M.T. Hayajneh, M.S. Tahat, 2007) In the present study Inconel-718 super alloy was used extensively in virtually every branch of sophisticated manufacturing. Other high-temperature applications of nickel-based alloys include amplitude vehicles, rocket engines, nuclear reactors, submarines, and other petrochemical equipment. Nickel-based alloys are currently used in a variety of applications, including aviation, marine, automated, and vehicular gas turbines. (E.O. Ezugwu, Z.M. Wang, 1999) Nevertheless, because of its exceptional quality and limited heat conductivity, Inconel-718 is frequently considered a complex material. As a result, standard machining this material is prohibitively expensive compared to nontraditional methods. (K. Venkatesan, R. Ramanujam, 2016) The cutting characteristics of Inconel-718 materials, which include a high cutting force, high heat absorption, tool failure due to plastic deformation at high cutting speeds, a short tool life, and a work hardening effect, present significant challenges when machining nickel-based super alloys conventionally. The Inconel-718 material exhibits a high degree of attraction due to its chemical characteristics, poor conductivity due to its thermal properties, and a high strength when the tool comes into contact with the specimen's surface, all of which contribute to the specimen's fatigue life being prolonged. (L. Chang, R. Chengzu, W. Guofeng, Y. Yinwei, 2015)

Metal cutting is a very complicated thermo-mechanical event in which heat is created during machining operations due to metal plastic deformation and friction at the tool–chip and tool–workpiece interfaces. Due to the complexity of machining mechanics, predicting the intensity and dispersion of heat is challenging. For many years, the complicated interaction between plastic deformation and temperature fields has been a subject of investigation. Because the plastic deformation of metals occurs in a small zone during machining, very high temperatures are predicted in this area. The tool–chip contact reaches its maximum temperature. At elevated temperatures, the tool wear rate and fracture significantly increase, limiting tool life. High cutting temperatures are detrimental in several ways. As a result, the cutting temperature must be reduced as much as feasible.(Bhirud & Gawande, 2017.) It was discovered that strong local heat may change various attributes such as heat treatment, artificial aging, hardness, and residual stress of the material, affecting the part's fatigue life. The increase in temperature of the work item will also impact dimensional tolerances.(Brinksmeier E, Minke E, 2003) It has also been observed that the component ofInconel 718 has a thermal expansion coefficient of 13 µm/m·K, and a length of 100 mm has increased to approx 102 µm on the rise in workpiece temperature by 100°C approximately. Most dies and moulds require high accuracy with less than 50 µm by an increase in workpiece temperature of more than 100°C, and their accuracy may be compromised.Many times, large-sized, thin-walled components with bounded sides may buckle if the temperature rises above a certain threshold. Therefore, it is essential to study the workpiece's temperature to improve the components' accuracy.

Using dry machining to reduce production costs and environmental impact while safeguarding workers' health is an excellent idea. Because of its detrimental effects on human and ecological health, the lubricant used in machining cannot be relied upon in the long term. The pollution may harm the skin and lungs of the operator in the air caused by applying lubricant. 7–17 percent of the tool cost is spent on lubrication (Ryzhkin, A.A.; Shuchev, K.G.; Aliev, M.M.; Gusev, 2008). Dry machining, as opposed to the more typical method, is a popular choice for reducing or eliminating the detrimental effects of lubrication. It is connected with excellent energy efficiency, minimal environmental concerns, better material flow, and lower health safety. It is thus an intelligent approach to sustainable production that employs the dry condition. Published studies have examined how machining behaves when it is dry. Roughness and cutting temperature correlations were developed using the fuzzy system (FS) (Aydın, M.; Karakuzu, C.; Uçar, M.; Cengiz, A.; Çavuşlu, 2013).

In the recent past, researchers have adopted various techniques for reducing the temperature of the workpiece, such as improvement in cutting strategy, the geometry of the tools, optimization of machining parameters etc. To optimize the workpiece's temperature, it is necessary to build a mathematical model to predict the temperature with the input parameter. These models developed by the researchers can be classified into three categories: statistical, artificial intelligence (AI), and analytical techniques. Researchers have commonly utilized Taguchi techniques in the recent decade to study experimental design to improve industrial processes effectively. It's an iterative experimental strategy aimed at determining the importance of individual process factors and their interactions' impact in eliciting reactions. Taguchi's design of experiments (DOE) approaches use orthogonal arrays to reduce the number of tests needed to assess the effect of process factors on process responses. (Ashutosh, 2019) (Jamil et al., n.d.) (Raza et al., 2020) minimum quantity lubrication (MQL Several researchers have turned to statistical modeling approaches to estimating work piece temperature and other reactions throughout the milling process. A significant number of experiments have been carried out using design of experiment methodologies such as response surface methodology, and regression models have been built based on these experiments to demonstrate the relationship between the dependent and independent variables(Suhaily et al., 2011)feed rate, and axial depth of cut using design of experiments and the response surface methodology (RSM, (Mokhtar et al., 2011) feed rate, and axial depth of cut using design of experiments and the response surface methodology (RSM, (Gopal, 2020). Several studies have investigated the effectiveness of the RSM method in end-milling optimization. Various studies have been used to optimize the machining characteristics (Sridhar & Sellamani, 2020) (Mangaraj & Singh, 2011) (Nurul Amin et al., 2012). In contrast, Surface roughness and quality, including topology, were investigated in various studies (Kumar et al., 2021) the Wire EDM is more popular due to its outstanding features of high dimensional accuracy, lower cost of production and good surface finish as there is no physical contact between the wire and work piece. However, for the steel with higher hardness, it is difficult to obtain these features up to the required extent. Moreover, with the help of optimum process parameters selection the WEDM performance characteristics should be improved. The most commonly studied responses for this process are material removal rate (MRR (Bhardwaj et al., 2014) (Gopikrishnan et al., 2018). A number of studies have focused on the successful prediction model of temperature generation, Tool wear, the Power consumption etc. (Gopal, 2020) (Aruna & Dhanalakshmi, 2012) Inconel 718 is extensively used in sophisticated applications due to its unique properties desired for engineering applications. Due to its peculiar characteristics, machining of Inconel 718 is complicated and costly. The present work is an attempt to make use of Taguchi optimisation technique to optimise cutting parameters during high speed turning of Inconel 718 using cermet tool. The performance of the cermet tool is described using response surface methodology (RSM(Sahu et al., 2014)a novel hybrid Differential Evolution (DE.

This study aims to determine the workpiece temperature, machining time consumption, and surface quality during 2. 5-D milling of Inconel 718 alloy using parameters such as Spindle speed (SS), feed per tooth (FT), axial depth of cut (D), and nose radius (NR). The temperature distribution was determined using a pyrometer and a k-type thermocouple, while the surface quality was determined with a surface tester. Additionally, the statistical model was designed to optimize the machining settings in order to achieve the lowest possible temperature increase, the shortest possible machining time, and the best possible surface quality using the Multi-Objective Genetic Algorithm (MOGA). The Box–Behnken design (BBD) model was explored for three levels of input process parameters. ANOVA was used to determine the significance and the impact of process factors on the temperature of the workpiece. Numerous responses, WT, MT, and SF, associated with the interaction impact of 2.5 D end milling process parameters have also been examined, assisting in selecting process parameters that maintain optimal values. The experimental findings were compared to those predicted by the predictive regression model. The prognostic model used in this work aims at providing response values close to those obtained experimentally. MOGA was used in the prognostic model in order to improve the machining settings. Additionally, conformational studies with a 5% error were done to confirm the findings.

