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Machining Parameters Optimization of AA6061 Using Response Surface Methodology and Particle Swarm Optimization

Rashmi LMalghan[1], Karthik Rao M C[2,#], ArunKumar S[3], Shrikantha S Rao[1], and Mervin A Herbert[1]

1 Department of Mechanical Engineering, NITK, Surathkal 575025, India
2 Department of Mechanical Engineering, Debre Markos University, Post box-269, Ethiopia
3 Department of Mechatronics Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, India
Corresponding Author / E-mail: karthik_rao@dmu.edu.et, TEL: +91-9986087148,+251970771639
ORCID: 0000-0002-3082-9309

KEYWORDS: Face milling, Regression, Particle swarm optimization, Desirability, Response surface methodology, Design of experiment

The influence of cutting parameters on the responses in face milling has been examined. Spindle speed, feed rate and depth of cut have been considered as the influential factors. In accordance with the design of experiments (DOE) a series of experiments have been carried out. The paper exemplifies on the optimizing the process parameters in milling through the application of Response surface methodology (RSM), RSM-based Particle Swarm Optimization (PSO) technique and Desirability approach. These aforesaid techniques have been applied to experimentally establish data of AA6061 aluminium material to study the effect of process parameters on the responses such as cutting force, surface roughness and power consumption. By adopting the multiple regression techniques, the interaction between the process parameters are acquired. The optimal parameters have been found by adopting the multi-response optimization techniques, i.e. desirability approach and PSO. The performance capability of PSO and desirability approach is investigated and found that the values obtained from PSO are comparable with the values of desirability approach.

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NOMENCLATURE

AMMC's = Aluminium Matrix Composites
ANFIS = Adaptive Fuzzy Interface System
ANOVA = Analysis of variance
ANN = Artificial Neural Network
CCFCD = Central Composite Face Centred Design
CNC = Computer Numerical Control
DOE = Design of Experiment
FX = Cutting Force, N
GA = Genetic Algorithm
gbest = Global best
pbest = Particle best
GSA = Genetic simulated annealing
MMC = Metal Matrix Composite
PSO = Particle Swarm Optimization
RSM = Response Surface Methodology
R-sq = Pre R-squared
R-sq (adj) = Adj R-Squared
RGA = Real Parameters Genetic Algorithm
RPD = Relative percentage deviation
HGA = Hybrid Genetic Algorithm SQP
SGA = Simple Genetic Algorithm
SR = Surface roughness, μm

1. Introduction

Present scenario, aluminium alloys has expanded their attention of many industrialists, researchers, engineers and designers as promising structural materials for aerospace applications or the automotive industry. Particularly, aluminium (6 series) alloys have been considered widely because of their benefits such as medium strength, formability, weldability, corrosion resistance, and low cost, comparing to other aluminium alloys.[1] Mithilesh[2] combined RSM and teaching learning based algorithm to optimize surface roughness for milling aluminium alloy Al2016-T6. Bhopalen[3] applied the RSM to study the effect of cutting parameters and inclination angle on the surface roughness for milling Inconel 718. A considerable number of studies have researched the effects of the spindle speed (A), feed rate (B) and depth of cut (C) on responses, i.e. cutting force (FX), surface roughness (SR) and power consumption. In recent research Tandon[4,5] and Conceicao[6] the models have been developed and identified the outcome of some factors on the SR and FX. A central task in science and engineering practice is to develop models that give an adequate description of the physical systems being observed. The main goal of this study is to attain a mathematical model that relates the responses to the three cutting parameters in face milling, precisely to the spindle speed, feed rate and depth of cut. In this work two different approaches have been adopted to attain the mathematical models. The first approach is DOE together with analysis of variance (ANOVA) and regression analysis. The second method is by means of the PSO technique. Generally, the machining parameters are chosen based on the machine data hand book, trial and error method or by literature. But adopting such trials is not a precise way for selecting the appropriate machining parameter as it leads to wastage of time and cost. Hence, to overcome the intricacy, it is necessary to develop a technique to predict the appropriate machining parameters. In the present study desirability and PSO techniques are incorporated to identify the optimal process parameters.

