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Optimization of 2.5d milling parameters using RSM and ANN-GA for Inconel 718

Optimización de parámetros de fresado 2.5d usando RSM y ANN-GA para Inconel 718

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Abstract. For the manufacturing of thin-walled-complex-shaped components used in complex dies and moulds it is important to manufacture these kinds of components with hard, tough, and heat-resistant materials such as Inconel 718. During the end milling of such types of components, there are many challenges related to surface roughness, tool wear, etc., identified in the recent past. Therefore, in this study, a prediction model for surface roughness with respect to the input parameters such as cutting speed, Depth of Cut, Feed rate and nose radius has been developed. In the present work, an attempt has been made to develop a prediction model of SR dur-ing milling of Inconel 718 with the help of BBD-RSM-Regression as well as ANN. Besides this, a comparative analysis has been conducted among these techniques, and it has been observed that the AI technique provides better prediction than the BBD-RSM-Regression. The ANOVA technique is also applied to find an estimate of the percentage contribution of each machine parameter with respect to machine time. Further, GA is used for the purpose of effective optimization. Five structural trials have also been conducted to validate this novel strategy, which has been proven to be more successful.

Keywords: inconel 718, RSM-BBD, surface roughness, 2.5d milling, artificial neural network, genetic algorithm.

Resumen

Para la fabricación de componentes con formas complejas de pared delgada que se utilizan en matrices y moldes complejos, es importante fabricar este tipo de componentes con materiales duros, tenaces y resistentes al calor, como Inconel 718. Durante el fresado final de este tipo de componentes, hay muchos desafíos relacionados con la rugosidad de la superficie, el desgaste de la herramienta, etc., identificados en el pasado reciente. Por lo tanto, en este estudio, se ha desarrollado un modelo de predicción para la rugosidad de la superficie con respecto a los parámetros de entrada como la velocidad de corte, la profundidad de corte, la velocidad de avance y el radio de punta. Por lo tanto, en el presente trabajo se ha intentado desarrollar un modelo de predicción de SR durante el fresado de Inconel 718 con la ayuda de BBD-RSM-Regresión y ANN. Además de esto, se ha realizado un análisis comparativo entre estas técnicas, y se ha observado que la técnica de IA proporciona una mejor predicción en comparación con la BBD-RSM-Regresión. También se aplica la técnica ANOVA para encontrar una estimación de la contribución porcentual de cada parámetro de la máquina con respecto al tiempo de la máquina. Además, GA se usa con el propósito de una optimización efectiva. Tam-

bién se han realizado cinco ensayos estructurales para validar esta nueva estrategia, que ha demostrado ser más exitosa.

Palabras clave: inconel 718, RSM-BBD, rugosidad superficial, fresado 2.5d, red neuronal artificial, algoritmo genético.

1 | INTRODUCTION

Inconel 718 is indeed a super-alloy that finds extensive use in the aerospace, marine and automotive sectors. In these sectors, Inconel 718 parts or components must have high strength and excellent surface quality. As it is a difficult-to-cut assisted with high cutting forces and temperatures, which can degrade the surface texture under certain machining operations. As a result, in production processes, it is critical for evaluating and predicting surface roughness of machined Inconel 718 workpieces [1]. Modelling and optimization of the machining operation are two key issues in milling that researchers in the machining studies extensively investigated and discussed. Modelling is the process to predictthe machining performance with respect to input parameters, whereas optimization is the process of determining the best possible level of machining responses under the optimal circumstances. Surface quality and Dimensional accuracy are the most frequent machining performance metrics that most machinists are concerned with [2].