Experimental setup and Work-piece Material:

For investigating the relationships between input parameters and workpiece temperature, time consumed during machining (MT), and surface finish, three levels of each input parameter were evaluated based on the material Inconel 718 and the machine tool specification. Experiments were done on a Bharat Fritz Werner, Agni++, BMV45++ TC24 vertical milling machine (in figure 1) at Dhiman plastic industry, Ambala district, using a CNC milling machine with a maximum spindle speed of 8000 rpm and a drive motor of 13.5 kW.

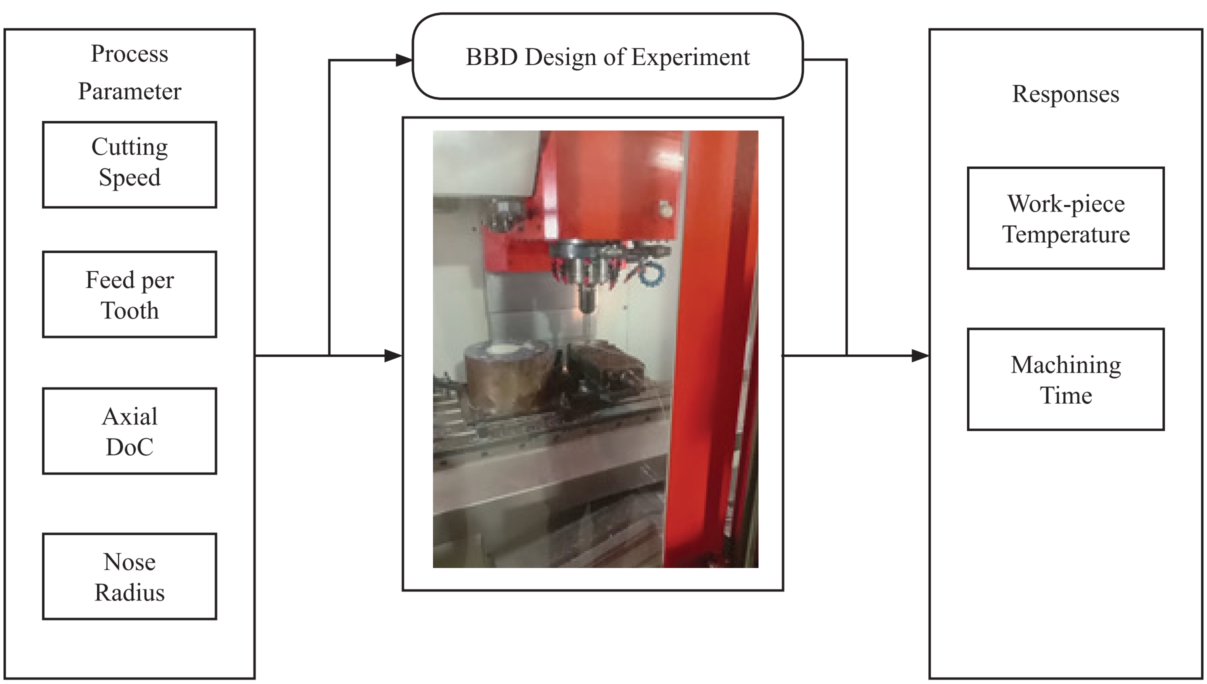


Figure 1: Experimental setup

Table 1: Chemical composition and properties of inconel 718.

Chemical Composition		Physical and Mechanical Properties		
Element	**Percentage**	**Property**	**Inconel 718**	**Tungusten Carbaide**
Chromium	16.5%	Density (g/cc)	8.19	15.25
Nickel	51.5%	Melting point(°C)	1260-1336	2870-3000
Molybdenum	2.80%	Elastic Modulus (GPa)	205	560
Columbium	4.20%	Thermal conductivity (W/mK)	11.4	84.02
Titanium	1.12%	Specific heat (J/KgK)	435	512
Cobalt	0.88%	Poisson's ratio	0.284	0.2
Aluminum	0.80%	Tensile strength (MPa)	1100	370
Iron	Balance	Hardness Rockwell C scale (HRC)	36	85

A three-set of k-type thermocouples was used for calculating the workpiece temperature, and Mahr Pocket Surf- surface tester was used for the testing degree of surface finish, as shown in figure 2. The range of temperature measurement is from -270°C to 1250°C, with the precision of ±0.75 to ±2%, and Special Limits of Error: +/- l°C or 0.4%. The responses were chosen for the experimental work at various input variables using Inconel 718 super alloy as a workpiece, and a flat end tungsten carbide with flutes and 20 mm diameter having two flutes has been used as a cutting tool. The chemical composition and mechanical properties of Inconel 718 are given in Table.

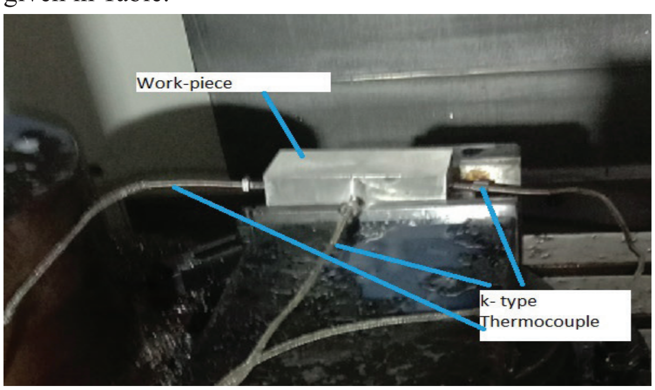


Figure 2. K typr thermocouple and surface tester used for calculating responses

The chromium component of the work material enhances its hardness, making it harder to treat conventionally.(Khullar et al., 2017) The workpiece material was provided as a rectangular piece with dimensions of 100mm × 50mm ×20 mm for experimenting. The workpiece was secured to the worktable utilizing an integrated component. The tool with two flutes and a 20mm diameter was fastened on the machine tool's tool holder by default. The tool holder had a mechanism for adjusting the electrode's alignment about the workpiece.

Design of experiments:

The design of an experiment (DOE) is arranging an investigation to examine control variables. Instead of analyzing one component at a time, the impact of all control factors on responses is examined collectively during this procedure. For this study, four control criteria were employed to arrange the trials. BBD was used in a total of 26 trials, and the input control factors with their range and levels are listed in Table 2.

Table 2: Independent parameters with their levels.

Control Variable Name	Units	Range	Levels		
			–1	0	+1
Cutting Speed	rpm	3000-5000	3000	4000	5000
DoC	mm	0.50-1.50	0.50	1.00	1.50
Feed	mm/ tooth	0.05-0.15	0.05	0.10	0.15
Nose Radius	mm	0.40-1.20	0.40	0.80	1.20
Tool Diameter	mm	20			

The DOE conditions for executing the experimental runs are shown in Table 2. The trials were carried out in a particular order to ensure the machine's stability.

