INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH & DEVELOPMENT

ISSN 2278 – 0211 (Online)

Prediction of Process Parameters in Machining of Aluminium Alloy 5083 Using Central Composite Design and Genetic Algorithm

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Abstract:
Aluminum alloys are widely used for demanding structural applications due to a good combination of formability, corrosion resistances and mechanical properties. Hence the present work is about machining of aluminum alloy at various combinations of process parameters such as speed, feed rate and depth of cut and to determine the effect these parameters on surface quality. The speed range was 100m/min to 200m/min, feed range was 0.05 mm/rev to 0.1 mm/rev, depth of cut range was 0.25 mm to 1mm.3^3 *full factorial design of experiments will be followed in this research work.*

Keywords: *Corrosion resistance, optimization, design, material, operating parameters*

1. Introduction

About the Machining, the most widespread process of shaping metal has become a very significant aspect of modern society and industry. The importance of the machining process is evident by the observation that nearly every device used by humanity in day-to-day life at least one machined part or surface. Weights saving materials are becoming increasing important, especially in the automotive and aerospace industries.

1.1. Project Objective

The aim of this project work is to study the machining effect on 5083 Aluminium alloy of varying combinations of process parameters such as speed, feed rate and depth of cut; and also to determine the effect of these parameters over the quality of finished product. A 33 Orthogonal Array (OA) based Design of Experiments (DOE) approach and Genetic algorithm was used to analyze the machining effect on the work material in this study. Using the practical data obtained, a mathematical model is developed to predict the temperature influence and surface quality of finished product. The ultimate goal of the study is to optimize the machining parameters for temperature minimization in machining zone and improvement in surface finish.

2. Experimental Set-Up and Procedure

2.1. Phases in Experimentation

The experimentation process for determining the surface roughness by optimizing machining parameters has been divided into the following phases as described below:

- Phase 1 - Plan of experiments
- Phase 2 - Tool and material selection
- Phase 3 - Collection of data
- Phase 4 - Analysis of data

2.2. Plan of Experiments

A well planned set of experiments in which all parameters of interest, are varied over a specified range is a better approach to obtain systematic data. Mathematically speaking such a set of experiments is complete and ought to give desired results. The effect of many different parameters on the performance characteristic in a condensed set of experiments can be examined by using the 3^3 orthogonal arrays (OA) Design of Experiments.

2.3. Design of Experiments

In general usage, Design of Experiments (DOE) or Experimental Design is the design of any information-gathering exercises where variation is present, whether under the full control of the experimenter or not. However, in statistics, these terms are usually used for controlled experiments. Other types of study, and their design, are discussed in the articles on opinion polls and statistical surveys (which are types of observational design).

In the design of experiments, the experimenter is often interested in the effect of some process or intervention on some objects which may be people, parts of people, groups of people, plants, animals, etc. Design of experiments is thus a discipline that has very broad application across all the natural and social sciences.

2.4. Numerical Optimization

Numerical Optimization will optimize any combination of one or more goals. The goals may apply to either factors or responses. The possible goals are: maximize, minimize, target, within range, none (for responses only) and set to an exact value (factors only). A minimum and a maximum level must be provided for each parameter included in the optimization. A weight can be assigned to a goal to adjust the shape of its particular desirability function. The default value of one creates a linear ramp function between the low value and the goal or the high value and the goal. Increased weight (up to10) moves the result towards the goal. Reduced weight (down to 0.1) creates the opposite effect. The "importance" of a goal can be changed in relation to the other goals. The default is for all goals to be equally important at a setting of 3 pluses (+++). If you want one goal to be most important, you could change it to 5 pluses (+++++).

2.5. Steps to Numerical Optimization

The numerical optimization, being a very significant part of RSM provides the best as well as various solutions for the combination of explanatory variables to achieve the most optimal responses and the steps are as below:

Goals are assigned for the explanatory variables according to their levels.