Surface roughness is a statistic that can be used to determine if something has improved in terms of quality (Ra). In general, machining settings, cutting phenomena, workpiece quality and cutting tool characteristics affect the Ra value[3]. When machining a component with different operational parameters, it was found that geometry of insert also played an important role on surface texture of the product. Studies have shown that an improvement in surface roughness can be achieved by using round inserts combined with a small depth of cut as well as a small Cutting speed [4]. Ra in Inconel 718 end milling was tested under various cutting parameter combinations, and it was discovered that the lowest value of Ra was achieved when the tiniest chip burrs were generated.[5]. Sarkar et al. analysed surface quality of the machined product under dry as well as wet conditioned with the experimentational process, it was found that depth of cut is a crucial factor which significantly affect Ra [6]. Dimensional accuracy as well as surface quality which is generally required in most of the products manufactured with Inconel 718 alloy has been analysed and it was found with the statistical analysis that feed per tooth is the most significant parameter than Cutting speed and Doc [7]. Jonas et al. succeeded in demonstrating that using ceramic tools is able to improve the surface quality of the machined Inconel 718 [8]. It has been demonstrated with the experimental study that Speed, Feed and tool angles are the major operational parameters which affect surface texture [9]. It has been experimentally concluded that by optimizing machine parameters with CBN tool can minimize the Ra value [10]. Kasim et al revealed that product topology of end milled machined Inconel 718 was observed to be lower in the feed direction. It has also determined that the Step over are to blame for the variations in Ra. The carbide particle phenomenon was found during low-feed rate machining, resulting in the additional third body abrasion on the machined part of the product. This will be caught in between the fragments zone and the tear part of the workpiece, increasing the Ra of the workpiece's surface. The feed rate has an effect on the quality of the machined surface, whereas WoC governs the variation in Ra, according to the combined effect between WoC and fz.[11]. It has been experimentally proved that the coating on a cutting tool is critical for boosting the instrument's wear resistance and longevity. And it was found that nose radius of the tool and the feed rate was the most active parameters. It was established that carbide inserts coated with TiAlN have a higher surface quality than carbide inserts that are not coated[12]. Modelling strategies for determining the theoretical minimum value of surface quallity, such as Ra, may be classified into two categories. Traditional methodologies, such as the Regression methodology, provide explicit models that need a deep physical knowledge of the modelling process. Using non-conventional or artificial intelligence (AI), provides implicit models which are easier to execute. As they have inbuild function with ion the system. As a consequence, optimising machining parameters such nose radius (rn) Cutting speed (vc) and Feed per tooth (Fz), and DoC(d) on the Ra on end milled Inconel-718 have been considered in the present study. The objective of this study is to develop a prediction model based on ANN of surface quality during 2.5D milling of Inconel 718 alloy using various selected parameters. The surface quality of the components has been measured with the help of Mitutoyo surftest S-310. ANOVA has been used to determine the significance and suitability of the suggested model, as well as the impacts of process parameters on surface quality. It has been observed that the ANN provides more accurate results as compared to Regression RSM. The relationship between the input parameters and surface roughness has been evaluated using an artificial neural network modelling approach, and then further GA optimization. In addition, five conformational tests have been conducted on the optimal parameter combination indicated by GA to validate this novel strategy, which has been proven to be more successful. Further, a comparison of the proposed model with the RSA optimization strategy referred to as the desirability approach.

2 | EXPERIMENTAL SETUP AND WORK-PIECE MATERIAL

To investigate the relationships between input parameters and surface roughness, three levels of each selected parameter were evaluated based on the material characteristics and the machine tool specification. Experiments are performed on the milling machine (Bharat Fritz Werner, Agni++, BMV45++ TC24 VMC) (in Fig. 1) Surface finish has been observed by Mitutoyo surface tester S-310 tester as shown in Fig. 2 . The range of temperature measure is from -270oC to 1250oC, with 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 work-piece and As a cutting tool, a 20 mm diameter, two-fluted, a flat-ended tungsten carbide with was employed. The chemical composition and various characteristics of Inconel 718 are shown in Table 1.

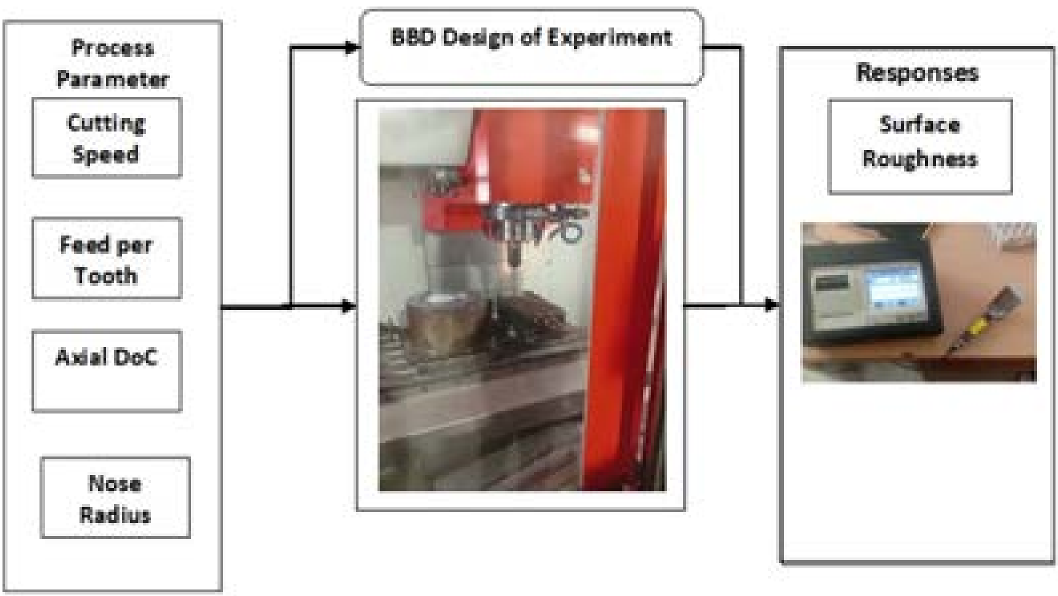

FIG. 1 Experimental setup.