Table 3: Experimental results

Std	Run	Cutting Speed	DoC	Feed	Nose Radius	W/P temp	MT
12	1	5000	1	0.15	0.8	114.0	205
23	2	3000	1	0.1	0.4	95.9	297
17	3	4000	0.5	0.1	1.2	90.9	251
4	4	4000	1	0.15	1.2	119.1	181
18	5	5000	1	0.05	0.8	85.1	248
1	6	5000	1	0.1	0.4	110.3	236
8	7	5000	0.5	0.1	0.8	93.3	247
21	8	3000	1	0.15	0.8	117.1	216
6	9	4000	1	0.15	0.4	126.2	212

26	10	3000	1	0.05	0.8	72.3	315
20	11	3000	0.5	0.1	0.8	81.1	330
22	12	4000	1.5	0.1	0.4	111.9	221
25	13	3000	1.5	0.1	0.8	107.9	209
15	14	4000	1.5	0.1	1.2	112.7	170
2	15	4000	1	0.05	0.4	79.4	305
10	16	4000	1.5	0.15	0.8	127.0	179
5	17	4000	0.5	0.1	0.4	94.4	301
11	18	4000	1.5	0.05	0.8	91.3	214
16	19	4000	1	0.05	1.2	80.9	231
13	20	4000	1	0.1	0.8	95.3	243
3	21	4000	0.5	0.05	0.8	67.3	357
7	22	4000	0.5	0.15	0.8	106.7	227
19	23	4000	1	0.1	0.8	94.3	220
14	24	5000	1	0.1	1.2	105.5	200
24	25	3000	1	0.1	1.2	94.9	235
9	26	5000	1.5	0.1	0.8	118.7	198

RESULTS AND DISCUSSION:

Table 2 shows the findings of the experiments, which were used to create several response surfaces, each with two parameters along the X- and Y-axes and one output parameter along the Z-axis. The response surface is presented for each output parameter, namely WT, MT, and SR and the data is analyzed using the computer programme Design Expert-12. Tables 3, 4, and 5 provide the results of the ANOVA tables for each answer. The findings are analyzed using the standard distribution curve, P-value, and lack of fitness test for the model's goodness of fit utilizing WT, MT, and SR acquired from the experimental study.

Workpiece Temperature:

Table 3 summarises the ANOVA findings for WT after pooling the parameters that were not statistically significant (i.e., P value > 0.05). The fit outline indicated a quadratic model for data analysis. The model's F-value is 129.90 with a P-value less than 0.05, indicating that it is a good model. ANOVA analysis shows that the quadratic terms of DoC and NR and the interaction between CS and Feed significantly determine the Workpiece temperature.

A significant model combined with a nonsignificant model The absence of fit shows that the model is good. Both of these scenarios are excellent models. R^2 is a measure of the process's variability as a result of both non-significant and significant terms in the data. The WT model can explain 98.06 percent of the variability when applied to the current research. Since adjusted R^2 solely explains the variability caused by major terms, its value is always less than or equal to R^2. The difference between adjusted R^2 and projected R2 is less than 0.2 for a good model, and less than 0.3 for a flawed model. In this case, the difference between the two is less than 0.2, and the model is considered good. The S/N ratio test is a new type of test, and the value of the S/N ratio must be larger than 4. The S/N ratio, which is the ratio of significant and non-significant factors, is determined by adequate precision. The value of acceptable accuracy in this ase is 41.34, which indicates that the model is fine.

Table: 4 ANOVA table for Work-piece Temprature

Source	Sum of Squares	DF	Mean Square	F-value	p-value	Significant/ Non Significant	Contribution
Model	6568.68	7	938.38	129.90	< 0.0001	significant	
A-Cutting Speed	277.54	1	277.54	38.42	< 0.0001	significant	04.23%
B-DoC	1537.83	1	1537.83	212.89	< 0.0001	significant	23.41%
C-Feed	4551.93	1	4551.93	630.14	< 0.0001	significant	69.29%
D-Nose Radius	16.37	1	16.37	2.27	0.1496	significant	00.24%
AC	63.12	1	63.12	8.74	0.0085	significant	00.96%
B^2	24.06	1	24.06	3.33	0.0846	significant	00.36%
D^2	116.08	1	116.08	16.07	0.0008	significant	01.76%
Residual	130.03	18	7.22				
Lack of Fit	129.53	17	7.62	15.24	0.1991	not significant	
Pure Error	0.5000	1	0.5000				
Cor Total	6698.71	25					
R^2	**0.9806**		**Predicted R^2 0.9518**				
Adjusted R^2 0.9730			**Adequate Precision 41.3410**				

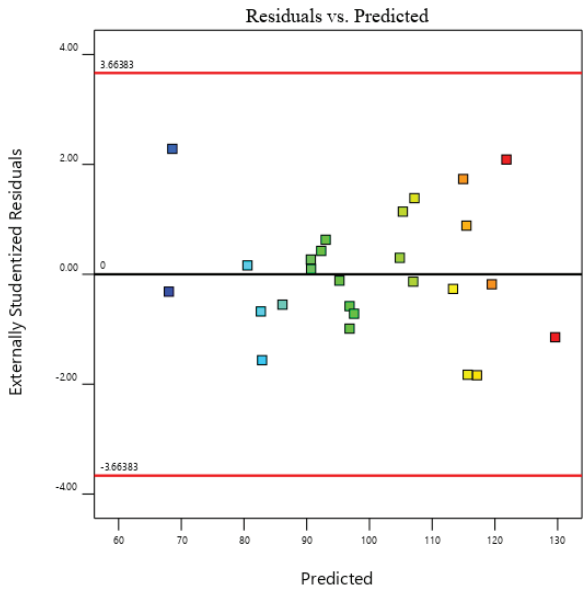


Figure 3 (a) Normality test

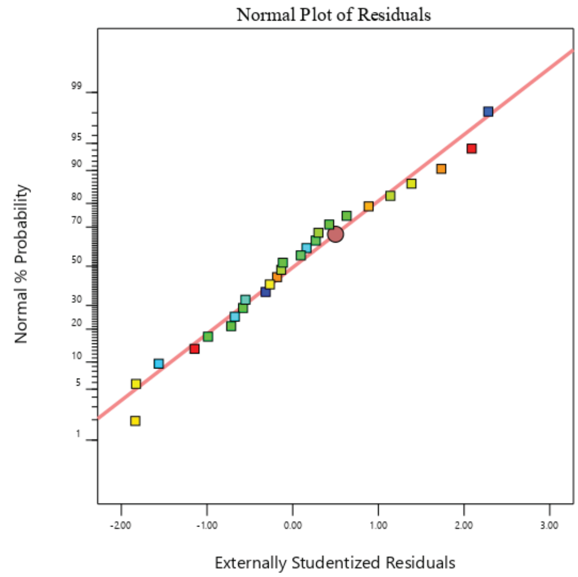


Figure 3(b) The residual vs. expected relationship

Figure 3 (a) illustrates a normality test, which is an extra check for the perdition of an acceptable model. It can be seen that the residuals for the test are linear, indicating that the model is significant. Whereas, Figure 3(b) illustrates the residual vs. expected relationship. All points in this graph are dispersed randomly to ensure that the model is valid. The regression model is denoted by the following equations 1 and 2 in terms of both coded and actual parameters:

$$W/P\ temp = 96.83 + 4.81*A + 11.32*B + 19.48*C - 1.17*D - 3.97*A*C + 1.99*B^2 + 4.36*D^2 \quad (1)$$

$$W/P\ temp = 11.96 + 0.01*CS + 6.75*DoC + 707.32*F - 46.56*NR - 0.08*CS*F + 7.95*DoC^2 + 27.28*NR^2 \quad (2)$$

