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Effect of Machining Parameters and Optimization of Machining Time in Facing Operation using Response Surface Methodology and Genetic Algorithm

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Abstract

The objective of this research is to select the machining parameters and its cutting conditions to increase the productivity and minimize of total machining time and machining cost. A significant improvement in process may lead to increase in the process efficiency and low cost of manufacturing. In this research, Spindle speed, Feed rate, Depth of cut and End relief angle are considered as input parameters for facing operation of the A22E Bimetal bearing material using M42 HSS tool material. A second order mathematical model was developed by using Design of Experiments (DoE) of Response Surface Methodology (RSM) to predict the machining time of Bimetal bearing material. The Analysis of Variance (ANOVA) was used to study the performance characteristics in facing operation. The direct and interaction effects of the machining parameters were also analyzed using Design Expert software. The values of Prob > F less than 0.05 indicate model terms are significant. The Genetic Algorithm (GA) was trained and tested by using MATLAB 7.0. The GA recommends 1.169 seconds as the best minimum predicted machining time value. The confirmatory test shows the predicted values and experimental values were very close and good agreement.

Keywords: Depth of Cut, End Relief Angle, Feed Rate, Genetic Algorithm (GA), Machining Time, Response Surface Methodology (RSM), Spindle Speed

1. Introduction

During the machining of hardened bearing steel, the work piece and tool is subjected to high strain, temperature and vibration results low surface roughness, tool wear, high increase in machining time etc. The machining parameters selection plays a major role in production based industries. Improper selection of machining parameters may leads to increase in machining time and production cost. To achieve the desired results the cutting parameters such as feed rate, spindle speed, axial/radial depth of cut, tool geometry (cutter diameter, number of teeth, side cutting edge angle, rack angle, shank diameter, helix angle, overall length of tool, nose radius etc.) torque, spindle motor current, cutting time, clearance angle, feed drive current, type of lubricants used etc. Optimized combination of the above mentioned parameters will increase in the surface finish, reduces the tool wear, machining time and increase the tool life[1]. It is necessary to develop a technique to predict the surface roughness, tool wear, machining time etc. Nowadays in order to obtain the exact end result several modeling procedure and techniques are used, they are classified as 1) Analytical based models, 2) Experimental based models, 3) DoE (Design of Experiments) based models, 4) AI (Artificial Intelligence) based models such as Response Surface Methodology (RSM), Genetic Algorithm (GA), Artificial Neural Network (ANN) etc.,

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were used in engineering applications particularly in machining related work[2].

This paper presents the optimization and prediction of machining parameters of machining on A22E Bimetal bearing considering the input parameter such as spindle speed, feed rate, depth of cut and end relief angle. A second order mathematical model was developed using Analysis of Variance (ANOVA). The Response Surface Methodology (RSM) was used to predict machining time and the interaction effect was analyzed using RSM. The non-traditional optimization technique Genetic Algorithm (GA) was employed for the optimum cutting parameters which minimizes the machining time.

The mathematical models have to develop to correlate the cutting parameters with cutting performance to determine the optimal cutting parameters. But yet well known the reliable mathematical models are not easy to obtain[3]. The authors[4] have optimized the cutting parameters (cutting speed, feed rate and depth of cut) considering maximum production rate and minimum production cost. The authors[5] expressed the equation for machining time.

$$t_m = \frac{\pi DL}{10FV} \tag{1}$$

Where,

- t_m - Machining time per piece (min/ pc),
- D - Diameter of the work piece (mm),
- L - Length of the work piece (mm),
- V - Cutting speed (m/min),
- F - Feed rate (mm/rev)

and also suggests that machining time decreases with an increase in cutting speed. An experimental investigation was done using aluminium to study the behavior and effect of machining parameters such as cutting speed, feed rate, and depth of cut on the surface roughness in minimum machining time on face milling process[6]. The authors[7] conducted the experiment to establish the correlation between cutting velocity, feed rate and cutting time by using Taguchi design of experiment. The mathematical model was developed by the authors[8] to estimate the machining time by measuring acceleration rate and tool path geometry, which results in good accuracy at high feed rate. The authors[9] developed a machining time calculation algorithm by considering feed angle and machining speed based on machine behavior in order to predict five-axis machining time. Machining time calculation algorithms have been developed to assess the selection of tools using machining performance related criteria[10]. The authors proposed a method for machining time prediction using a mechanistic approach[11]. A mechanistic approach was proposed to estimate real machining time more accurately[12]. An investigation was carried by the author[13] to estimate the actual machining time varies depending on the machining conditions in a practical operation. The authors[14] investigated that for machining, it is difficult to select the cutting speed, depth of cut and feed rate combination and suggests that required depth in one pass to keep machining time and low cost.