The chromium component of the work material enhances its hardness, making it harder to treat conventionally [13]. The rectangular workpiece material was provided with dimensions of 100mm × 50mm ×20 mm for experimenting. The workpiece is secured to the worktable by means of an integrated component. The tool with two flutes and a 20 mm diameter is fastened on the machine tool's tool holder by default. The tool holder had a mechanism for adjusting the electrode's alignment with regard to the workpiece.

TABLE 1 Inconel 718 chemical composition and characteristics.

Chemical Composition	Element	Cr	Ni	Mo	Nb	Ti	Cobalt	Al	Iron
	%	0.165	0.515	0.028	0.042	0.0112	0.0088	0.008	Balance
Physical and Mechanical Properties	Property	Density (g/cc)	Melt. Temperature (°C)	Modulus of elasticity (GPa)	Thermal cond. (W/mK)	Specific heat (J/KgK)	Poisson's ratio	Tensile strength (MPa)	Hardness Rockwell C scale (HRC)
	Inconel 718	8.19	1260-1336	205	11.4	435	0.284	1100	36
	TiAlNCarbaide	15.25	2870-3000	560	84.02	512	0.2	370	85

2.1 | Design of experiments:

The experimenthas been designed on design expert software. The RSM-BBD design of experiment has suggested 26 experiments for four input parameters with three level each. Instead of analyzing one component at a time, the impact of all independent parameters on responses is examined collectively during this procedure. For the purposes of this study, four control criteria were employed to arrange the trials. The input control factors with their range and levels are illustrated 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 suggested combination of input parameters as per BBD are shown in Table 2. The trials are carried out in a certain order to ensure the machine's stability.

3 | RESULTS AND DISCUSSION

The responses are tabulated in Table 3 shows the findings of the experiments, which were used to create several response surfaces each having two input parameters along the X and Y axes and one machine response such as Ra along the Z axis. For each output parameter, SR, the response surface is presented. The data is analyzed using the computer programmed Design Expert-12. Table 4 provides the results of the ANOVA tables for each answer. The findings are assessed by employing the normal distribution curve, the P-value, and a lack of fitness test to determine whether or not the model is a good match for the data utilizing the SR that was obtained from the experimental investigation.

TABLE 3 Table 3: Experimental results

Run	Cutting Speed	DoC	Feed	Nose Radius	SR
1	5000	1	0.15	0.8	0.263
2	3000	1	0.1	0.4	0.230
3	4000	0.5	0.1	1.2	0.279
4	4000	1	0.15	1.2	0.281
5	5000	1	0.05	0.8	0.223
6	5000	1	0.1	0.4	0.219
7	5000	0.5	0.1	0.8	0.228
8	3000	1	0.15	0.8	0.285
9	4000	1	0.15	0.4	0.242
10	3000	1	0.05	0.8	0.233
11	3000	0.5	0.1	0.8	0.235
12	4000	1.5	0.1	0.4	0.242
13	3000	1.5	0.1	0.8	0.285
14	4000	1.5	0.1	1.2	0.288
15	4000	1	0.05	0.4	0.183
16	4000	1.5	0.15	0.8	0.271
17	4000	0.5	0.1	0.4	0.198
18	4000	1.5	0.05	0.8	0.258
19	4000	1	0.05	1.2	0.280
20	4000	1	0.1	0.8	0.255
21	4000	0.5	0.05	0.8	0.201
22	4000	0.5	0.15	0.8	0.262
23	4000	1	0.1	0.8	0.260
24	5000	1	0.1	1.2	0.288
25	3000	1	0.1	1.2	0.270
26	5000	1.5	0.1	0.8	0.262

3.1 | Surface Finish Analysis:

The fit summary shows that the two interaction (2FI) model is significant for investigation.. Table 4 summarizes the ANOVA results for the Ra. As ANOVA contains no quadratic terms, but the interactions term converts it to a 2FI model. As shown, the model f value is 49.87, P-value is 0.05 and the lack of fit is more than 0.05. Thus, the model is significantly useful, although the LOF is not significant. SF analysis is used to conduct all the tests for the presence of a fine model. R2, adjusted R2, anticipated R2, and an appropriate precision are all indicators of a solid model.

In coded and actual factors, a mathematical model of SF is given by Eqs. (1) and (2).

TABLE 4 ANOVA table for Surface Finish

	Summations of Squares	DF	Mean of Squares	F-value	p-value	Significant (Yes/No)	Contribution
Model	0.0214	08	0.0027	49.87	<0.0001	Yes	
Vc	0.0003	01	0.0003	4.82	0.0423	Yes	01.40%
Da	0.0034	01	0.0034	63.52	<0.0001	Yes	15.89%
Fz	0.0043	01	0.0043	79.24	<0.0001	Yes	20.09%
Rn	0.0116	01	0.0116	215.19	<0.0001	Yes	54.20%
Vc*Fz	0.0002	01	0.0002	3.92	0.0643	Yes	00.93%
Da*Fz	0.0006	01	0.0006	10.74	0.0044	Yes	02.80%
Da*Rn	0.0003	01	0.0003	5.77	0.0280	Yes	01.40%
Fz*Rn	0.0008	01	0.0008	15.73	0.0010	Yes	03.73%
Residuals	0.0009	17	0.0001				
LOF	0.0009	16	0.0001	4.50	0.3563	No	
Pure Error	0.0000	1	0.0000				
Cor Total	0.0223	25					
R2	0.96			Predicted R2 0.90			
Adjusted R2 0.94				Adequate Precision 24.00			