- Speed - in range-(100m/min to 200m/min)
- Depth of cut - in range - (0.25mm to 1mm)
- Feed rate - in range - (0.05mm/rev to0.1mm/rev)
- Goals are assigned to maximize, minimize or set in the range the response variables. Temperature surface finish, and cutting force – to minimize
- Limits and weights are set as required.
- Importance of each goal is assigned. Here equal importance of 3pluses is assigned to each response.
- Generation of reports, ramps and bar graphs.

3. Analyses of Data

3.1. Response Surface Methodology (RSM)

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving and optimizing the design process. RSM

- ➢ Encompasses a point selection method (also referred to as Design of Experiments, Approximation methods and Design Optimization) to determine optimal settings of the design dimensions.
- ➢ Have important applications in the design, development, and formulation of new products, as well as in the improvement of existing product designs.

In statistics, response surface methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The method was introduced by G. E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a set of designing experiments to obtain an optimal response. Box and Wilson suggest using a first-degree polynomial model to do this.

3.2. Capabilities of RSM

RSM enables to:

- Determine the factorial levels that will simultaneously satisfy a set of desired specifications.
- Determine Cause and effect relationships between true mean responses and input control variables influencing the responses.
- Determine the optimum combination of factors that yield a desired response and describes the response near the optimum.
- Determine how a specific response is affected by changes in the level of factors over the specified levels of interest.
- Helps to analyze the data both analytically and graphically and creates optimum solutions both numerically and graphically.
- Enables to analyze study and interpret the results by various types of plots.

3.3. RSM Procedure

The steps involved in the procedure towards optimization are:

- The development of mathematical model.
- Calculating the coefficients of the model.
- Checking the adequacy of the model developed.
- Testing the significance of the regression coefficients, recalculating their values and arriving at the final values.
- Presenting the main effects and the significant interaction effects of process parameters on the responses in two and three dimensional (contour) graphical form.
- Analysis of results.
- Optimization of parameters.

3.4. Development of Mathematical Model

As the first step towards optimization, a mathematical model was developed for correlating the interactive and higher order influences of various milling parameters on surface roughness at various locations, during the milling phenomena using RSM. In order to ensure that the experiment is valid, it is useful to develop a mathematical model for the entire system. By doing this, anomalies and infeasible ideas can be weeded out immediately. By basing the experiment upon valid mathematical principles, it ensures that all aspects of the experiment are practical and feasible. Representing the temperature and sound level as the response functions, the relationship between the turning control parameters and the responses can be expressed as:

$$T= f (A, B, C)$$

$$Ra = f (A, B, C)$$

$$F_X = f (A, B, C)$$

$Fx =\alpha0 + \alpha1 (A) + \alpha2 (B) + \alpha3 (C) + \alpha4 (AB) + \alpha5 (AC) + \alpha6 (BC) + \alpha7 (A2) + \alpha8 (B2) +\alpha9 (C2)$

$T =\beta0 + \beta1 (A) + \beta2 (B) + \beta3 (C) + \beta4 (AB) + \beta5 (AC) + \beta6 (BC) + \beta7 (A2) + \beta8 (B2) +\beta9 (C2)$

$Ra =\gamma0 + \gamma1 (A) + \gamma2 (B) + \gamma3 (C) + \gamma4 (AB) + \gamma5 (AC) + \gamma6 (BC) + \gamma7 (A2) + \gamma8 (B2) \gamma9 (C2)$

The values of the coefficients of ‘α’, ‘β’ and ‘γ’ were calculated by linear regression analysis using design expert software, and after determining the significant coefficients, the final model was developed in coded values.

4. Regression Equations

A statistical technique used to explain or predict the behavior of a dependent variable. Generally, a regression equation takes the form of Y=a+bx+c, where Y is the dependent variable that the equation tries to predict, X is the independent variable that is being used to predict Y, a is the Y-intercept of the line, and c is a value called the regression residual. The values of a and b are selected so that the square of the regression residuals is minimized.