From the literature sources, there is a limited research available in hard turning and facing operation of bearing materials in order to reduce machining time. It is found that the machining of A22E (BIMETAL BEARING MATERIAL) metal matrix composite is an important area of research.

Bimetal bearings are used to support the crank shaft and connecting rods. Bimetal bearing are constructed of two layers having a steel back, which supports the bearing structure shown in Figure 1. The second layer is the bearing lining. It is relatively thick. Its thickness is about 0.012″. Commonly, the lining is made of an aluminum alloy containing 6–20% of tin. Tin serves as a solid lubricant and provides anti-friction properties. Another additive is 2–4% of silicon dispersed in aluminum in form of fine particles. Hard silicon strengthens the alloy and also serves as an abrasive polishing the journal surface. Presence of silicon is particularly important for engines with cast iron crankshafts. The alloy may be additionally strengthened by copper, nickel and other elements. The two main layers (steel and aluminium) are bonded to each other by means of a bonding layer.

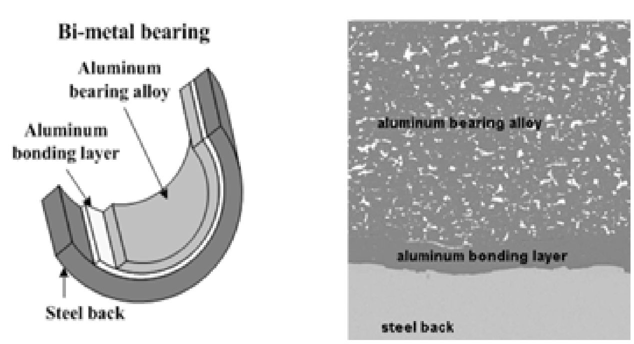

Figure 1. Aluminium alloy bearing (Bimetal bearing).

2. Response Surface Methodology (RSM)

Response Surface Methodology (RSM) consists of a group of mathematical and statistical techniques used in the development of an adequate functional relationship between a response of interest *y*, and a number of associated control (or input) variables denoted by x_1, x_2, . . . , x_k,. In general, such a relationship is unknown but can be approximated by a low-degree polynomial model of the form[15]

$$y = f'(x)\,\beta + \varepsilon \qquad (2)$$

Where.

$x = (x_1, x_2, \ldots, x_K)$.
f(x) is a vector function of *p* elements
ε is a random experimental error assumed to have a zero mean.
$f'(x)\,\beta$ = the mean response

The most frequently used second-order designs are the 3^K factorial, central composite, and the Box-Behnken designs. The steps concerned with RSM are as follows

1. Design the set of experiment for adequate and reliable measurement.
2. Define the mathematical model
3. Setting maximum and minimum response value for experimental factors
4. Direct and interaction effect of process variable of the machining parameters.

3. Optimization by using Genetic Algorithm (GA)

Genetic Algorithm (GA) is a global optimization algorithm derived from evolution and natural selection. Genetic algorithms tend to thrive in an environment in which there is a very large set of candidate solutions and in which the search space is uneven and has many hills and valleys. GA is one of the most powerful methods with which to (relatively) quickly create high quality solutions to a problem[16–18].

3.1 Selection

This operator selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce.

3.2 Crossover

This operator randomly chooses a locus and exchanges the sub sequences before and after that locus between two chromosomes to create two offspring. For example, the strings 10000100 and 11111111 could be crossed over after the third locus in each to produce the two offspring 10011111 and 11100100. The crossover operator roughly mimics biological recombination between two single-chromosome (haploid) organisms.

3.3 Mutation

This operator randomly flips some of the bits in a chromosome. For example, the string 00000100 might be mutated in its second position to yield 01000100. Mutation can occur at each bit position in a string with some probability, usually very small (e.g., 0.001).