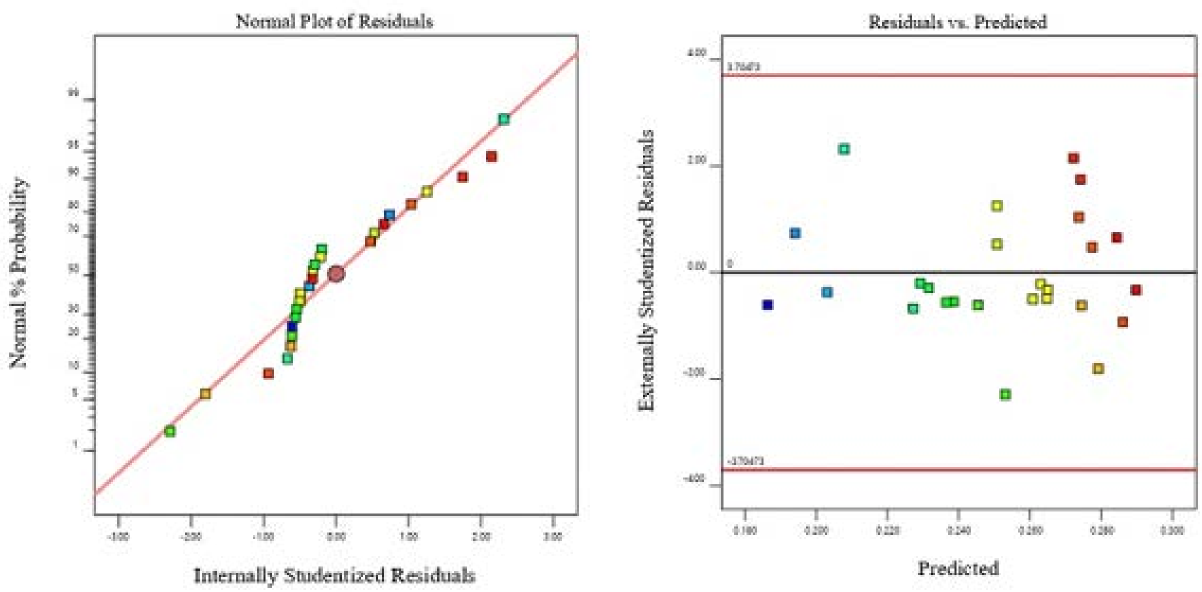

Figure 2 (a) Normality test Figure 2 (b) Residual vs. Expected relationship

FIG. 2 Residuals.

$$SF = 0.052544 - 0.000019 * x(1) + 0.116947 * x(2) + 1.43814 * x(3) + 0.121732 * x(4) + 0.000018 * x(1) * x(4) - 0.480292 * x(2) * x(3) - 0.044002 * x(2) * x(4) - 0.726615 * x(3) * x(4) \quad (1)$$

$$SF = 0.052544 - 0.000019 * CuttingSpeed + 0.116947 * DoC + 1.43814 * Feed + 0.121732 * NoseRadius + 0.000018 * CuttingSpeed * NoseRadius - 0.480292 * DoC * Feed - 0.044002 * DoC * NoseRadius - 0.726615 * Feed * NoseRadius \quad (2)$$