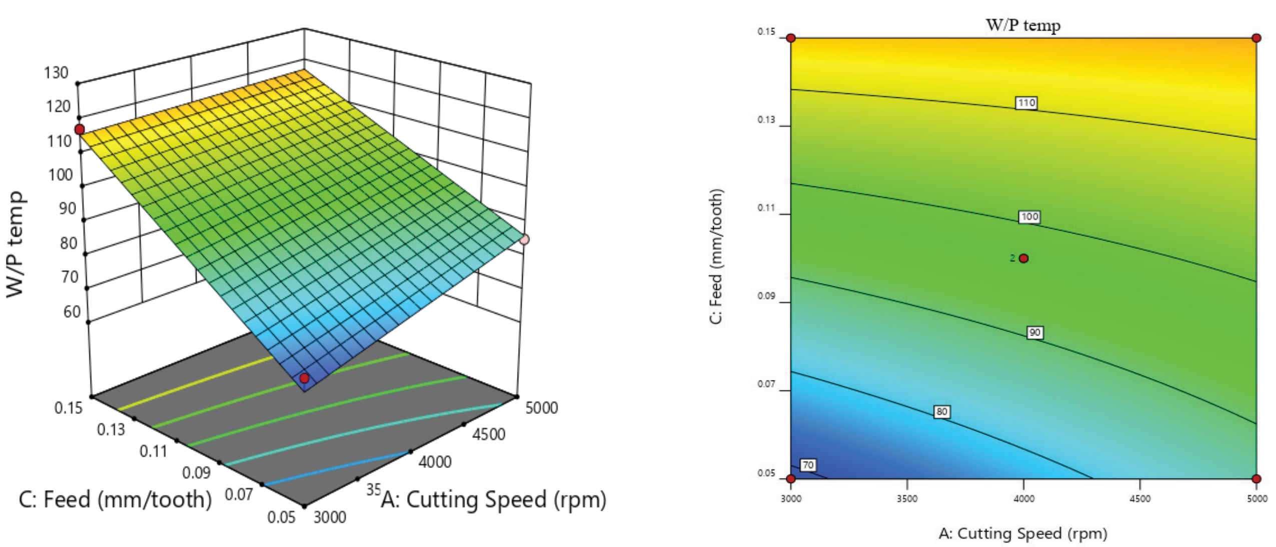


Figure 4: 3d interaction and Contour plot of F and Cs for W/P temp

Table: 4 ANOVA table for Machine Time

Source	Sum of Squares	DF	Mean Square	F-value	p-value	Significant/ Non Significant	Contribution
Model	58426.35	9	6491.82	94.78	< 0.0001	Significant	
CS	6004.98	1	6004.98	87.67	< 0.0001	Significant	**10.28%**
DoC	22654.21	1	22654.21	330.74	< 0.0001	Significant	**38.77%**
Feed	16827.41	1	16827.41	245.67	< 0.0001	Significant	**28.80%**
NR	7675.61	1	7675.61	112.06	< 0.0001	Significant	**13.17%**
CS*DoC	1296.33	1	1296.33	18.93	0.0005	Significant	02.29%
CS*F	780.96	1	780.96	11.40	0.0038	significant	01.33%
Doc*F	2280.39	1	2280.39	33.29	< 0.0001	significant	03.90%
F*NR	480.96	1	480.96	7.02	0.0175	significant	00.82%
CS^2	425.50	1	425.50	6.21	0.0240	significant	00.72%
Residual	1095.94	16	68.50				
Lack of Fit	835.50	15	55.70	0.2139	0.9528	not significant	
Pure Error	260.44	1	260.44				
Cor Total	59522.29	25					
R^2	0.9816		**Predicted R^2** 0.9518				
Adjusted R^2	0.9712		**Adequate Precision** 33.8055				

Figure 4 shows the 3d surface plot and contour plot of F and Cs for W/p temperature. It can be seen from the graphs that with increasing the values for feed and cutting speed, W/p temperature increases. Contributions of the independent parameters in the calculations of W/p temperature have been observed in table 3. ANOVA reveals that F and DoC are the major contributing factors for generating the W/p temperature.

Machine Time analysis:

Table 5 illustrates the ANOVA findings for MT after pooling the parameters that were not statistically significant (i.e., P value > 0.05). The fit outline indicated a quadratic model for data analysis. The model's F-value is 94.78 with a P-value less than 0.05, suggesting it is a good model. ANOVA analysis shows that the quadratic terms of CS and the interaction between CS and DoC, CS and F, Doc and F, and F and NR are very significant in determining the machine time.

Like Workpiece temperature, ANOVA analysis shows a not-significant lack of fir for a significant model, implying an acceptable model. R2 refers to the process's variability as a result of both non-significant and effective terms. The MT model can account for 98.16 percent of the variability in the current investigation. Because adjusted R2 describes just the variability caused by important terms, its value is always less than or equal to R2. For a decent model, the difference between adjusted and projected R2 is less than 0.2. The difference between the two is less than 0.2 in this case, indicating a reasonable model. The S/N ratio test is a specific test; the S/N ratio must be larger than 4. Good accuracy results in the S/N ratio, which is the ratio of significant to non-significant components. The value of acceptable precision is 33.80 in this case, indicating that the model is valid.

Figure 5 (a) illustrates a normality test, which is an extra check for the perdition of a fine model. It can be seen that the residuals for the test are linear, indicating that the model is significant. Whereas, figure 5(b) illustrates the residual vs. expected relationship. All points in this graph are dispersed randomly to ensure that the model is valid. The regression model is denoted by the following equations 3 and 4 in terms of both coded and actual parameters:

$$\text{Machine Time} = + 236.53 - 22.37*A - 43.45*B - 37.45*C - 25.29*D + 18.00*A*B + 13.97*A*C + 23.88*B*C + 10.97*C*D + 8.11*A^2 \quad (3)$$

$$\text{Machine Time} = 1063.39571 - 0.15124*CS - 326.42399*DoC - 3260.45071*F - 118.05449*NR + 0.03601*CS*DoC + 0.27946*CS*F + 955.06896*DoC*F + 548.27027*F*NR + 0.00001*CS^2 \quad (4)$$

Figure 6 shows the 3d surface plots and contour plots of various independent parameters interacting to influence W/p temperature. Contributions of the input parameters in the calculations of machine time have been observed from table 4. ANOVA reveals that D & F are the major contribution factors for the generation of the Machine Time.