2. Literature Survey

Though a lot of research in milling operation has been attempted by a few researchers and papers relevant to optimization and the issues related to milling operation have been discussed. Tandon[4] implemented particle swarm optimization for optimizing multiple machining parameters and results indicated in a reduction in machining time by 35%. Tandon[5] incorporated the ANN approach to develop a comprehensive model for critical machining parameters. The developed model was tested and validated for specific pocket milling scenario originated in the industry. From the testing and validation, it was concluded that there was an excellent agreement between the experimental and simulated forces. Jinhua[7] developed integrated multi objective optimization technique and applied to Inconel 718 in the milling process for to attain minimum surface roughness and maximum compressive residual stress. Conceicao[6] developed model for the multi-pass cutting parameter in face milling by incorporating the genetic search. Furthermore, the novel approach based on substituting the depth of cut with a sequence of depths of cut was developed. The performance of the developed model was compared with rest of multi-pass models. Saffari[8] used a Genetic Algorithm (GA) to obtain a minimal tool deflection in the milling process. In the study, the tool deflection was considered as the objective while tool-life and surface roughness were the constraints. A comparative study was made to validate the performance of the optimization, the attained results illustrate that optimized parameters are proficient of machining the workpiece more precisely with better surface finish. Patwari[9] illustrated mathematically the effect of machining parameters on response surface roughness in the milling of Medium Carbon Steel using the TiN tool in dry condition and included a genetic algorithm. The results indicated that the proposed model could efficiently describe the performance indicators within the boundary of the factors that are being considered in the study. Gupta[10] anticipated a Hybrid Genetic Algorithm (HGA) to optimize the non-productive tool path in which the initial seed solution is generated by heuristic and collectively with an initial solution created by a simple genetic algorithm (SGA). The results were analyzed by using Relative percentage deviation (RPD) and it was derived that the HGA is more superior compared to SGA for a same computation time limit (stopping norm). Basker[11] incorporated Tabu search, GA, Ant Colony Algorithm and Particle swarm optimization algorithm for optimizing machining parameters in the milling operation. Mainly the work was concentrated on the development and utilization of the mentioned optimization techniques and the optimization system which helps in identifying the optimum machining parameters for milling operation. Wang[12] integrated Genetic simulated annealing (GSA) for identifying the optimal machining parameter in case of multi-pass milling. The comparative study was made and the results signified that the GSA was effective over GA. Reddy[13] implemented the mathematical model, based on the concept of Response Surface Methodology (RSM) to establish the cutting conditions and effect of tool geometry related to machining performance and even optimize the surface roughness response GA technique was utilized and the respective optimal condition was determined. Savas[14] used GA for optimization of surface roughness and concluded that surface roughness increases with the increase of the machining parameters feed rate and depth of cut. Abburi[15] used RGA (real-parameters Genetic Algorithm) in turning operation for optimal process parameters, thus the concept leading in minimal product time, which in turn acts as the base for the SQP (Sequential Quadratic Programming) code and results in an increase in the performance. The overall indication and suggestion were towards the usage of the numerical approach for attaining the optimum solution in case of unequal depth of cut involvement. Mukherjee[16] addressed the proposed a generic framework in metal cutting processes in order to opt and attain an efficient approach and showed a path to identify the optimal cutting conditions or near optimal cutting conditions in various categories of metal cutting process. Onwubolu[17] proposed an optimization concept based on Tribes for determination of the machining parameters in multi-pass plain milling and face milling operations. The machining parameters are decided based on the strategy of maximizing and minimize the production rate and derived that developed Tribes based approach is efficient. Developed a model for predicting the surface roughness in face milling for aluminium material by adopting the PSO technique. The conclusion was made that PSO is in good agreement with current surface roughness values. Ship-peng[19] developed an adaptive fuzzy interface system (AFIS) to predict the surface roughness in the milling process and proved that greater prediction (nearly of 96%) accuracy was achieved. Julie[20] implemented Taguchi approach to optimize the surface roughness in the milling operation. The authors analyzed the experiments using analysis of variance (ANOVA) and concluded that the Taguchi approach was successful in optimizing the surface roughness. Xain[21] considered and specified the significance of Artificial Neural Network (ANN) for predicting the surface roughness in milling operation and concluded a better surface finish is achieved at a high rake angle, low feed rate and high speed. Astilturk[22] developed full factorial design of experimented (FFD). The FFD was adapted to reliability during turning operation and authors concluded that the ANN model yielded better results as compared to the statistical model and even the results indicated that by varying the number of layers and nodes in the hidden layer the prediction accuracy of respective response can be increased. Benardos[23] developed an ANN model for predicting the surface roughness in the milling process and indicated that the ANN model was able to predict the surface roughness with a mean error of 1.86%.

A sufficient amount of research articles is available on identifying the optimal machining parameters by incorporating the soft computing techniques precisely fuzzy logic, GA, and ANN. A sufficient amount of research articles is available for identifying the optimal machining parameters by incorporating the soft computing techniques precisely Fuzzy logic, GA, and ANN. Therefore, this work explores the feasibility for multiobjective optimization with the RSM-PSO method. And it is employed to optimize cutting force, surface roughness and power consumption for milling AA6061. The paper gives the information regarding conducting the experiments, performing RSM technique to attain the response equations. Further, these response equations are used as fitness function in PSO. The experimental results are compared with RSM predicted results and later on the desirability and PSO results are compared.