The most important components in a GA consist of:

- Representation (definition, of individuals)
- Evaluation function (or fitness function)
- Population
- Parent selection mechanism
- Variation operators (crossover and mutation)
- Survivor selection mechanism (replacement)

4. Identification of Important Process Parameters

The ranges of machining parameters, conditions and tool end relief angle were selected from the tool manufacturer and machining data handbook[19]. The author[20] discussed the steps and procedure to conduct the experiment. The authors[21] discussed for hard and tough material, the relief angle should be 6 to 8 degrees for HSS tools and 5 to 7 degrees for carbide tools. For medium steels, mild steels, cast iron, the relief angle should be 8 to 12 degrees for HSS tools and 5 to 10 degrees for carbide tools. For ductile materials such as copper, brass, bronze and aluminium, ferritic malleable iron, the relief angle should be 12 to 16 degrees for HSS tools and 5 to 14 degrees for carbide tools. The authors finally concluded that larger relief angle generally tend to produce a better surface finish. Optimal performance of any machining process is based on choosing the right combination of input parameters. The independently controllable process parameters affecting the machining time were identified to carry the experimental work and mathematical model were developed. The important controllable process parameters considered for this investigation are spindle speed *(rpm),* feed rate *(mm/min),* depth of cut *(mm)* and end relief angle *(degree)* as shown in Table 1.

5. Development of Design Matrix

The Design Of Experiment (DOE) is used to develop a design matrix. The central composite second order rotatable design was utilized to design using Design Expert V 9.0.4 software. The design matrix, consists of three-level, four factor central composite rotatable factorial design (CCD) consisting of 30 sets of coded conditions. The upper limit of a given parameter was coded as (+2) and the lower limit was coded as (–2). The intermediate levels of –1, 0, +1 of all the variables have been calculated by interpolation. Thus, all the 30 experimental runs to allow the estimation of the linear, quadratic and two way interactive effects of the process parameters.

6. Experimental Set Up and Conditions

Bimetal Bearing Specimen of size 95 mm diameters and thickness 3mm are selected for experimental purpose. The bimetal bearing consists of steel alloy on inner side and aluminium alloy on outerside. The aluminium bonding layer is used for binding of the alloys.

Bimetal bearing is softest and it consists of

6 - 20% tin,
1 % copper,
2 - 4% silicon and highly strengthened by nickel and other elements.

Table 1. Process factors and their levels

Variables	Unit	Coded Variable Level				
		Lowest	Low	Centre	High	Highest
		–2	–1	0	+1	+2
Spindle Speed	rpm	400	500	600	700	800
Feed Rate	mm/rev	0.04	0.06	0.08	0.1	0.12
Depth of Cut	mm	1	1.2	1.4	1.6	1.8
End Relief Angle	Degree	8	10	12	14	16

The **M42 HSS** single point cutting tool is used for facing operation. The properties of M42 HSS tools are

1.08% -carbon,
3.8% - Chromium,
9.4% - Molybdenum,
1.5% -Tungsten,
8% - Cobalt,
1.2% - Vanadium

The special type industrial CNC lathe was used to conduct the experiments under dry condition. The machining experimental set-up of Bimetal Bearing experimental is shown in Figure 2.

The response parameters machining time was measured. Table 2 shows the experimental design matrix and the measured response of machining time.

7. Response Surface Model for the Prediction of Machining Time

RS model was developed to predict the machining time. The Design Expert V 9.0.1 software of state ease was carried out with the experimental and analysis purpose. The model is checked for its adequacy using ANOVA (analysis of variance). ANOVA table for the prediction of Machining Time is shown in Table 3. The model is significant and the lack of fit is not significant which infers the significance of the model. Values of Prob> F less than 0.05 indicate the model terms as in significant and the values greater than 0.10 indicate the model terms as not