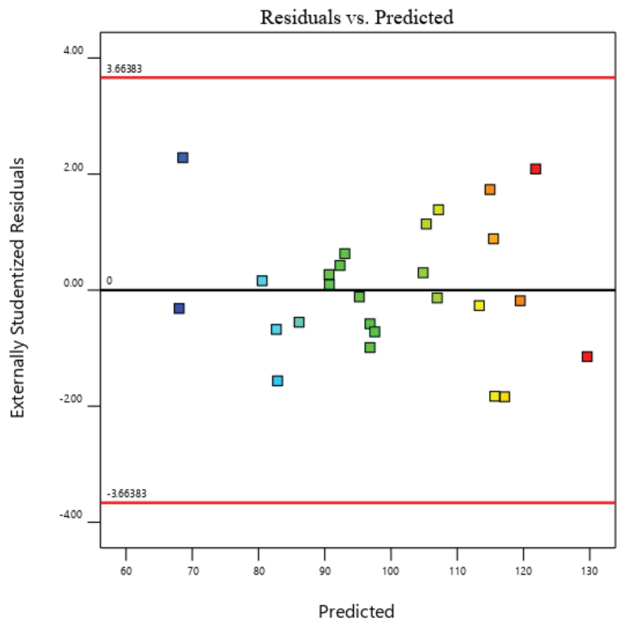


Figure 5 (a) Normality test

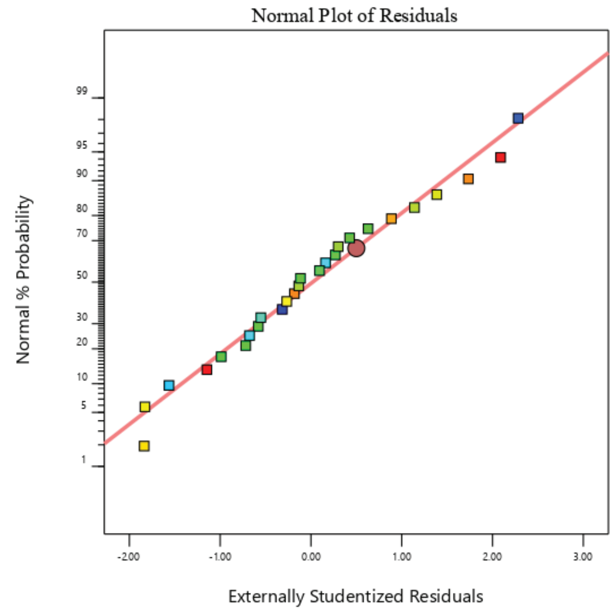


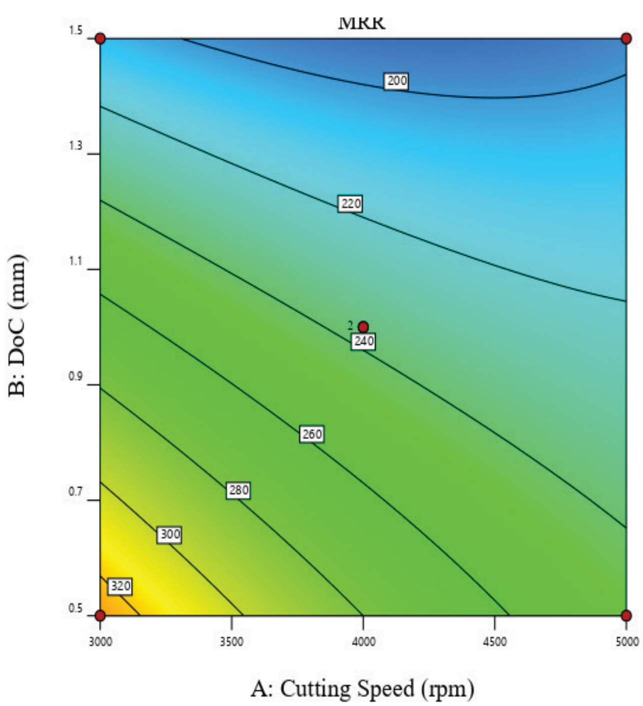
Figure 5(b)Rresidual vs.Expected relationship

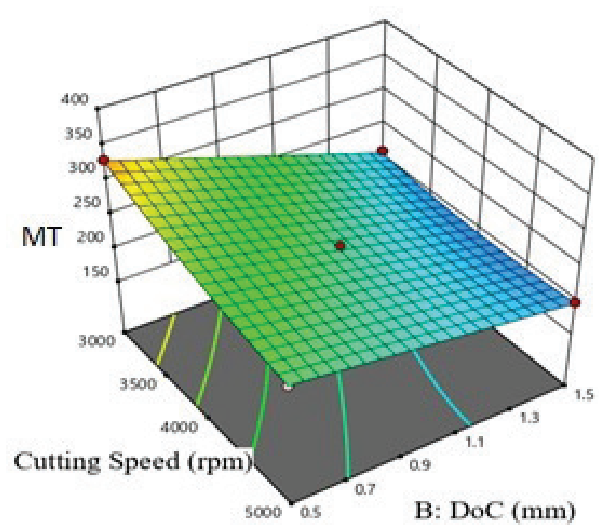
Multi-objective Genetic Algorithms (MOGA)

Multi-objective genetic algorithms have been widely used to optimize machining settings to get the best possible values for different machined surface characteristics, including surface roughness, cutting forces, and surface integrity. Genetic Algorithms have been primarily used to solve situations with a single purpose. However, a large number of real-world issues contain several objective functions. To be handled by a single-objective genetic algorithm, these objective functions need be integrated into a scalar fitness function. When numerous goal functions are combined with a constant weight, the search path in the MOGA algorithms is fixed in the multiple objective spaces, as shown in figure 8. (Murata & Ishibuchi, 1995)

Objective 1 (Workpiece Temperature)

Objective 2 (Machine Time)