4.1. Regression Equations In Terms Of Actual Factors

Ra=-0.65347129+0.017027667*cuttingspeed+11.78566667*feedrate+0.377665079* depth of cut-4E-05*cutting speed-5.90356E-05*cutting speed^2-39.90222222*feed rate^2-0.291051852*depth^2

R-Squared=0.999998

T= -3.720833333 + 1.263*cutting speed -40.5*feed rate+11.3642857*depth of cut+0*cutting Speed* feed rate-1.07424E-16*cutting speed*depth of cut -0.85742857*feed rate *depth-0.00402*cutting speed^2+2440*feed rate^2+23.6*depth of cut^2

R-Squared=0.999977

Fx=-215.060601+2.90566305*cutting speed-2454.229233*feed rate+600.2634263*depth-1.378774*cutting speed *feed rate-0.046044381*cutting speed*depth-230.7326857*feed rate *depth of cut-0.010453524*cutting speed^2+32885.44622*feed rate^2-324.0718937*depth of cut^2

R-Squared=0.997634

4.2. Regression Equations In Terms Of Coded Factors

Ra=1.353075463-0.034971429*A+0.145004167*B+0.005327778*C-5E-05*A*B-4.2857*E-05*A*C+8.75E-05*B*C-0.147688889*A^2-0.024938889*B^20.040929167*C^2

R-Squared=0.999998

T=122.2479167+2.85*A+8.124107143*B+15.3*C+0*A*B+0*A*C-0.008035714*B*C-10.05*A^2+1.525*B^2+3.31875*C^2

R-Squared=0.999977

Fx=204.4285943-18.12900357*A+53.18909179*B+64.11073167*C-1.7234675*A*B-0.86332143*A*C-2.163118929*B*C-26.13381111*A^2+20.55340389*B^2-45.57261*C^2

R-Squared=0.997634

Where, A – Cutting speed in m/min
- B – Feed rate in mm/rev
- C – Depth of cut in mm
- T – Temperature in °C
- Ra – Surface finish in micrometer
- F_X – cutting force in N

5. Report Generation

5.1. Numerical Optimization Report

The "Report" is the most detailed of the optional views of optimization outcomes. It presents its results in several sections:
- The constraints on the design space
- Factors and responses and the goal for each.
- A list of solutions (the optimums found).
- A list of the random starting points where the searches began. (To verify that the space was thoroughly searched.)

Design-Expert eliminates multiple starts that lead to the same optimum, so fewer results than the number of starting points may be reported. The list of solutions has been sorted with the highest desirability first. Only solutions that meet the criteria are reported.

5.2. Report Generated In Design-Expert Constraints

The constraints are set such that the software optimizes within the parameters limits and according to their importance and minimizes the response variables.
- UpperLimit = 200 to 295.47
- LowerWeight = 1
- UpperWeight = 1

Name	Goal	Lower Limit	Importance
A:Cutting Speed	is in range	100	3
B:Feed Rate	is in range	0.05	3
C:Depth of cut	is in range	0.25	3
Temperature	minimize	90.8	3
Surface finish	Minimize	0.9546	3
Cutting force	minimize	21.00231	3

Table 1: Optimization report: Constraints information

6. Solutions
- Cutting Speed = 100 t0 200
- Feed Rate = 0.05
- Depth of cut = 0.25 to 0.99
- Temperature = 90.7595 to 126.793

Number	Surface finish	Cutting force	Desirability	
1	0.954396	18.2704	0.967317	Selected
2	0.955915	18.3706	0.966251	
3	0.955445	20.1608	0.966154	
4	0.960711	18.702	0.962461	
5	0.963768	20.1989	0.95861	
6	0.958777	26.2232	0.955819	
7	0.974922	19.8438	0.951041	
8	0.980475	20.381	0.946475	
9	0.975069	22.5328	0.946149	
10	0.961963	32.1092	0.944697	
11	1.0016	22.6962	0.926889	
12	1.00597	23.4208	0.922299	
13	1.02415	49.3548	0.918538	
14	1.02508	51.0457	0.915518	
15	1.02771	49.6554	0.915424	