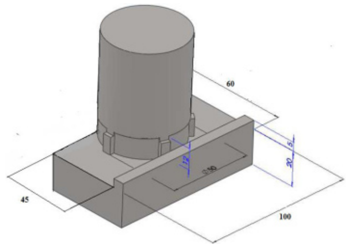

Fig. 1 AA6061 material with the tool

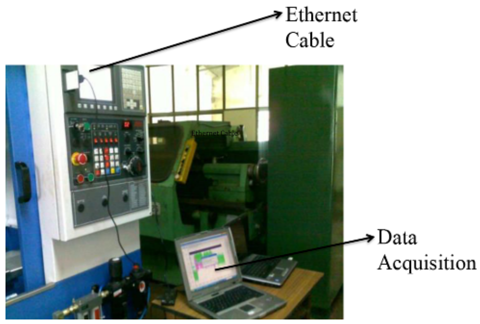

Fig. 2 Data acquisition

3. Conditions of Experiment

Test samples made up of AA6061 with dimensions: length of 100 mm length, 60 mm breadth and 12 mm thickness. The face milling experiments were carried out by a tool SDMT 1205PDR-HQ-M IC28 as depicted in Fig. 1. The cutting tool has 5 inserts. The details of the insert, it is square type insert, side clearance angle 15°, tolerance 0.08 mm, type T, cutting edge length 12 mm, thickness 5 mm, type of mount 90°, lead 15°, the radius of nose 0.4 mm. The tool holder selected is having the BT 30 taper type (Tool Holder: F90SD D50, 2F2, 12) produced by Iscar. The type of machine utilized for the milling test was CNC Vertical Milling machine (Spark DTC 250) by AMS. The experiments were performed with dry run machining condition of the selected material. The cutting force was calculated via indirect approach based on the current consumption by each axis. These current values were fetched through Ethernet cable provided by FANUC as depicted in Fig. 2. The SR values of finish - milled work pieces were measured by the Mitutoyo Surface Roughness Tester. The SR values were acquired at a minimum of three different locations, later on; the measured surface roughness was obtained by averaging the surface roughness values. The chemical composition of the selected material is depicted in Table 1. The cutting parameters considered were spindle speed, feed rate, and depth of cut. The experiments were designed and conducted based on the design and analysis of the experiment. In the present study, Design of Experiment (DOE), Response Surface Method (RSM) three factors of cutting parameters and three levels have been considered as shown in Table 2.

Table 1 Composition of AA6061

Element	Al	Si	Cu	Mg	Cr
Weight (%)	97.9	0.60	0.28	1.0	0.20

Table 2 The Cutting Parameters and their levels

Symbol	Levels	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)
A	L-I	1000	300	1
B	L-II	2000	400	2
C	L-III	3000	500	3

4. Statistical and Optimization Concepts: Design of Experiment, Desirability, and PSO

In the current study, the design of the experiment was realized using the central composite design (CCD). The main goal of this work is to identify the mathematical models that describe the dependence of responses on the three machining parameters: spindle speed (A) rpm, feed rate (B) mm/min, depth of cut (C) mm. The CCD models the responses by using the empirical second-order polynomial equation. In the present study, the RSM technique was incorporated in the analysis and design of the experiments. RSM technique helps with its strategies to overcome the analysis quandaries thus leading to a better result. It usually identifies the significance of the process parameters on the responses and the main purpose of RSM is to optimize the response. The Central Composite Face Centered Design (CCFCD) was used to implement the response models using RSM. A total of 20 experiments was performed which incorporates of 8 cube points, 6 centre points in a cube, 6 Axial points, and the alpha value is 1. The range of the process parameters was set by taking into consideration of the tool or inserts specification and even by performing the trial experiments in order to achieve the desired responses. RSM has been used for mathematical modeling of Fx, SR and power consumption, The next step is, the experiments were performed using the multiple regression equations in order to identify the interaction effect between the process parameters and the responses. Later on, The Desirability and PSO techniques were employed to determine the optimal parameters. The validation step is carried out by conducting the experiments in order to verify the established model.

4.1 Methodology on desirability and PSO

The desirability Function approach is a multiple-response optimization method. This approach was first introduced in 1980 by Suich and Deringer. The method finds operating conditions "targeted" that the most desirable response value. The general approach first converts each response x1 into an individual desirability function di that varies over the range 0 < di < 1.The desirability functions are categorized into three sectors based on the response characteristics.