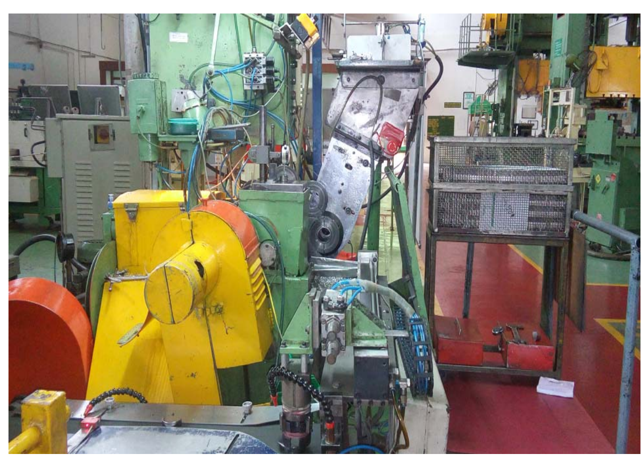

Figure 2. Machining of bimetal bearing.

Table 2. Experimental design matrix and output response factors

Run	Spindle Speed (A) rpm	Feed Rate (B) mm/rev	Depth of Cut (C) mm	End Relief Angle (D) degree	Output Response Machining Time (T) Sec
1	500	0.06	1.6	14	**1.29**
2	500	0.06	1.2	10	**1.46**
3	600	0.12	1.4	12	**1.28**
4	500	0.1	1.2	10	**1.78**
5	700	0.06	1.2	14	**1.35**
6	600	0.08	1.4	12	**1.45**
7	700	0.1	1.2	14	**1.56**
8	600	0.08	1.4	16	**1.28**
9	600	0.08	1.4	12	**1.33**
10	500	0.06	1.6	10	**1.26**
11	700	0.1	1.2	10	**1.78**
12	600	0.08	1.4	8	**1.48**
13	700	0.06	1.6	14	**1.52**
14	700	0.1	1.6	14	**1.25**
15	500	0.1	1.6	10	**1.52**
16	600	0.08	1.4	12	**1.61**
17	500	0.1	1.2	14	**1.6**
18	400	0.08	1.4	12	**1.68**
19	700	0.06	1.6	10	**1.32**
20	500	0.1	1.6	14	**1.64**
21	700	0.1	1.6	10	**1.54**
22	600	0.08	1.4	12	**1.52**
23	600	0.08	1.8	12	**1.29**
24	600	0.06	1.4	12	**1.34**
25	700	0.06	1.2	10	**1.80**
26	800	0.06	1.4	12	**1.52**
27	600	0.08	1.4	12	**1.33**
28	600	0.04	1.4	12	**1.52**
29	500	0.06	1.2	14	**1.42**
30	600	0.08	1	12	**1.39**

significant. The Model F-value of 4.72 implies that the model is significant. There is only a 0.25% chance that an F-value this large could occur due to noise. The "Lack of Fit F-value" of 2.97 implies the Lack of Fit is not significant relative to the pure error. There is a 12.05% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good. The Fig.5 shows the Predicted Vs Actual model. The regression equation obtains from the Design Expert software in terms of actual factors are given:

Machining Time (T) - + 1.13315- 4.63660E-003* A+7.18586* B-0.29985* C+0.26515* D-9.53125E-003* A * B - 6.40625E-004* A * C +4.06250E-005* A* D +1.71875* B *C - 0.24219* B * D+7.03125E-003* C * D + 4.49781E-006* A^2-3.17982* B^2+0.18695* C ^{2}-0.010943* D^2

Where,

A- Spindle Speed
B- Feed Rate
C- Depth of cut
D- End Relief angle

8. Results and Discussion

In this work, the effects of end relief angle, spindle speed, feed rate and depth of cut were experimentally investigated. The effect of process parameters on the machining time is discussed below. Figure 3 shows the normal plot of residuals and Figure 4 shows the Predicted value vs actual value of machining time.

Figure 5 shows the interaction effect of feed rate and spindle speed on Machining time. From the figure it is clearly noticed that the machining time is high between the range from 400 rpm to 500 rpm and 600 rpm to 800 rpm, whereas the machining time also increase when the feed rate is increased. Therefore lower feed rate and the spindle speed between 500 rpm to 600 rpm to be chosen for the best output result.

From the Figure 6 it influence that the depth of cut plays a major role for increase in the machining time, when the depth of cut increases the machining time also increased. For spindle speed the same result is attained as shown in Figure 5.