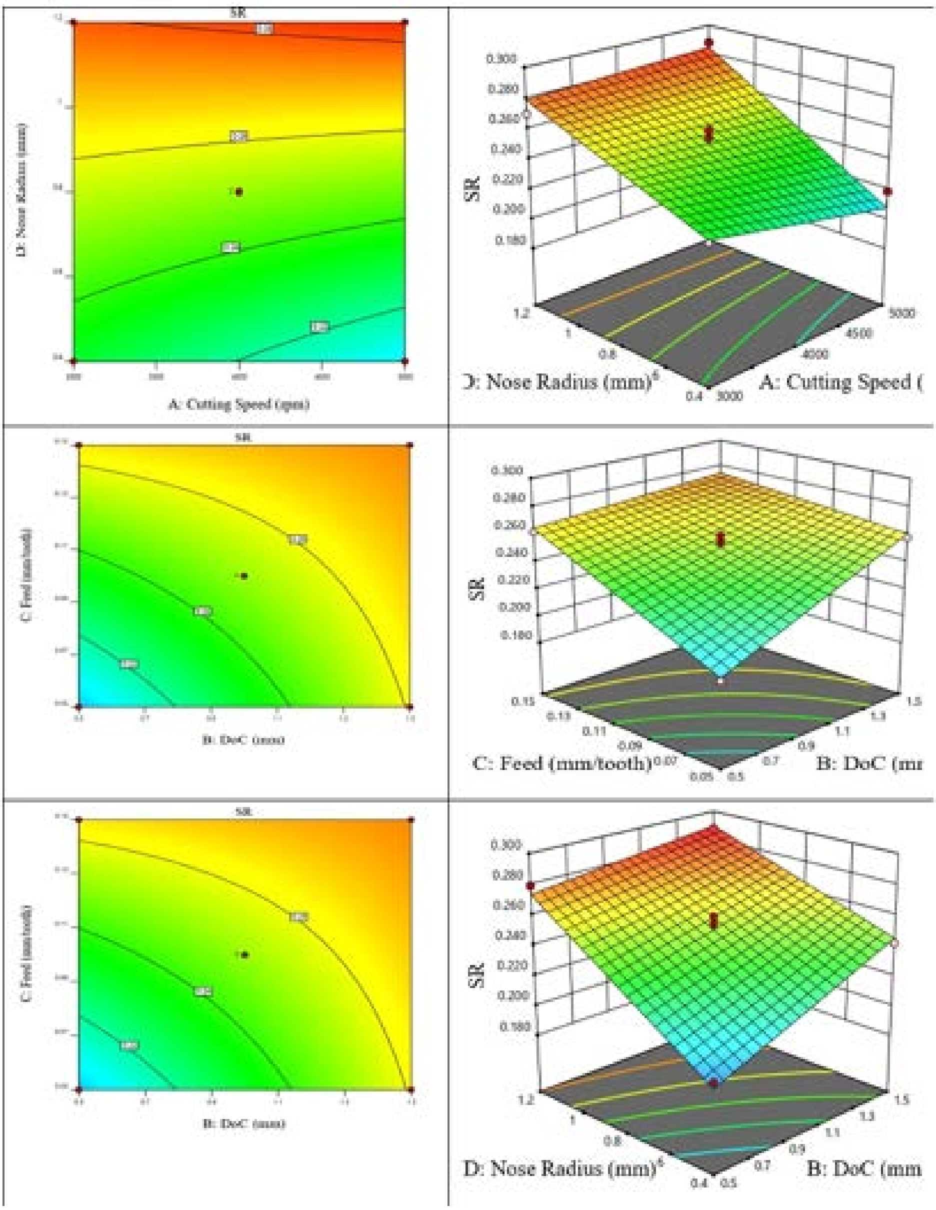

FIG. 3 Surface and contour plots.

In normal probability (Fig. 2), the majority of residual points lie along a straight line., indicating a good fit. The anticipated versus residuals figure (Fig. 2) also suggests a good model, as the residuals are dispersed randomly.

Fig. 3 illustrates the 3d surface plots and the contour plots of various interactions of independent parameters for influencing Ra. Contributions of the input parameters in the calculations for the degree of Surface finish have been observed from Table 4. Feed and Nose radius were found to be the major contributed factor analyzed by the ANOVA.

Artificial Neural network

In the last two decades, the application of neural networks (NN) has shown considerable potential in addressing challenges in various sectors. The Adaptation, generalization, global function approximation, and other benefits of Neural Network in various application areas, such as pattern recognition, classification, prediction, optimization, and control systems, NN can solve a variety of issues. NN has been widely employed in the manufacturing industry for decades and has been proven to be successful at modelling nonlinear and highly correlated data sets. ANNs are also known as information processing systems since they can solve a variety of issues such as modelling and prediction.

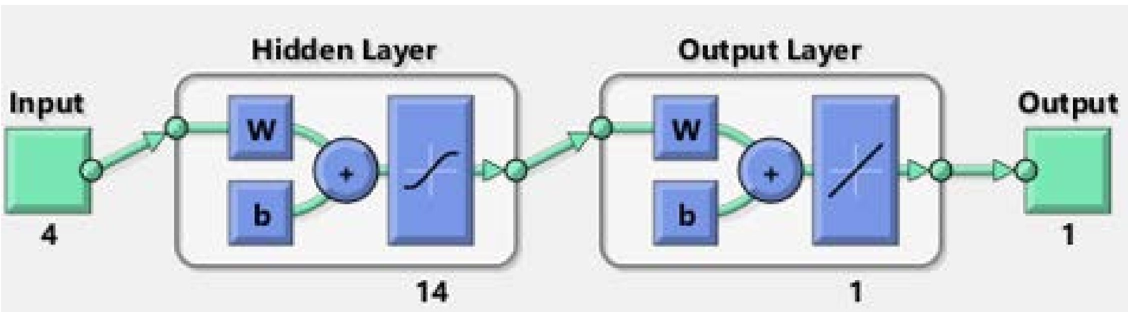

FIG. 4 Structure of ANN.