1. If the target for the response is a maximum value / "Higher is Better".

$$\begin{cases} 0 & ri \le ri^* \\ \left[\dfrac{ri-ri^*}{ri'-ri^*}\right]a & ri^* < ri < ri' \\ 1 & ri \ge ri' \end{cases}$$

Where: ri^* is the minimum adequate value of ri, ri' is the maximum adequate value of ri and a describes

2. If the target for the response is a minimum value / "Smaller is better"

$$\begin{cases} 1 & ri \le ri'' \\ \left[\dfrac{ri^*-ri}{ri^*-ri''}\right]b & ri'' < ri < ri^* \\ 0 & ri \ge ri^* \end{cases}$$

Where: ri'' is the minimum value of ri, ri^* is the maximum adequate value of ri

4.2 Concept of PSO

PSO was developed by Eberhart and Kennedy in the year 1995. This approach is an evolutionary computational method that has been based on the swarm intelligence of a flock of birds. One difference from other evolutionary algorithm is that the particle does not use selection criterion in the iterative procedure. Therefore, population members will survive from the beginning to the end in the optimization process. This algorithm has been widely successfully applied to solve many engineering problems,[24-27] by imitating the seeking behavior of a swarm of birds, the individual particles in an algorithm look for the overall best result of the fitness function. The particles get updated with their momentum and act as per the situation and particles usually update their momentum based on the gained previous experience and global effort put up by other particles in the search space. There are three constraints, social, cognitive and inertia that are responsible for the updating of the momentum of the particles.[34-37] The social constraint is accountable to move faster the particle to the best position followed by another swarm so far, known as the gbest position. The cognitive factor rushes the particle towards its individual best location proficient till then, known as the pbest. The inertia factor is used to maintain the stability between the current and overall investigation capabilities among the search space. The gbest position is determined to be changed on progressive era. In the progressive iteration if it is found that the pbest position is better than gbest position, then the pbest position will be traded by the gbest to renovate the overall best solution. The supplementing equations are adopted to change the individual particle's position to reach an overall best possible solution in the search space.

$$k_m^{n+1} = w \cdot k_m^n + c1 \cdot Q1 \cdot (pbest_m - R_m^o) + c2 \cdot Q2 \cdot (gbest - R_m^o) \quad (1)$$

Where: k_m^n = 'mth' particle momentum at 'nth' iteration, w = inertia weight, $c1$, $c2$ = learning rates, $Q1$, $Q2$ = random numbers between 0-1, $pbest_m$ = pbest position of mth particle, $gbest$ = gbest position of swarm, $R_m^o = [R_{m1}^o, R_{m2}^o, \ldots, R_{mN}^o]$, '$m$th' particle current position at 'oth' iteration in N-dimensional search space.

Once the momentum is calculated, the next position of 'mth' particle is calculated using the following Eq. (2).

$$R_m^{o+1} = R_m^o + k_m^{n+1} \quad (2)$$

Inertia weight can be selected any random value or it can be determined by opting the following Eq. (3).

$$W = w_{max} - \frac{[(w_{max} - w_{min}) \times iteration_{current}]}{iteration_{total}} \quad (3)$$

Where: w_{max} = upper limit inertia weight, w_{min} = lower limit inertia weight, $iteration_{current}$ = current iteration, $iteration_{total}$ = total number of iteration.

5. Results and Discussion

Response surface methodology (RSM) is a collection of the mathematical and statistical technique used for analyzing problems in which several independent variables influence a dependent variable or response and the goal is to optimize the response. Second-order polynomial equation with interaction terms was fitted to the experimental results to develop a mathematical model, which will help to predict the extraction efficiency of different sets of combinations of four process variables on the responses. Three empirical models were developed from this study to predict the cutting force, surface roughness and power consumption. The attained regression equations are depicted in Table 3. The considered experiments with their respective input parameters and outcome of the responses are shown in Table 4. The experimental V/S predicted values for all the considered experiments are represented in Table 4.

Generally, ANOVA comprises the sum of square, the degree of freedom (DF), mean square, F-value, and P-value.[38] The inclusion of ANOVA is essential to find out the influential parameters on the responses.[39,40] The performance of the model was validated with ANOVA. From the Tables 5-7, it can be observed that spindle speed has a major contribution to all the responses followed by the feed rate and depth of cut. As depicted in Table 5 spindle speed has 91.183% contribution on the response FX, 6.299% of the feed rate and followed by the depth of cut with a 0.89267% contribution. The remaining contribution is contributed by the interaction of the process parameters. Similarly, In Table 6, it can be identified that spindle speed plays a vital role with the contribution of 40.526%, 14.210% of feed rate and 22.1053% of the depth of cut. The rest of the contributions are by the