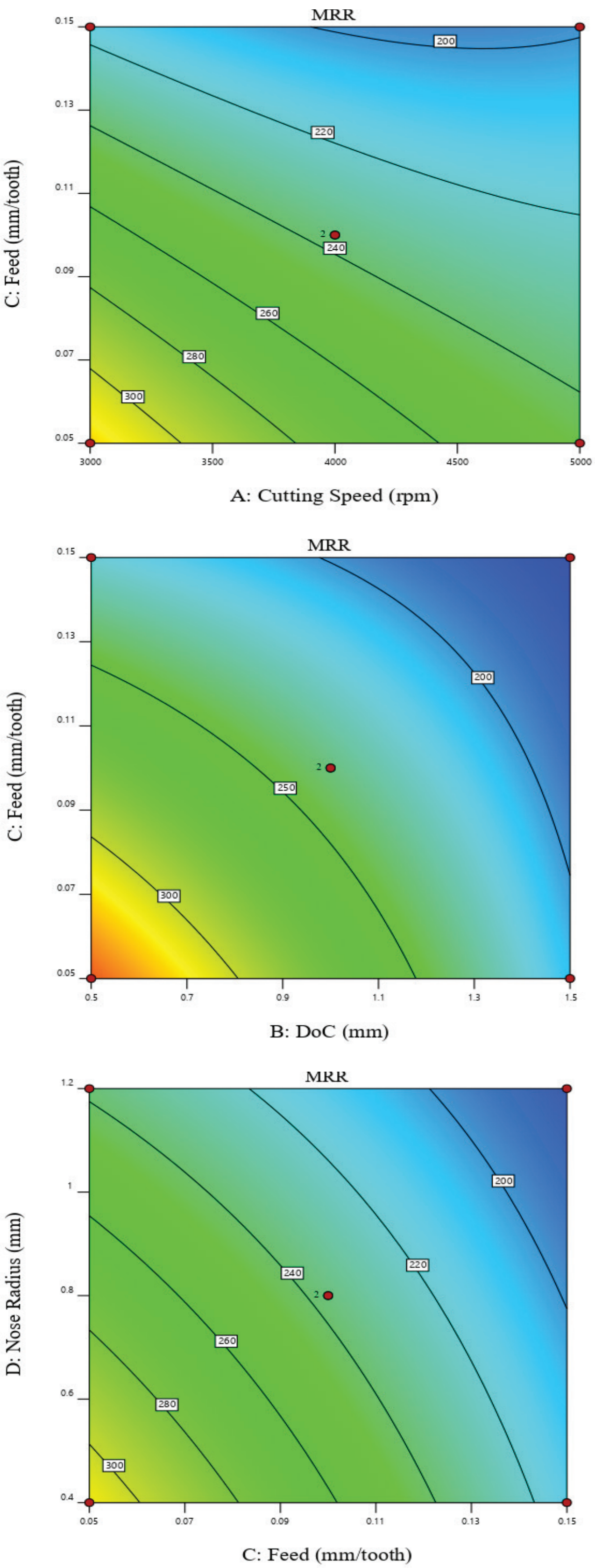


Figure 6(a): Contour plots for MT

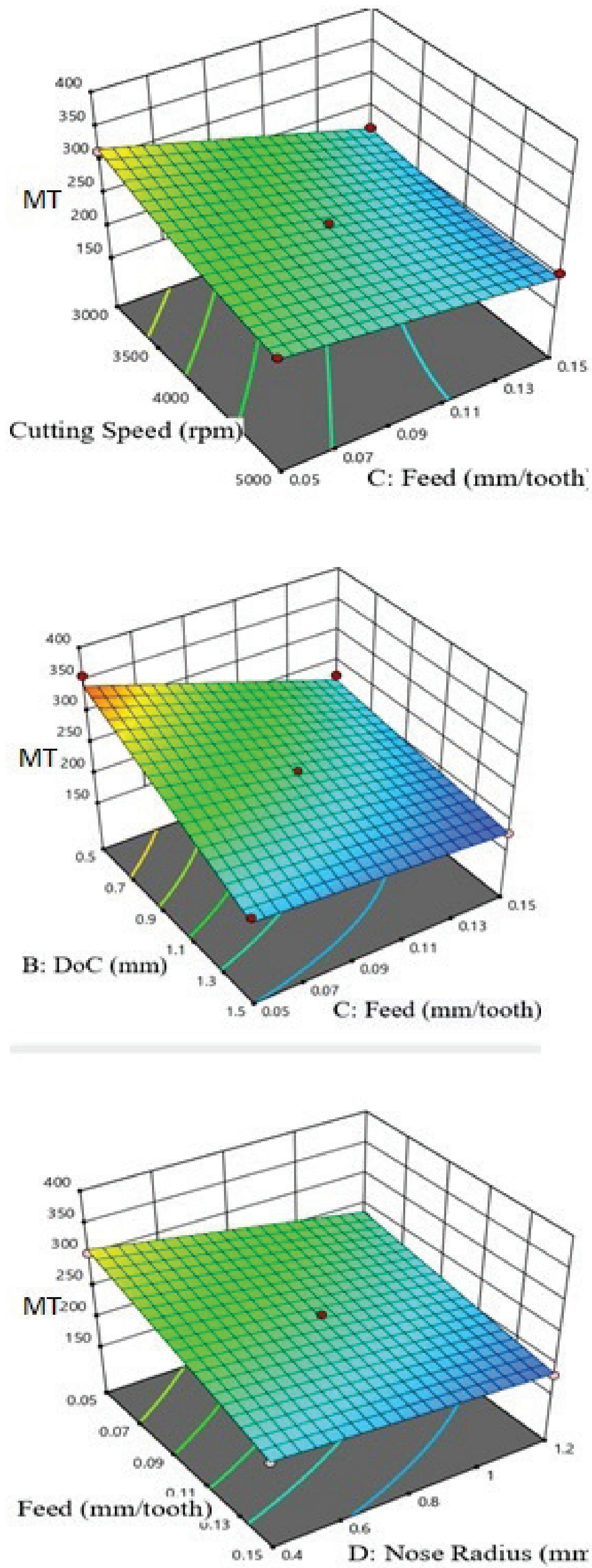


Figure 6 (b): 3d Interactions for MT

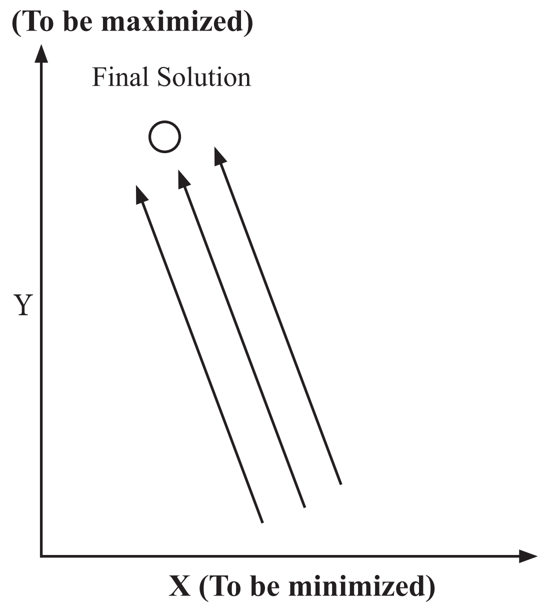


Fig 8(a): Direction of search on MOGA

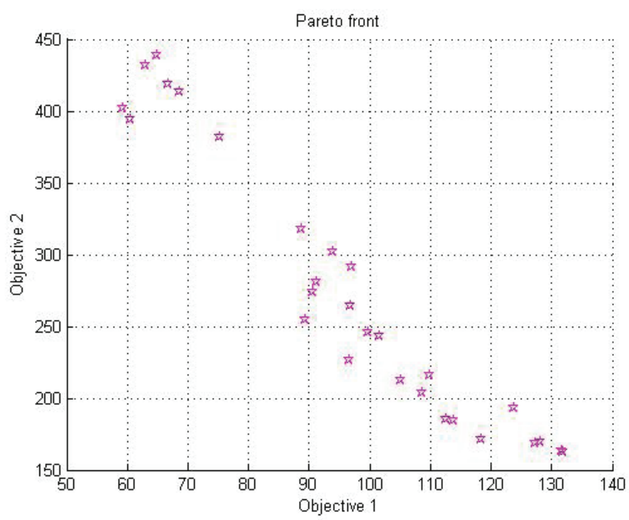


Fig 8(b): Pareto front

MOGA can consider various responses, such as Machine time and Surface finish in the present work for optimizing the workpiece temperature. While GA may solve problems with several objectives, it must choose one as the objective function; other functions must be sacrificed. To achieve the lowest possible workpiece temperature, getting a better surface with less machine time will be challenging, similar to obtaining the highest possible surface finish, less machine time, or temperature generation, which might be difficult. As a result, using MOGA processes maintains a balance between the workpiece temperature, a high-quality surface finish, and the machine time restriction. Figure 9 shows the block diagram for MOGA how it works. At the beginning of the MOGA, initial population (N(pop) is generated thereafter calculating the resulting string's value for each objective function with updating a collection of Pareto optimum solutions. In the next step, select a pair of strings from the current population according to the selection probability, then crossover occurs, generating two strings. Mutation probability will be pre-specified for each bit of string that was developed by the crossover function. In the elitist strategy, N (elite) string will be removed randomly from N (pop), which was generated by the Mutation, and it will replace with N (elite) strings which are further randomly selected from a tentative set of Pareto optimal solutions.