From the Figure 7 it is noticed that at lower end relief angle between 8° to 10° the machining time is low whereas the spindle speed the same result is obtained as shown in Figure 5.

From the Figure 8 of interaction diagram the feed rate and depth of cut increases the machining time also increases.

From the Figure 9 of interaction diagram the feed rate and end relief angle increases the machining time also increases.

From the Figure 10 shows the interaction between the depth of cut and end relief angle. The depth of cut

Table 3. ANOVA table for the prediction of Machining Time

ANOVA for Response Surface Quadratic model						
Analysis of variance table [Partial sum of squares - Type III]						
	Sum of		Mean	F	p-value	
Source	Squares	df	Square	Value	Prob > F	
Model	0.55	14	0.039	2.67	0.0348	significant
A-Spindle Speed	0.12	1	0.12	8.29	0.0115	
B-Feed Rate	6.050E-003	1	6.050E-003	0.41	0.5306	
C-Depth of cut	0.011	1	0.011	0.73	0.4055	
D-End Relief angle	0.087	1	0.087	5.91	0.0280	
AB	0.093	1	0.093	6.34	0.0237	
AC	0.042	1	0.042	2.86	0.1113	
AD	0.017	1	0.017	1.15	0.3003	
BC	0.012	1	0.012	0.82	0.3783	
BD	0.024	1	0.024	1.64	0.2203	
CD	2.025E-003	1	2.025E-003	0.14	0.7156	
A^2	0.084	1	0.084	5.71	0.0304	
B^2	6.707E-005	1	6.707E-005	4.568E-003	0.9470	
C^2	2.318E-003	1	2.318E-003	0.16	0.6967	
D^2	0.079	1	0.079	5.41	0.0345	
Residual	0.22	15	0.015			
Lack of Fit	0.13	10	0.013	0.66	0.7312	not significant
Pure Error	0.095	5	0.019			
Cor Total	0.77	29				

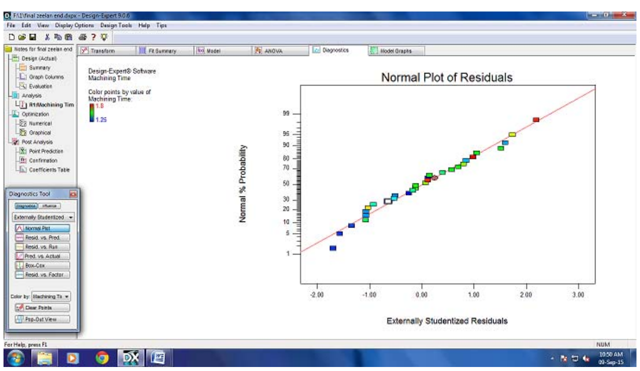

Figure 3. Normal plots of residuals.

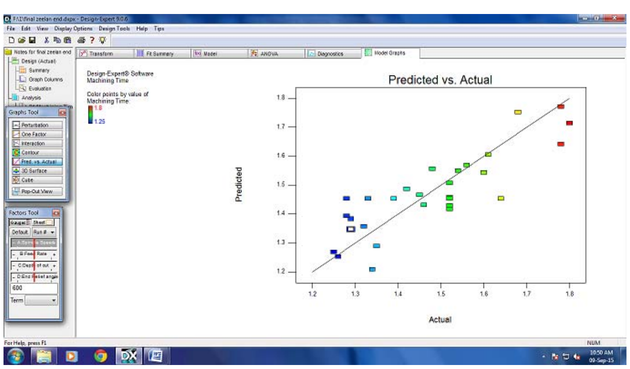

Figure 4. Predicted vs actual.

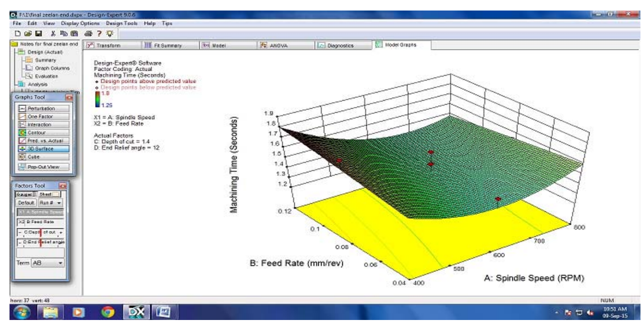

Figure 5. Interaction effect feed rate vs spindle speed on machining time.