16	1.02781	49.8706	0.913912	
17	1.0299	49.8459	0.913369	
18	1.01696	24.7913	0.911263	
19	1.03304	50.131	0.910392	
20	1.03138	50.3659	0.909223	
21	1.03703	50.5113	0.906573	
22	1.03348	50.6625	0.906415	
23	0.973562	54.4786	0.901126	
24	1.03768	51.248	0.900832	
25	1.04336	51.1548	0.900408	
26	1.01466	30.8126	0.899133	
27	1.03222	27.2292	0.895016	
28	1.02015	31.9768	0.892597	
29	1.03173	63.3505	0.891729	
30	1.04125	28.8518	0.885037	
31	1.05143	30.977	0.872543	
32	1.06505	54.4012	0.86892	
33	1.03791	75.1939	0.868297	
34	1.05077	38.5588	0.856166	
35	0.985572	80.1583	0.847988	
36	1.05256	105.602	0.80527	
37	1.12341	61.7011	0.782436	
38	1.1369	62.4792	0.76322	
39	1.13619	62.214	0.76243	
40	1.1379	62.0365	0.759284	
41	1.06145	127.233	0.757184	
42	1.14041	57.7339	0.75465	
43	1.06609	141.063	0.724452	
44	1.20364	89.7863	0.69741	
45	0.999231	142.849	0.685973	
46	0.998436	144.702	0.678813	
47	0.968755	150.095	0.588927	
48	1.05451	186.7	0.57494	

Table 2: Optimal solutions table

48 optimal solutions were found which are tabulated and the best possible solution is given as ‘selected’. It can be inferred that the most significant factors of depth of cut and feed rate are to be maintained at the optimum speed, even though varied can minimize surface roughness.

6.1. Numerical Optimization Ramp

The Ramps show the desirability for each factor and each response, as well as the combined desirability. It is generated for each optimum found. The solutions are sorted from best to worst. The ramp drawings are the graphic shown when the optimization criteria are entered. A highlighted point shows both the exact value of the factor or response (horizontal movement of the point) and how well that goal was satisfied (how high up the ramp.)

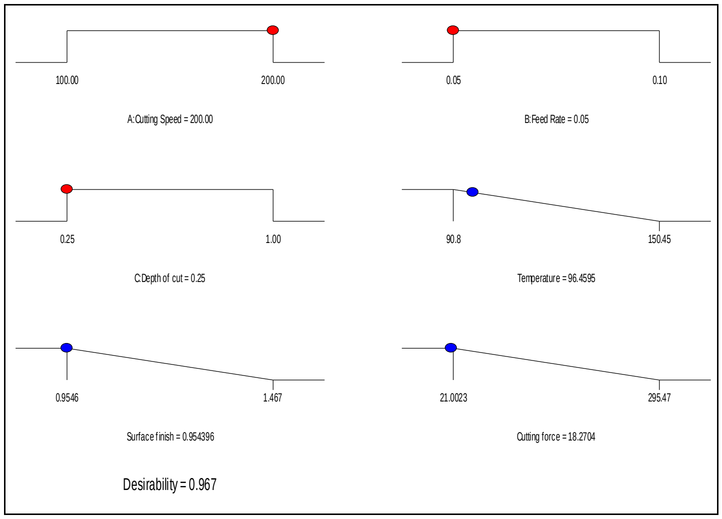

Figure 1: Numerical Optimization Ramp

6.2. Numerical Optimization Histograms

This shows the desirability for each factor and each response individually. It can be generated for each optimum found and can change to a new optimum as required. The solutions are sorted with the most desirable first. The input factors have been set "in range", thus preventing extrapolation. These and any responses set "in range" are represented by bars that differ in color from variables that have more ambitious goals (minimize, maximize, etc.) The bottom histogram bar is the combined desirability of all the factors and responses.