Back propagation (BP) neural network design has been discovered to be the most extensively employed among the numerous types of neural network architectures in process modelling.[14][15][16], [17]It contains three layers: input units, one or more hidden layers, and output layers. The structure of a ANN is depicted in the Fig. 4. Training is the initial stage in the ANN. The ANN is given an input along with the intended outputs, and randomly distributed weights. When the network reaches the required level of performance, the training will be terminated. The weights calculated at this step are used to make judgments about output assessment. The NN codes of Matlab were used for ANN training and testing in this study. Feedforward Back Propagation was used in the ANN study (BP). The neurons in the hidden layer part and the Levenberg-Marquardt (LM) training technique is used to optimise the ANN model. Three neurons represent the speed (vc), depth of cut (da), feed per tooth (ft), and nose radius in the input layer (nt). Surface roughness is the result. During training and testing, the tansig activation function is employed in the hidden as well as output layer. The ANN projected values were derived from the outcomes of 26 data experiments. Training, validation and testing was done with the default setting of ANN such that 70% of experiment values were taken for training the functional network, 15% used for validation and 15% for the testing purpose. A size of 14 neurons were taken for the hidden layer for defining the fitting of the neural network as shown in Fig. 4. In the next step training of network were done by using Levenberg-Marquardt backpropagation methodology. Mean square error has been used for checking the performance of the algorithm i.e. for training, validation, and testing as shown in Fig. 5.