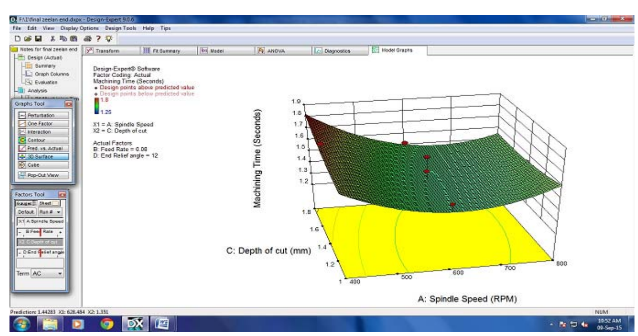

Figure 6. Interaction effect depth of cut vs spindle speed on machining time.

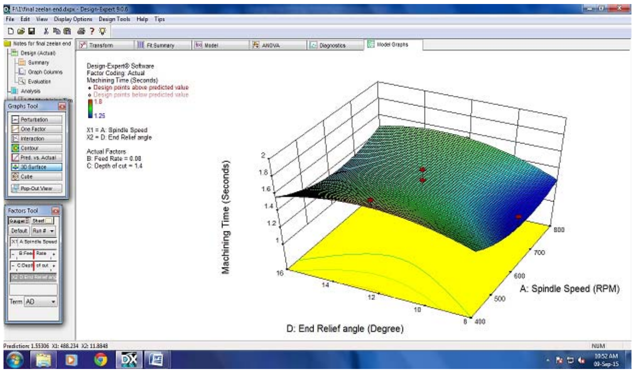

Figure 7. Interaction effect end relief angle vs spindle speed on machining time.

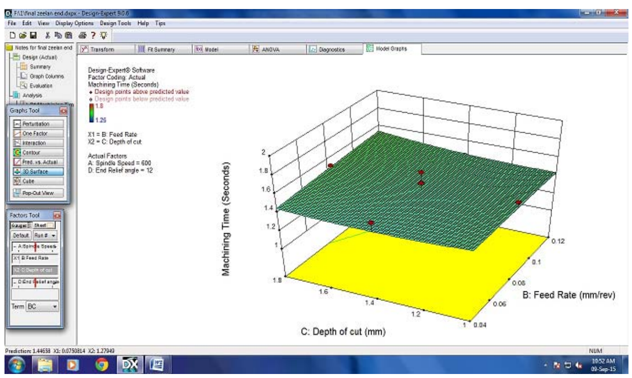

Figure 8. Interaction effect depth of cut vs feed rate on machining time.

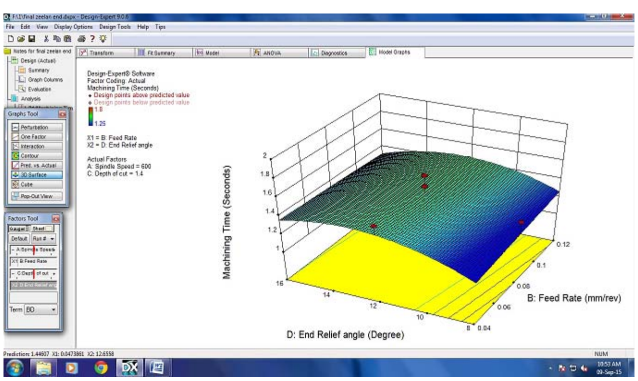

Figure 9. Interaction effect end relief angle vs feed rate on machining time.

and end relief angle increases the machining time also increases.

The above interaction diagram it is interesting to observe that for low machining time, the end relief angle should be in between 8º to 10º.

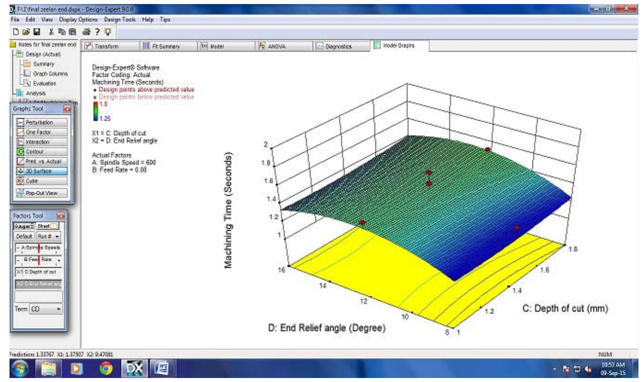

Figure 10. Interaction effect end relief angle vs depth of cut on machining time.