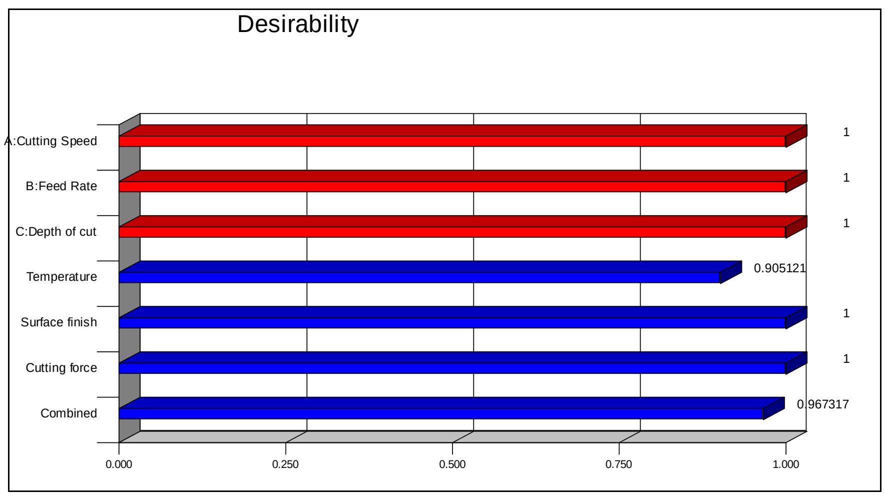

Figure 2: Numerical Optimization Histogram

6.3. Numerical Optimization Graphs

A graph of desirability is generated for any of the solutions found via numerical optimization. The solutions are sorted from best to worst. The graphs that are used to represent the optimization are contour, 3D surface, or perturbation (trace) graphs. The 2D contour graphs have a flag planted at the optimum points. In addition to graphing the overall desirability, graph of any individual response is also generated as shown below. It is useful to see how a single response behaves in the vicinity of a particular optimum.