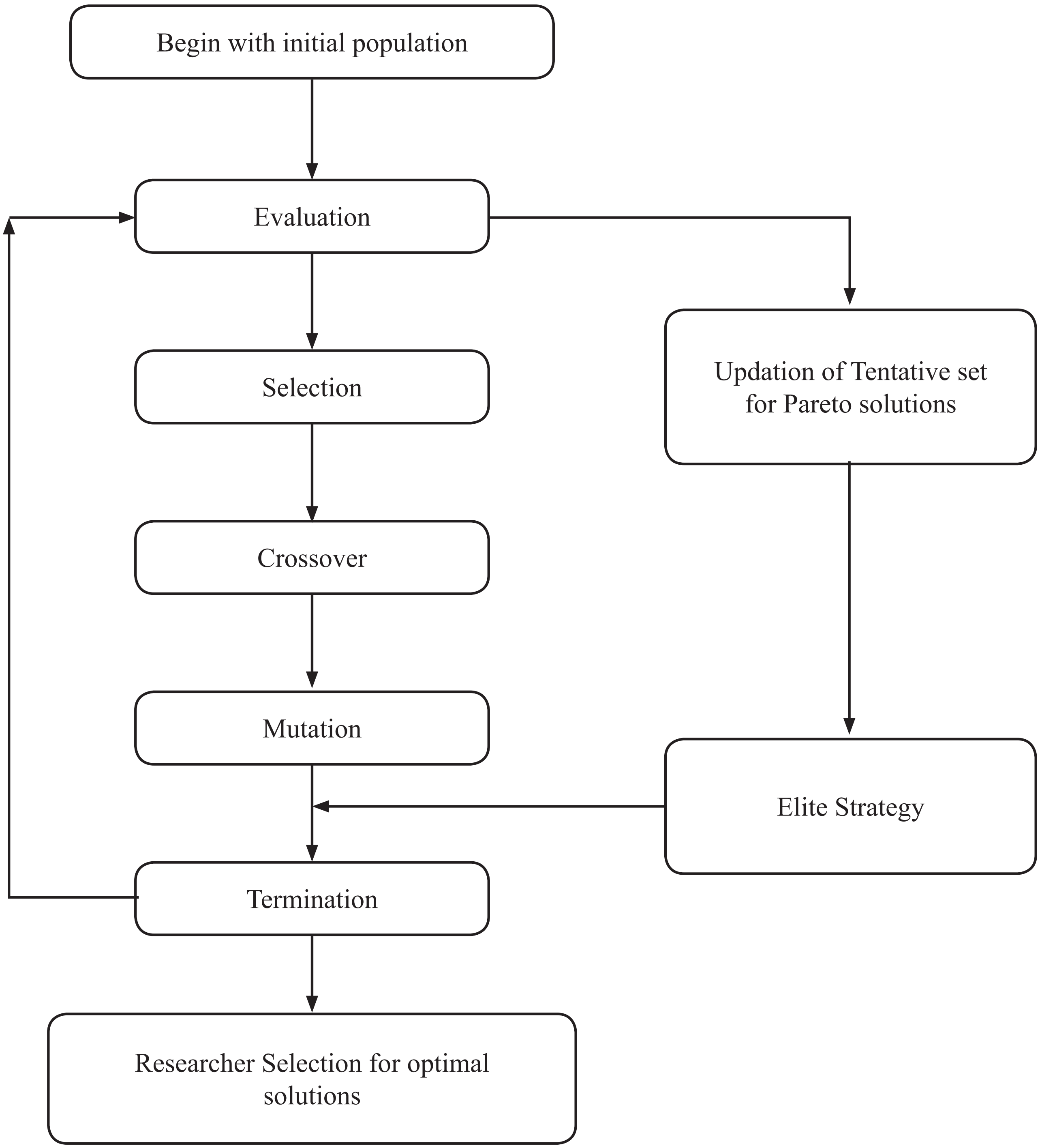


Figure 9: Block diagram of MOGA

Table 6: Pareto optimal solutions

Sr. No	CS	DoC	F	NR	W/p Temp	Machine Time
1.	3104	0.64	0.05	0.80	64.0	368
2.	3116	0.56	0.06	0.67	65.5	386
3.	3096	0.54	0.05	0.45	65.8	418

Table 7: Confirmatory Experiments

S. No	CS	DOC	F	NR	W/p Temp (Predicted)	W/p Temp (Observed)	% error	MT (Predicted)	MT (Observed)	% error	SF (Predicted)	SF (Observed)	% error
1	3096	0.54	0.05	0.45	65.8	67.1	1.84	418	422	0.96	0.228	0.223	2.19
2	3096	0.54	0.05	0.45	65.8	66.3	0.65	418	427	2.15	0.228	0.232	1.75
3	3096	0.54	0.05	0.45	65.8	67.5	2.44	418	415	0.72	0.228	0.23	0.88
4	3096	0.54	0.05	0.45	65.8	64.8	1.65	418	430	2.87	0.228	0.235	3.07
5	3096	0.54	0.05	0.45	65.8	67.4	2.29	418	424	1.44	0.228	0.225	1.32

After all, if the pre-specified stopping conditions are not satisfied, then the algorithm will run from the evaluation process, i.e., step 1. At last, the final set of Pareto solution (in table 6) combinations will be displayed by MOGA to the user. After that, the selection of the best solution according to the user preference can be made. Figure 8(b) shows the Pareto front graphs taken out by using MOGA on Matlab software it may be noticed that algorithm takes Workpiece temperature as objective function one while machine time as objective function 2, and the solutions of these can be seen as Pareto front analysis. It has been noticed that there is an inverse relationship in both of these objective functions.

Further, table 7 shows the results of five optimal trials of the MOGA set selection and confirmation studies conducted to ensure the response of the 2.5-D end milling process parameter was genuine. The most significant percentage error [10] is 2.44% for W/p temp, 2.87% for MT, and 3.07% for SF, and the results of the relevant combination from the conformational experiments are reported in table 7.

To sum up, the suggested MOGA regression model has a lower proportion of errors in its prediction performance and, as a result, is at least passable in its current state of development.