9. Evaluation of GA Results

In this present study, the optimization of machining parameters such as spindle speed, feed rate, depth of cut, end relief angle was carried out to minimize the machining time. Genetic Algorithm is used to optimize the machining time. MAT LAB 7.0 software is used for optimization purpose. The minimization of machining time by using GA can be expressed by the equation

Minimize: T (A, B, C, D)
Within ranges of cutting parameters,
$400 \text{ rpm} \leq A \leq 800 \text{ rpm}$
$0.04 \text{ mm/rev} \leq B \leq 0.12 \text{ mm/rev}$
$1 \text{ mm} \leq C \leq 1.8 \text{ mm}$
$8° \leq D \leq 16°$ (degree)

To obtain the best optimal results, the number of the initial population size, the type of selection function, the Scaling function, the crossover rate, the mutation rate and the generations as follows.

Population type: double vector
Population size: 100
Selection function: Rank
Scaling function: Rank
Function Stochastic: uniform
Mutation function: Gaussian
Mutation rate: 0.1
Crossover function: Scattered
Crossover rate: 1.0
Generations: 1000

For the machining of the Bimetal bearing, GA predicted the optimum machining time as 1.169 seconds.

Table 4. Optimized process parameter predicted by GA

Trial	Spindle Speed (A)	Feed rate (B)	Depth of cut (C)	End relief angle (D)	Confirmatory test for Machining Time		% error
					Predicted GA model	Experimental Value	
	rpm	mm/rev	mm	degree	µm	µm	
1	610	0.06	1.4	12	1.61	1.58	1.89
2	700	0.12	1.6	14	1.52	1.49	2.00
3	500	0.08	1.8	10	1.41	1.39	1.43

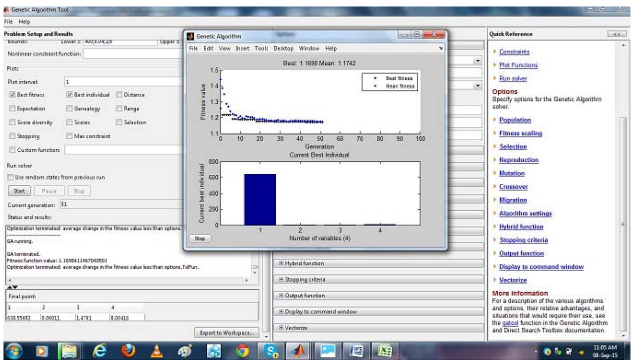

Figure 11. The performance of fitness value with generation and the best individual performances of variables in coded form.

10. Validation of the Model

The predicted result of Design of experiments using Central Composite Design of RSM and GA is further validated using physical measurements and verified using confirmatory test. The percentage of error is found to be within ±2% which shows the validity of the model. The experimental results predicted by GA of machining time show good agreement. Table 4 shows the comparison of predicted vs experimental value of Machining time. Figure 11 shows the performance of fitness value with generation and the best individual performances of variables in coded form.

11. Conclusion

The following conclusions has been drawn on facing operation of a bimetal bearing using Response Surface Methodology (RSM) and Genetic Algorithm (GA), considering the machining parameters such as Spindle Speed, Feed Rate, Depth of cut, and End relief angle using design of experiments. The Spindle Speed and Feed rate are the most important parameters to be considered for better Machining time compared to the other factors such as depth of cut and end relief angle.

During machining operation the end relief angle should be in between the 8°-10°, spindle speed should be in between the 600 rpm to 800 rpm, feed rate should be in between 0.04mm - 0.08 mm, depth of cut should be in 1mm - 1.4 mm. Further the optimization was carried out on machining time using GA. The predicted result of machining time was 1.169 seconds of Bimetal bearing. The confirmatory result shows good arguments for experimental vs predicted value.

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