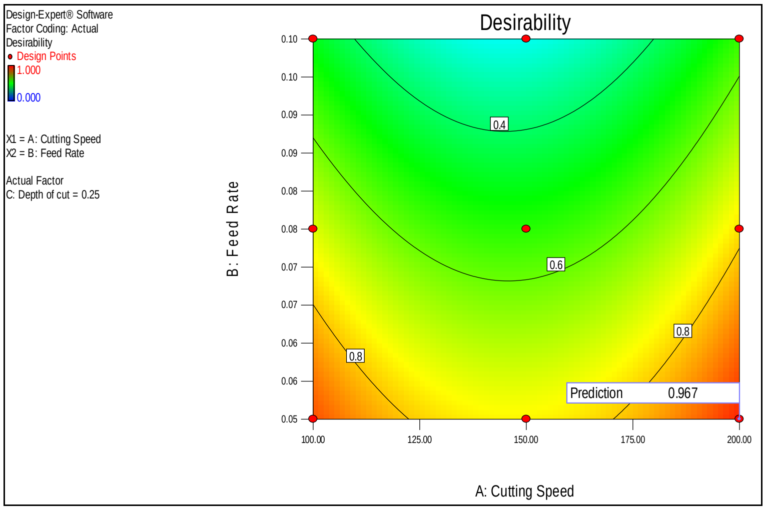

Figure 3: Numerical Optimization contour plots

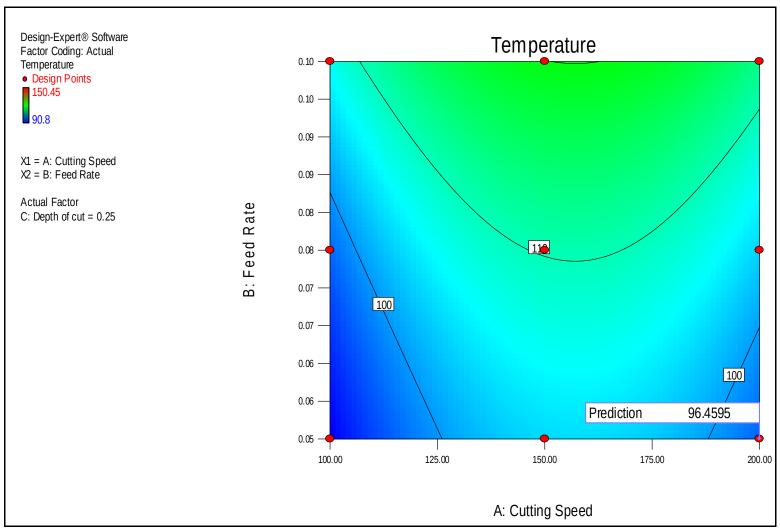

Figure 4: Numerical Optimization contour plots

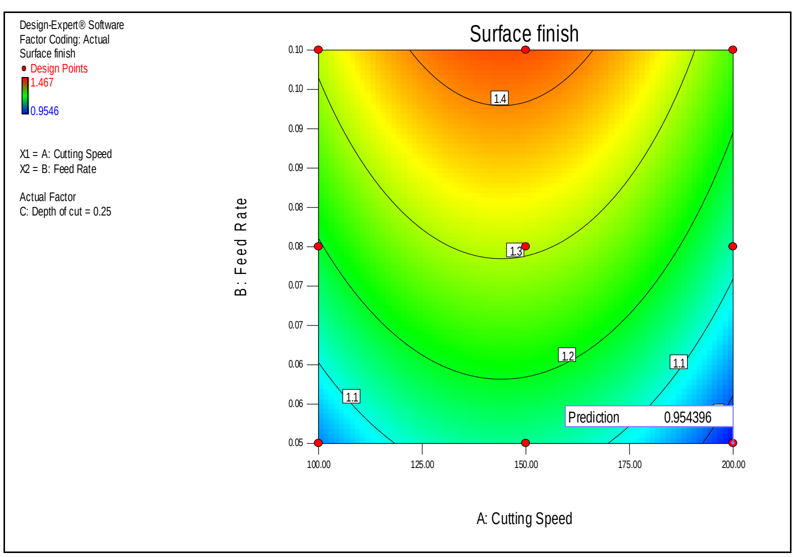

Figure 5: Numerical Optimization contour plots

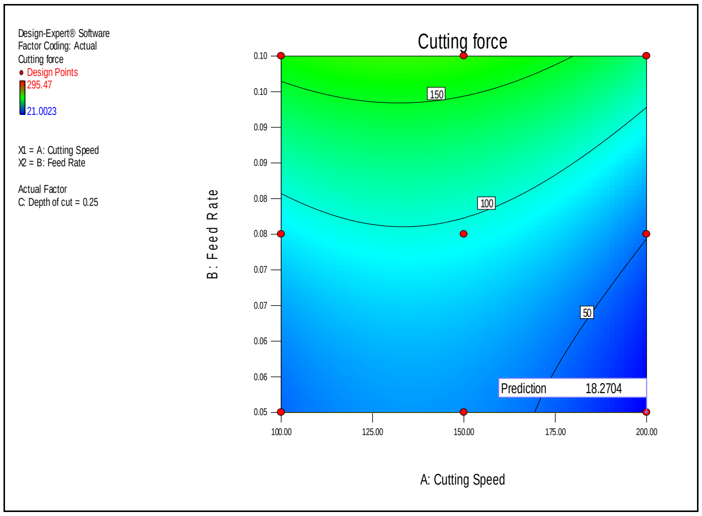

Figure 6: Numerical Optimization contour plots

All the graphical interpretations above show that the predicted temperature, surface finish and cutting force values at different locations can be minimized if the optimal parameters are set to: Cutting Speed-200m/min Feed Rate 0.05mm/rev Depth of cut-0.25mm.

6.4. Graphical Optimization

With multiple responses it is required to find regions where requirements simultaneously meet the critical properties, the "sweet spot". By superimposing or overlaying critical response contours on a contour plot one can visually search for the best compromise. If there are many input variables, first numerical optimization is done. Graphical optimization displays the area of feasible response values in the factor space. Regions that do not fit the optimization criteria are shaded. For multiple responses several overlapping shaded areas are found. Any window that is not shaded satisfies the multiple constraints on the responses. The areas that satisfy the constraints are lightly shaded, while the area that does not meet criteria is dark. Flags show predictions for all responses at that location in space. A graphical Optimization criterion is to choose the response limits, lower and/or upper, for each response to be included in the optimization.