Table 3 Regression Equations

SL. No	Responses	Regression Equations
1	FX	-81.78776 + 0.081353*A + 0.18242*B + 4.42441*C - 3.24420E-005*A*B - 5.91517E-006*A*A
2	SR	0.15850 - 2.80000E-005*A + 2.22000E-003*B + 0.13500*C - 2.50000E - 007*A*B + 2.00000E-005*A*C - 6.00000E-004*B*C
3	Power Consumption	-0.030842 + 4.72657E-005*A - 2.33913E-004*B + 6.10045E-003*C + 1.15949E-007*A*B -8.91940E-009*A*A + 6.31394E-007*B*B

Table 4 Experimental V/S RSM predicted results

	Experimental						RSM Prediction			Error (%)		
SL No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	FX (N)	SR (µm)	Power consumption (kW)	FX predicted (N)	SR predicted (µm)	Power consumption predicted (kW)	FX error (%)	SR error (%)	Power consumption error (%)
1	1000	300	1	45.49	0.7	0.037	43.068	0.697	0.035	5.325	0.500	6.438
2	3000	300	1	143.3	0.52	0.132	138.987	0.531	0.128	3.003	-2.019	3.184
3	1000	500	1	73.26	0.96	0.108	73.063	0.971	0.112	0.268	-1.094	-4.035
4	3000	500	1	158.3	0.71	0.249	156.006	0.705	0.252	1.443	0.775	-0.902
5	1000	300	3	56.69	0.63	0.048	51.971	0.647	0.047	8.420	-2.619	2.037
6	3000	300	3	150.5	0.56	0.139	147.836	0.561	0.140	1.777	-0.089	-0.976
7	1000	500	3	83.56	0.68	0.125	81.912	0.681	0.125	1.972	-0.074	0.645
8	3000	500	3	164.2	0.48	0.262	164.855	0.495	0.264	-0.399	-3.021	-0.705
9	1000	400	2	63.42	0.76	0.074	64.290	0.749	0.074	1.466	1.513	0.219
10	3000	400	2	153.3	0.58	0.191	151.921	0.573	0.189	0.893	1.293	0.655
11	2000	300	2	100	0.61	0.090	101.367	0.609	0.096	-1.357	0.246	-6.919
12	2000	500	2	134.2	0.71	0.205	124.874	0.713	0.197	6.963	-0.352	3.737
13	2000	400	1	110.2	0.73	0.134	108.696	0.726	0.134	1.373	0.616	-0.297
14	2000	400	3	119.8	0.62	0.148	117.545	0.596	0.147	1.907	3.952	0.685
15	2000	400	2	115	0.66	0.141	113.121	0.661	0.140	1.651	-0.076	0.224
16	2000	400	2	115	0.66	0.141	113.121	0.661	0.140	1.651	-0.076	0.224
17	2000	400	2	114.8	0.65	0.139	113.121	0.661	0.140	1.480	-1.615	-1.388
18	2000	400	2	113	0.67	0.143	113.121	0.661	0.140	-0.089	1.418	1.622
19	2000	400	2	115	0.66	0.141	113.121	0.661	0.140	1.651	-0.076	0.224
20	2000	400	2	114	0.66	0.137	113.121	0.661	0.140	0.789	-0.076	-2.448

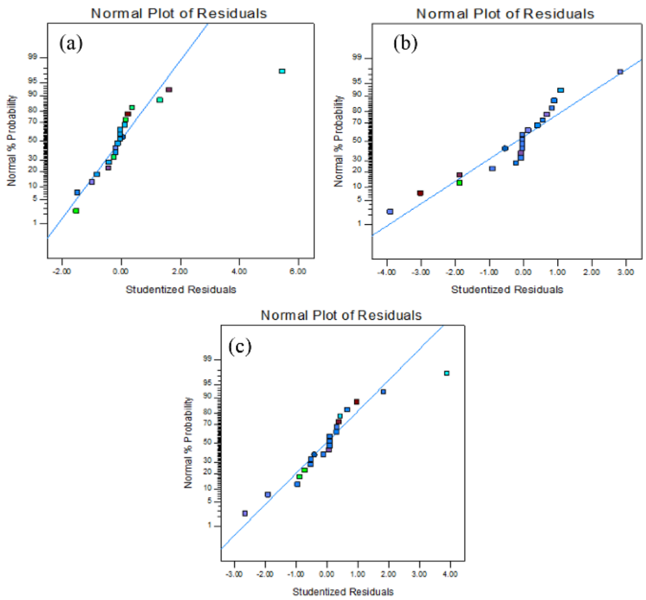

Fig. 3 Normal Probability plots of residuals for (a) FX, (b) SR, (c) power Consumption for AA6061