CONCLUSION:

The response curves derived from the data provide the best results for Inconel 718 nickel-based super alloy within the range evaluated in this study. The WT and Machine time are evaluated using an integrated technique of RSM (BBD) and MOGA. According to the research, the following findings have been made:

W/p temp is mainly affected by F and DoC compared to CS and NR and increases with F and CS.

MT is mostly affected by DOC and F, compared to NR and CS

With the help of an integrated methodology, users can choose the best solution based on their needs for increased productivity or quality. According to the algorithm's predictions, the experimental findings are similar to the projections.

The proposed model's percentage error is less than 4%.

Minimum W/p temperature 67^0 with MT 430 sec have found with the optimum combination of machining parameters as CS (3096 rpm), DoC (0.54mm), Feed (0.05mm/tooth), and NR (0.45mm)

Acknowledgments:

We express our sincere thanks to the Head of the Department for his critical suggestions and encouragements. We also declare that we have followed all ethical guidelines while pursuing the present study.

Declaration: *We also declare that all ethical guidelines have been followed during this work and there is no conflict of interest among authors.*

REFERENCES

Aruna, M., & Dhanalakshmi, V. (2012). Optimisation of turning parameters of Inconel 718 alloy using RSM. In *Int. J. Manufacturing Technology and Management* (Vol. 25, Issue 3).

Ashutosh. (2019). *Parametric Optimization of CNC milling of Al-7075 Based MMCs*. 377–388.

Aydın, M.; Karakuzu, C.; Uçar, M.; Cengiz, A.; Çavuşlu, M. . (2013). Prediction of surface roughness and cutting zone temperature in dry turning processes of AISI304 stainless steel using ANFIS with PSO learning. *Int. J. Adv. Manuf. Technol*, *67*, 957–967.

Bhardwaj, B., Kumar, R., & Singh, P. K. (2014). An improved surface roughness prediction model using Box-Cox transformation with RSM in end milling of EN 353. *Journal of Mechanical Science and Technology*, *28*(12), 5149–5157. https://doi.org/10.1007/s12206-014-0837-4

Bhirud, N. L., & Gawande, R. R. (2017). *OPTIMIZATION OF PROCESS PARAMETERS DURING END*. *LXIV*. https://doi.org/10.1515/meceng-2017-0020

Brinksmeier E, Minke E, N. L. (2003). Residual stresses in precision components. *Proceedings of the 5th International Conference on Industrial Tooling, Southampton*.

E.O. Ezugwu, Z.M. Wang, A. R. M. (1999). The machinability of nickel-based alloys: a review. *J. Mater. Process. Technol*, *86*.

Gopal, M. (2020). OPTIMIZATION OF MACHINING PARAMETERS ON TEMPERATURE RISE IN CNC TURNING PROCESS OF ALUMINIUM 6061 USING RSM AND GENETIC ALGORITHM. In *International Journal of Modern Manufacturing Technologies: Vol. XII* (Issue 1).

Gopikrishnan, P., Akbar, A., Asokan, A., Bhaskar, B., & Sumesh, C. S. (2018). Numerical Modelling and Optimization of Surface Finish during Peripheral Milling of AISI 4340 Steel using RSM. In *Materials Today: Proceedings* (Vol. 5). www.sciencedirect.comwww.materialstoday.com/proceedingsIConAMMA_2017

Jamil, M., Khan, A. M., Hegab, H., Gupta, M. K., Mia, M., & He, N. (n.d.). *Milling of Ti – 6Al – 4V under hybrid Al 2 O 3 -MWCNT nanofluids considering energy consumption , surface quality , and tool wear : a sustainable machining*.

K. Venkatesan, R. Ramanujam. (2016). Statistical approach for optimization of influencing parameters in laser assisted machining (LAM) of Inconel alloy. *Measurement*, *89*, 97–108.

Khullar, V. R., Sharma, N., Kishore, S., & Sharma, R. (2017). RSM- and NSGA-II-Based Multiple Performance Characteristics Optimization of EDM Parameters for AISI 5160. *Arabian Journal for Science and Engineering*, *42*(5), 1917–1928. https://doi.org/10.1007/s13369-016-2399-5

Kumar, S., Gupta, A. K., Chandna, P., Bhushan, G., & Kumar, A. (2021). A novel approach of GEF and GA for the optimization of multi-objective wire EDM process during the machining of DC53 super alloy. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, *235*(4), 1119–1131. https://doi.org/10.1177/0954408921992918

L. Chang, R. Chengzu, W. Guofeng, Y. Yinwei, Z. L. (2015). Study on surface defects in milling Inconel 718 super alloy. *Journal of Mechanical Science and Technology*, *29*, 1723–1737.

M.T. Hayajneh, M.S. Tahat, and J. B. (2007). A study of the effects of machining parameters on the surface roughness in the end-milling process. *Jordan Journal of Mechanical and Industrial Engineering*, *1*(1), 1–5.

Mangaraj, S., & Singh, K. P. (2011). Optimization of Machine Parameters for Milling of Pigeon Pea Using RSM. *Food and Bioprocess Technology*, *4*(5), 762–769. https://doi.org/10.1007/s11947-009-0215-x

Mokhtar, S., Amin, A. N., & Patwari, A. U. (2011). Machinability improvement by workpiece preheating during end milling AISI H13 hardened steel. *Advanced Materials Research*, *264–265*, 888–893. https://doi.org/10.4028/www.scientific.net/AMR.264-265.888

Murata, T., & Ishibuchi, H. (1995). MOGA: multi-objective genetic algorithms. *Proceedings of the IEEE Conference on Evolutionary Computation*, *1*, 289–294. https://doi.org/10.1109/icec.1995.489161

Nurul Amin, A. K. M., Mokhtar, S., & Arif, M. D. (2012). Analysis of machinability of inconel 718 in high speed end milling with ceramic inserts under room temperature conditions. *Advanced Materials Research*, *538–541*, 1351–1355. https://doi.org/10.4028/www.scientific.net/AMR.538-541.1351

Raza, M. H., Hafeez, F., Zhong, R. Y., & Imran, A. (2020). Investigation of surface roughness in face milling processes. *International Journal of Advanced Manufacturing Technology*, *111*(9–10), 2589–2599. https://doi.org/10.1007/s00170-020-06188-8

Ryzhkin, A.A.; Shuchev, K.G.; Aliev, M.M.; Gusev, V. V. (2008). Dis- sipative properties of lubricant and coolant fluid in cutting and friction. *Russ. Eng. Res*.

Sahu, R. K., Panda, S., & Yegireddy, N. K. (2014). A novel hybrid DEPS optimized fuzzy PI/PID controller for load frequency control of multi-area interconnected power systems. *Journal of Process Control*, *24*(10), 1596–1608. https://doi.org/10.1016/j.jprocont.2014.08.006

Sridhar, S., & Sellamani, R. (2020). Investigation of input variables on temperature rise while end milling Al/SiC metal matrix composite. *World Journal of Engineering*, *17*(4), 599–607. https://doi.org/10.1108/WJE-01-2020-0031

Suhaily, M., Nurul Amin, A. K. M., & Patwari, M. A. U. (2011). Prediction of surface roughness in high speed machining of Inconel 718. *Advanced Materials Research*, *264–265*, 1193–1198. https://doi.org/10.4028/www.scientific.net/AMR.264-265.1193