- Overlay Plot

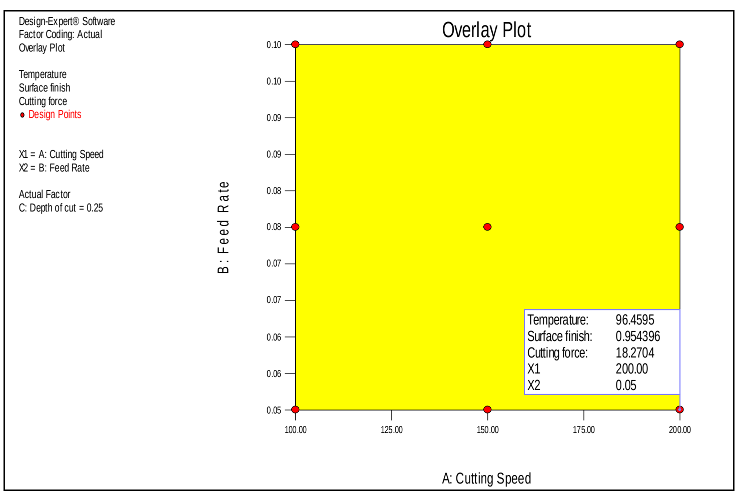

Figure 7: Overlay Plot of the three responses

6.5. Point Prediction

The final step in the experiment is to predict the response at the optimal settings. Point prediction allows entering levels for each factor or component in the current model. The software calculates the expected responses and associated confidence intervals based on the prediction equation that was shown in the ANOVA output. The predicted values are updated as the levels are changed.

The 95% CI (confidence interval) is the range in which the process average is expected to fall into 95% of the time. The 95% PI (prediction interval) is the range in which any individual value is expected to fall into 95% of the time. The prediction interval will be larger (a wider spread) than the confidence interval since there will be more scatter in individual values than in averages.

Factor = A, B and C
Standard deviation = 0
Coding = Actual

Name	Level	Low Level	High Level
Cutting Speed	200	100	200
Feed Rate	0.05	0.05	0.1
Depth of cut	0.25	0.25	1

Table 3: Factor Levels for Point Prediction

Prediction
- Temperature = 96.4595238
- Surface finish = 0.95439550
- Cutting force= 18.2704307

SE Mean
- Temperature = 0.064196
- Surface finish = 0.000175
- Cutting force= 3.030244

SE Pred
- Temperature = 0.11356
- Surface finish = 0.00030
- Cutting force= 5.36068

Response	95% CI low	95% CI high	95% PI low	95% PI high
Temperature	96.32408	96.59496	96.2199	96.69912
Surface finish	0.954027	0.954763	0.95374	0.955047
Cutting force	11.87717	24.66368	6.96036	29.58049

Table 4: Point prediction Table

The point prediction table shows that the process average for the responses will be the figures listed under CI 95% of the time. And the individual values will be as shown by the PI 95% of the time.

6.6. Parameters Used in Experimentation

The set of parameters shown as the best solution was given as input to the central lathe machine and the result was found as in the tabulation below;

Cutting Speed= 200

Feed Rate	Depth of cut	Temperature	Surface finish	Cutting force	Mode
0.05	0.25	96.5	0.9546	21	Experimentation
0.05	0.25	96.45	0.9543	18.27	RSM Optimization

Table 5: Response values after optimization

The accuracy of prediction was found to be good.

Cutting Speed(m/min)	Feed Rate(mm/rev)	Depth of cut(mm)	Desirability
200	0.05	0.25	0.967317

Table 6

7. Conclusion

The optimal control variables have been found as:

1. The surface and generated profile show that the temperature, surface finish and cutting force can be minimized using these set of parameters which significantly improves the surface finish and reduce power consumption.
2. Significant scope still exists to design and conduct further experiments for determining exhaustive combination of factors and levels by including parameters like cutting tool materials, tool life, tool wear, tool rake angles etc. These findings would enable the machining of components with higher degrees of surface finish.

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