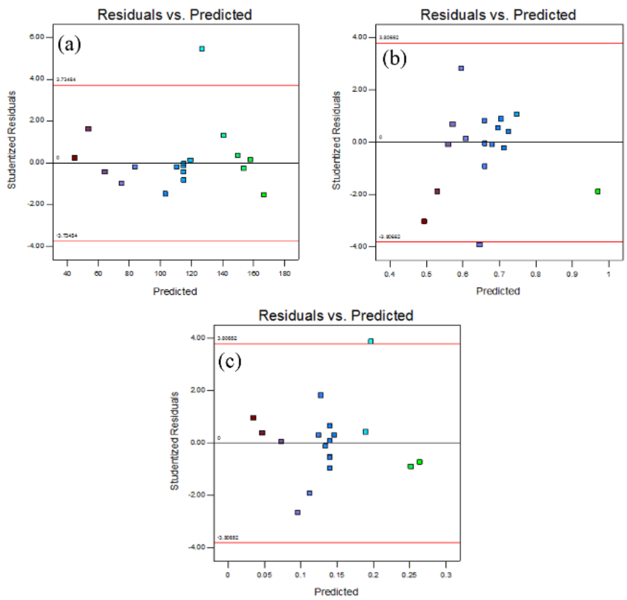

Fig. 4 Plot of residuals v/s predicted: (a) FX, (b) SR, and (c) power consumption

interactions of the process parameters. As depicted in Table 7, it can be concluded that spindle speed has 55.737% major contribution, the feed rate of 40.983% and followed by the depth of cut 0.6101%. The other contributions are contributed by the interactions occurred among the

Table 5 ANOVA analysis for cutting forces (FX)

Sources	Sum of squares	DF	Mean square	F-value	p-value Prob > F	Remarks	P (%)
Model	21831.51	5	4366.3	630.33	< 0.0001		
A-A	19995.16	1	19995.2	2886.56	< 0.0001	significant	91.1835
B-B	1381.45	1	1381.45	199.43	< 0.0001	significant	6.2998
C-C	195.75	1	195.75	28.26	0.0001	significant	0.89267
AB	84.2	1	84.2	12.16	0.0036	significant	0.00384
A^2	174.95	1	174.95	25.26	0.0002	significant	0.79782
Residual	96.98	14	6.93				
Lack of fit	93.64	9	10.4	15.61	0.0037		
Pure error	3.33	5	0.67				
Cor total	21928.49	19					

Table 6 ANOVA analysis for surface roughness (SR)

Sources	Sum of squares	DF	Mean square	F-value	p-value Prob > F	Remarks	P (%)
Model	0.18	6	0.031	225.54	< 0.0001		
A-A	0.077	1	0.077	570.38	< 0.0001	significant	40.5263
B-B	0.027	1	0.027	199.16	< 0.0001	significant	14.2105
C-C	0.042	1	0.042	311.19	< 0.0001	significant	22.1053
AB	5.00E-03	1	5.00E-03	36.83	< 0.0001	significant	2.63158
AC	3.20E-03	1	3.20E-03	23.57	0.0003	significant	1.68421
BC	0.029	1	0.029	212.12	< 0.0001	significant	15.2632
Residual	177E-03	13	1.36E-04				
Lack of fit	1.57E-03	8	1.96E-04	4.89	0.0485		
Pure error	2.00E-04	5	4.00E-05				
Cor total	0.19	19					

Table 7 ANOVA analysis for Power Consumption

Sources	Sum of squares	DF	Mean square	F-value	p-value Prob > F	Remarks	P (%)
Model	0.061	6	0.01	749.4	< 0.0001		
A-A	0.034	1	0.034	2492.41	< 0.0001	significant	55.7377
B-B	0.025	1	0.025	1877.39	< 0.0001	significant	40.9836
C-C	3.72E-04	1	3.72E-04	27.6	0.0002	significant	0.61016
AB	1.08E-03	1	1.08E-03	79.78	< 0.0001	significant	1.76393
A^2	2.55E-04	1	2.55E-04	18.88	0.0008	significant	0.41738
B^2	1.28E-04	1	1.28E-04	9.46	0.0088	significant	0.20918
Residual	1.75E-04	13	1.35E-05				
Lack of fit	1.55E-04	8	1.94E-05	4.87	0.0489		
Pure error	1.99E-05	5	3.99E-06				
Cor total	0.061	19					

process parameters. From the Tables 5-7, in the remarks column, the process parameters and interactions of process parameters are assigned significant, this assigning of the values is entirely based on the condition of "Prob > f <5% or 0.05".[28] If the aforesaid condition is satisfied, then the values are assigned as significant else not significant. The significance of the regression fitted model is determined by incorporating the R2 coefficient correlation. The attained R-sq and R-sq (adj) for the model is 99.65 and 99.33 respectively. From the Fig. 3, it can be observed that there is a normal distribution of errors takes place as residuals for all the models falls on the straight line. Fig. 4 exhibits the plot of residuals v/s predicted values of responses. From Fig 4, it can be observed that all the points of the experimental runs were spotted randomly inside the reliable range of residuals over the graph.