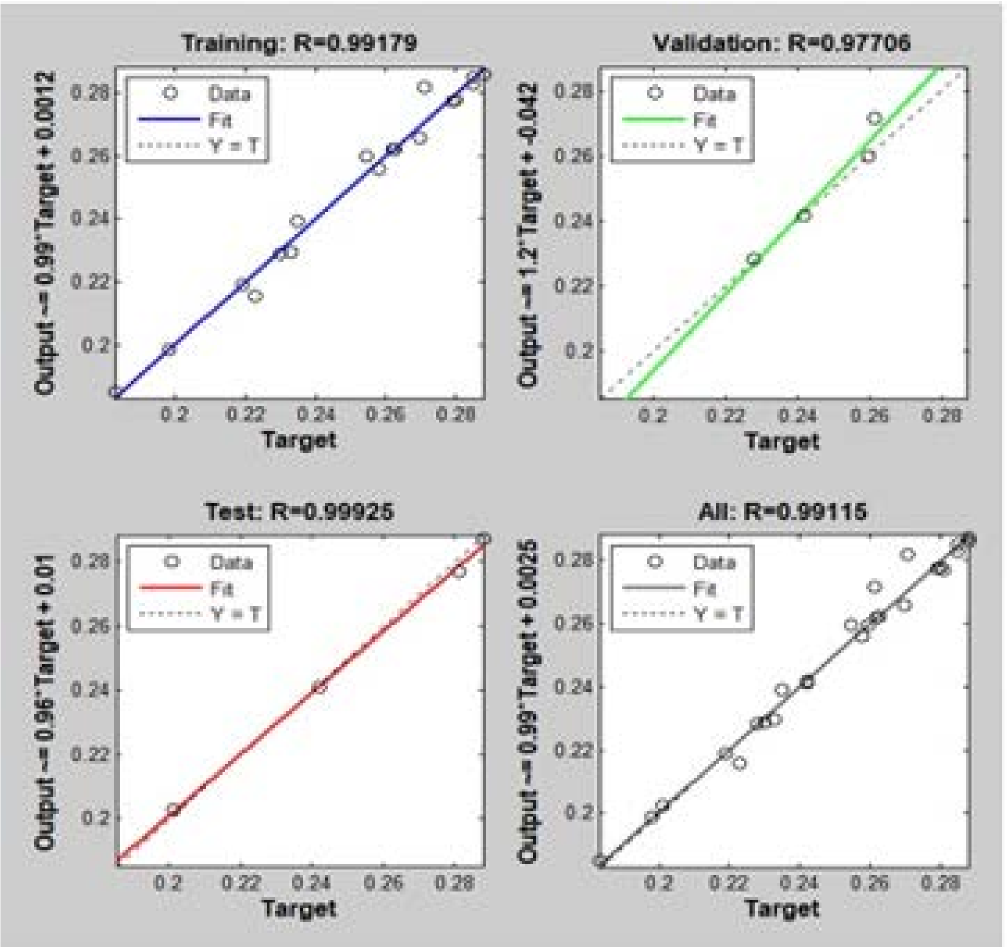

FIG. 5 Performance of ANN

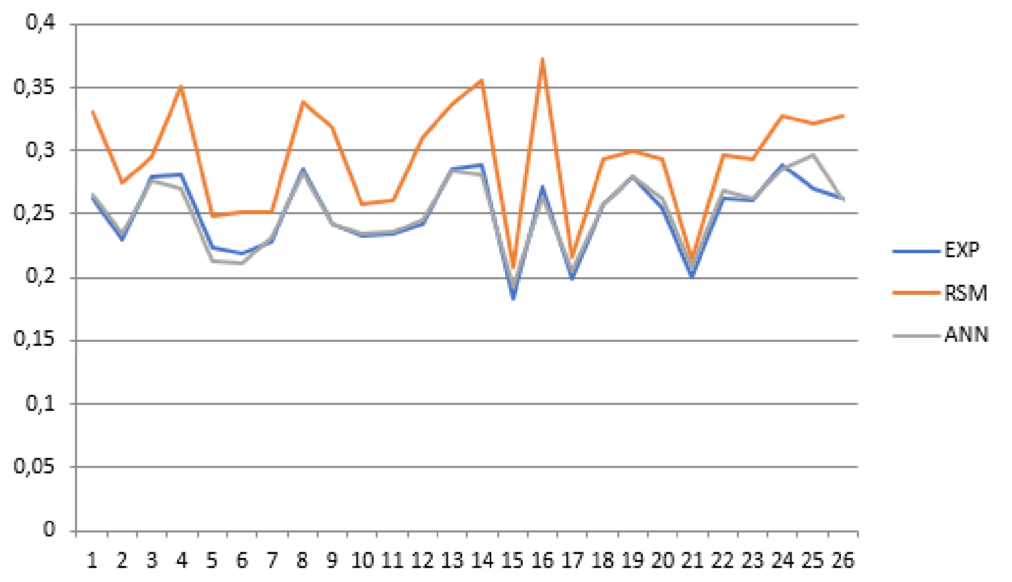

FIG. 6 Comparison charts between experimental values vs predicted values

Surface roughness of the machined Inconel 718 component was calculated by successfully implementing different models and their values are illustrated in below table. Root mean square has used for calculating the standard error in between experimental findings with RSM and ANN which is also shown in table.

TABLE 5 The used DoE and the model results with % error

Run	Cutting Speed	DoC	Feed	Nose Radius	EXP SR	RSM SR	% error (Exp vs RSM)	ANN SR	% error (Exp vs ANN)
1	5000	1	0.15	0.8	0.263	0.330	25.6	0.265	1.0
2	3000	1	0.1	0.4	0.230	0.275	19.6	0.234	1.5
3	4000	0.5	0.1	1.2	0.279	0.295	5.7	0.277	0.9
4	4000	1	0.15	1.2	0.281	0.351	24.9	0.270	3.7
5	5000	1	0.05	0.8	0.223	0.249	11.8	0.212	4.9
6	5000	1	0.1	0.4	0.219	0.252	14.9	0.211	3.7
7	5000	0.5	0.1	0.8	0.228	0.251	10.2	0.232	1.7
8	3000	1	0.15	0.8	0.285	0.339	19.0	0.283	0.8
9	4000	1	0.15	0.4	0.242	0.318	31.5	0.242	0.2
10	3000	1	0.05	0.8	0.233	0.258	10.9	0.235	0.8
11	3000	0.5	0.1	0.8	0.235	0.260	10.8	0.236	0.4
12	4000	1.5	0.1	0.4	0.242	0.311	28.3	0.245	1.2
13	3000	1.5	0.1	0.8	0.285	0.337	18.3	0.284	0.3
14	4000	1.5	0.1	1.2	0.288	0.355	23.1	0.281	2.3
15	4000	1	0.05	0.4	0.183	0.208	13.9	0.192	5.2
16	4000	1.5	0.15	0.8	0.271	0.372	37.2	0.264	2.7
17	4000	0.5	0.1	0.4	0.198	0.216	9.1	0.205	3.7
18	4000	1.5	0.05	0.8	0.258	0.293	13.7	0.258	0.1
19	4000	1	0.05	1.2	0.280	0.299	6.8	0.280	0.1
20	4000	1	0.1	0.8	0.255	0.294	15.5	0.263	3.2
21	4000	0.5	0.05	0.8	0.201	0.214	6.5	0.208	3.7
22	4000	0.5	0.15	0.8	0.262	0.297	13.5	0.268	2.1
23	4000	1	0.1	0.8	0.260	0.294	13.3	0.263	1.2
24	5000	1	0.1	1.2	0.288	0.328	13.7	0.286	0.5
25	3000	1	0.1	1.2	0.270	0.322	19.4	0.296	9.5
26	5000	1.5	0.1	0.8	0.262	0.328	25.4	0.261	0.3

It has been clearly seen from the table the prediction made by artificial intelligence model i.e ANN are very close to the experimental findings, Consequence to this ANN model is better predictor tool for calculating the surface roughness value. A chart better illustrates in the Fig. 6 it could be clearly seen that predicted value from ANN is overlapped with experimental values.

Optimization using integrated ANN and GA approach

In this study, the optimal milling process parameters for Inconel 718 alloy were determined using an integrated model incorporating ANN and GA. The search range for the four input parameters is set at 3000-5000 rpm for the speed parameter, 0.05-0.15mm/tooth for the feed parameter, 0.5-1.5 mm for the depth of cut parameter, and 0.4-1.2 mm for the nose radius parameter. Each search range is dispersed in 100 equal intervals after normalization. Figure 8 depicts the projected result of using the Matlab GA tool to optimize/minimize the surface roughness value. It has been shown that, for up to 30 generations, the fitness value decreases constantly, with only minor fluctuations thereafter. The black dots reflect the best fitness, while the blue dots represent the average fitness. The best and average fitness are close to converge at the 18th generation, however the local minimums are attained during the 33rd generation and coincide for the remainder of the generations. For the end milling process parameter problem, it can be determined that local minima may be reached in 25-35 generations, while global minima can be reached in 51 generations using the trial-and-error approach.