5.1 Effect of Process Parameters on responses SR, FX and Power consumption

Fig. 5(a) represents that the SR value decreases as the spindle speed increases this is due to vanishing of the formed built up edge at the cutting edge tip leading to better surface finish.[41] On the other side as the feed rate increases the value of SR increases this is due to increase in axial movement of the cutting tool as it will not completely remove the required material because of alteration of the tool to a new position. In the case of influence of depth of cut on SR the value of SR decreases as the depth of cut reduces this is due to the rigidity effect of the machine occurred during the machining process.

Similarly, as represented in Figs. 5(b) and 5(c) the influence of spindle speed, feed rate and depth of cut on FX and power consumption signify the directly proportional relationship, i.e., as the spindle speed, feed rate and depth of cut increase the responses FX and power consumption increases. This direct proportional relationship occurs due to the higher chip tool interface area.[42] From the Fig. 6, it can be recognized that the optimal values attained for all the responses by the influence of process parameters through the desirability approach are as follows: spindle speed (3000 rpm), feed rate (500 mm/min) and depth

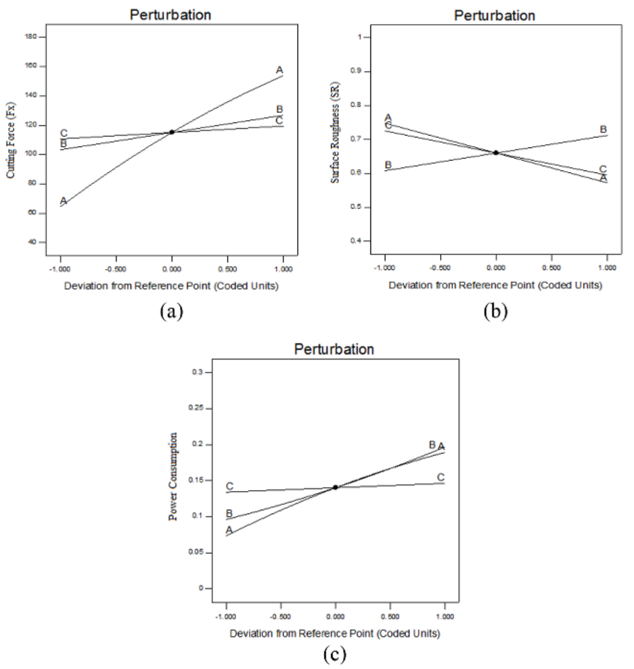

Fig. 5 Effect of process parameters on (a) SR (b) FX (c) Power

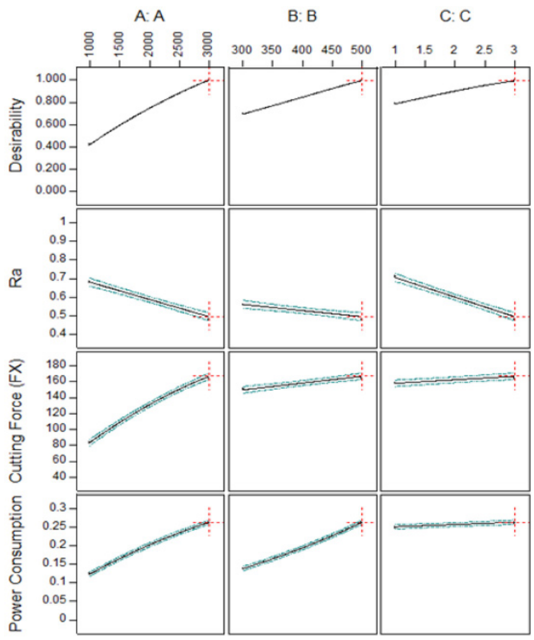

Fig. 6 Results of Desirability Approach: (a) All power consumption Responses-Desirability Approach

Table 8 RSM Experimented V/S Predicted (Validation Data sets)

Test No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	FX (N)	SR (μm)	Power consumption (kW)	FX predicted (N)	SR predicted (μm)	Power consumption predicted (kW)	FX error (%)	SR error (%)	Power consumption error (%)
1	1200	340	1.2	47.62	0.69	0.038	48.41	0.72	0.06	-1.67	-4.88	-5.26
2	1800	340	1.8	103.28	0.57	0.094	98.61	0.6	0.1	4.52	-5.26	1.1
3	2400	340	2.6	108.44	0.59	0.103	113.44	0.59	0.14	-1.61	0.42	-0.97
4	1200	390	1.2	59.96	0.88	0.082	55.59	0.82	0.08	7.29	6.4	-3.66
5	1800	390	1.8	114.38	0.67	0.14	104.82	0.69	0.12	8.36	-2.24	7.14
6	2400	390	2.6	120.23	0.63	0.148	128.85	0.59	0.16	-7.17	6.27	-1.35
7	1200	460	1.2	74.26	0.97	0.109	69.63	0.93	0.11	6.23	4.36	-0.92
8	1800	460	1.8	136.32	0.72	0.21	139.5	0.73	0.16	-2.33	-1.85	-4.76
9	2400	460	2.6	140.87	0.61	0.23	134.99	0.59	0.2	4.17	2.51	4.35
10	2800	340	1.2	144.22	0.51	0.14	140.07	0.51	0.14	2.88	-0.59	0.71
11	2800	390	1.8	152.93	0.6	0.18	146.31	0.6	0.17	4.33	0.75	0.56
12	2800	460	2.6	163.96	0.49	0.28	164.13	0.5	0.22	-0.11	-2.45	3.57
13	1200	340	1.8	52.27	0.65	0.039	51.07	0.7	0.06	2.3	-7.18	-2.56
14	1200	390	1.2	57.86	0.87	0.069	55.59	0.89	0.08	3.93	-2.72	-1.45
15	2800	460	1.8	160.02	0.58	0.27	149.72	0.58	0.06	6.44	0.59	3.7

of cut (3 mm) on the responses 0.4945 (m), 166.85 (N) and 0.263 (kW).

5.2 Desirability approach

Table 8 represents the experiments carried out by using the RSM technique for validation purpose and also it can be observed that the % of error attained between the experimental and predicted values carried out by using RSM technique. The RSM technique to predict individual response it needs an individual equation, thus at a single go only one response from its respective equation can be predicted, thus the multi objective optimization technique is suitable if more than one response is incorporated. Table 9 clearly indicates projected model and signifies the parameters that play a vital role in obtaining finer convergence characteristics of PSO and indicates the best operating parameters recommended for milling process of AA6061. These parameters play a significant role in obtaining good convergence characteristics of PSO. If the number of parameters increases, the learning rate increases. In turn, the number of iterations increases in the search space. The outcome leads to a probability of getting a global optimum solution and leading the convergence to be accomplished in a smaller number of iterations. Table 10 summarizes the optimal parameters attained through adopting different techniques. The deviations between the PSO predicted results and experimental results are marginal. However, the experimental error is quite considerable and lies within the acceptable range of ±5%. Moreover, the comparative results presented in Table 10 have indicated that PSO predicted values have good agreement with the experimental results. It can be concluded that PSO technique gives fairly accurate values as compared to that of the desirability approach and thus PSO has a better computational efficiency.

5.3 Numerical elucidation of PSO

Table 9 Parameters of PSO

Number of parameters	3
Number of particles	100
Number of iterations	100
Learning rate	
C1 max = C2 max	1.4
C1 min = C2 min	1.8
C1=C2=Cmin+R*(Cmax-Cmin)	Where R = total iterations
X_{ulim}	[1000, 300, 1]
X_{llim}	[3000, 500, 3]

Table 10 Optimal process parameters

Parameters	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	SR (μm)	FX (N)	Power (kW)
Desirability	3000	500	3	0.520	167.86	0.264
PSO	3000	500	3	0.494	166.85	0.265
Experimental	3000	500	3	0.480	164.20	0.262

6. Conclusions

The optimization issue of machining parameters is dealt with as a multi-objective optimization problem. Keeping in mind the end goal to influence manufacturing engineers to have more control on the machining operations, the optimization strategy is to simultaneously reduce production time and decrease production cost and enhance profitability in the interim subject of fulfilling the imperatives on the spindle speed, feedrate, depth of cut, cutting force, surface roughness and power consumption. A proficient multi-objective PSO to optimize the machining parameters is developed to solve such multi-objective optimization problem in optimization of face milling. The proposed PSO algorithm does not have any difficulty in accomplishing optimal solutions with good convergence for multi-objective optimization problems and the significant upgrades are made in contrast with the outcomes by desirability approach.

Based on the experimental studies the following findings are found:

- The developed second order equation has shown good co-relation between the predicted and experimental values.
- The results of ANOVA has revealed that the effect of spindle speed is much more pronounced than the effects of feed rate and depth of cut, on the surface roughness, power consumption and cutting force. The validation test of RSM model has shown ±7% of error.
- The results procured through PSO are likewise compared with the customary desirability approach and it was found that PSO technique displays extensive favorable position contrasted with outcomes accomplished with the desirability approach.
- Test data set demonstrate that the anticipated PSO model results matches well with experimental results. The verification experiments show that the optimal level combination of machining parameters with the PSO yields better results compared to that of desirability and are in good concurrence with the experimental results.

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