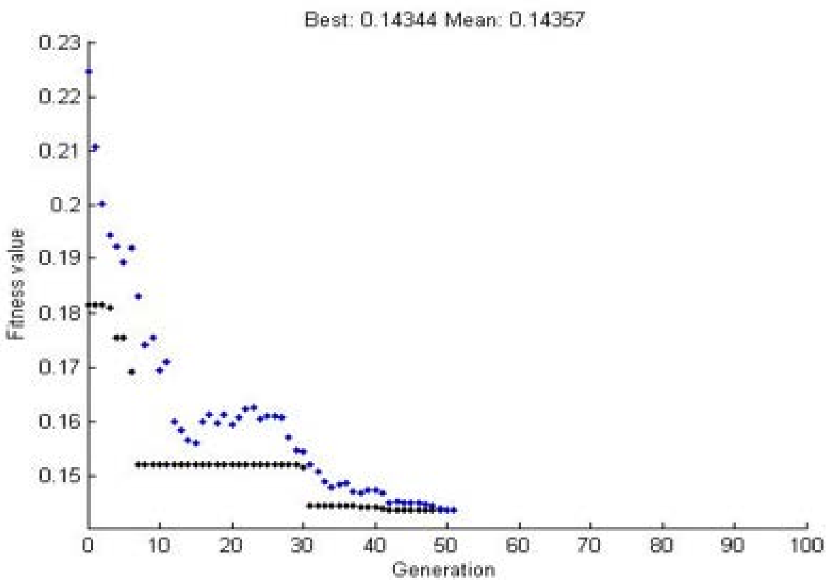

FIG. 7 Optimized process parameters obtained from genetic algorithm

MATLAB (R2011a) is utilised to determine the optima parameters in the Inconel 718 milling operation by embedding ANN and GA, within which variable X1, X2, X3, and X4 symbolise cutting speed, depth of cut, feed per tooth, and Nose radius, and parameter Y1 signifies the Surface roughness in the work piece during machining. Before and throughout optimization, the ideal response values are compared in Table 7.

As fitness metrics for GA, the output of an ANN trained using the surface roughness of a product as inputs may be used. In the GA approach, this fitness function is then utilised to determine the fitness of each chromosome. The operating settings for GA used in this research are as follows: population size = 60, crossover rate = 0.95, mutation rate = 0.01, and maximum generations = 1500. The evolutionary algorithm has selected the ideal solution to be (X1, X2, X3, X4) = (4566, 0.52, 0.055, 0.4) with a response value (Y1) of 0.148. The minimum value in Table 2 is adjusted from 0.183 to 0.148. From the lowest temperature rise numbers in Table 7, we find an improvement of more than 4 percent.

TABLE 6 The optimal combination of cutting settings for response

ANN-GA	Machining Parameters				Surface Roughness	Reduction
	Vc	Da	Ft	Nr		
Before optimization	5000	1	0.1	0.4	0.183	~4%
After optimization	4566	0.52	0.055	0.42~0.4**	0.148	

** As 0.42 mm Nose radius tool was not available so we use 0.4mm tool.

Conformational experiments show that the measured results of surface roughness for the best values of parameters by the GA-ANN approach match up well with very small differences, as shown in Table 7.

TABLE 7 Conformational Experiments

Exp No	Cutting Speed	Depth of Cut	Feed Rate	Nose radius	Surface Roughness (experimental)	Optimum Value of Surface Roughness	Variation
1.	4566	0.52	0.055	0.4	0.155	0.148	0.007
2.	4566	0.52	0.055	0.4	0.143	0.148	0.005
3.	4566	0.52	0.055	0.4	0.151	0.148	0.003
4.	4566	0.52	0.055	0.4	0.144	0.148	0.004
5.	4566	0.52	0.055	0.4	0.156	0.148	0.008

4 | CONCLUSION

It has been studied from literature that the 2.5 D milling technique is one of the most essential Inconel 718 machining methods. The process must be enhanced in terms of surface quality, i.e. the surface roughness of the machined sample. In this work, an integrated system is developed to detect and regulate factors in the 2.5 D milling process so that a minimal value of the work piece's surface roughness may be obtained, therefore facilitating the attainment of a high level of performance and quality. The combination of GA and ANN was able to minimise surface roughness, which is regarded an improvement in machining conditions, and work piece experiments were able to validate the results. In addition, it can be stated that the established approach is effective and sufficient for estimating the optimal performance parameter values in the 2.5 D end milling process for Inconel 718 alloy. As an extension, the suggested integrated technique may be utilised to solve additional optimization issues for other processes.

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