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Parameter optimization for surface roughness and wall thickness on AA5052 Aluminium alloy by incremental forming using response surface methodology

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Abstract

Surface quality and wall thickness mainly depends on the input parameters during forming process. This study aims to optimize surface roughness and wall thickness through incremental forming on AA5052 Aluminium alloy at room temperature by controlling the effects of forming parameters. Design of experiments has been used to study the effects of forming parameters. The influence of three input parameters, (spindle speed, tool feed, and steps size) along with surface roughness and wall thickness as output parameters were analyzed. Obtained experimental results from incremental forming were used for analysis. The optimal results were predicted based on Response Surface Methodology and the analysis of variance. The obtained results predict a predominant interaction between the forming parameters which can be effectively and efficiently identified to produce minimum surface roughness and maximum wall thickness.

Keywords: Incremental forming; Optimization; Surface roughness; Wall thickness; Response surface methodology

1. Introduction

Incremental forming (IF) is one of the most promising techniques due to its various applications. Single Point Incremental Forming (SPIF) is a process for producing complex external shapes and profiles in a sheet metal using a

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hemispherical shaped tool controlled by means of a CNC milling machine. Since it does not require dies and punch to form a complex shape, it is very appropriate for rapid prototyping. The tool travels in the programmed path and deforms the sheet into desired shape. Some of the outstanding features, such as flexibility, low cost tooling, makes it suitable for various applications. It is capable to manufacture various irregular complex components and highly customized medical components [1-3].

Many researchers studied the metal forming parameters like spindle speed, tool feed and step size. In this study, an attempt has been made to optimize the metal forming parameters such as surface roughness and sheet thickness after forming [4-7]. The aim in this study is to obtain minimum surface roughness and maximum wall thickness in incremental forming. Response surface methodology has been used to develop mathematical relations between the forming parameters (spindle speed (V), tool feed (F) and step size(S)) and response parameters (surface roughness (Ra) and wall thickness (t)) by using the experimental data obtained through experimentation [8-10]. A five level full central composite factorial design was chosen with quadratic model to optimize the forming parameters. Analysis of variance test has been done to test the adequacy of the developed mathematical model.

Nomenclature

Ra	surface roughness in micro m
t	wall thickness in mm
A	first factor or input variable investigated
B	second factor or input variable investigated
C	third factor or input variable investigated
V	spindle speed in mm/min
F	tool feed in mm/rev
S	step size in mm
DF	degree of freedom
Prob>F	portion of time or probability on would expect to get the stated F-value

2. Material and Methodology

AA5052 Aluminium alloy sheet metal of thickness 1 mm in cold rolled condition was used for experimentation. Tensile test specimens were prepared according to ASTM E8 standard. The chemical composition of AA5052 was given in table 1 [11]. Tensile tests were carried out to determine the mechanical properties [12-14]. The yield strength is 243.4 MPa, ultimate tensile strength is 272.5 MPa, percentage of elongation is 13% and average hardness is 96.63 (HV 0.5). To carry out the experiments on numerically controlled milling machine HAAS V2 was used (figure 1). The blank with size 150 mm x 150 mm was held in a fixture shown in figure 2(a). The fixture along with the sheet metal is mounted on the table of the CNC machine is shown in figure 2(b). A frustum of a cone with 100 mm as maximum diameter, 50 mm as minimum diameter and 50 mm depth was formed incrementally in AA5052 Aluminum sheet (figure 3).

Table.1 Chemical composition of Al 5052 alloy both nominal and actual (wt %)

Composition	Mg	Cr	Si	Fe	Cu	Mn	Zn	Al
Nominal	2.23	0.18	0.14	0.31	0.01	0.05	0.001	Remaining
Actual	2.24	0.15	0.25	0.40	0.10	0.10	0.10	

Fig. 1 CNC Machine for metal forming process

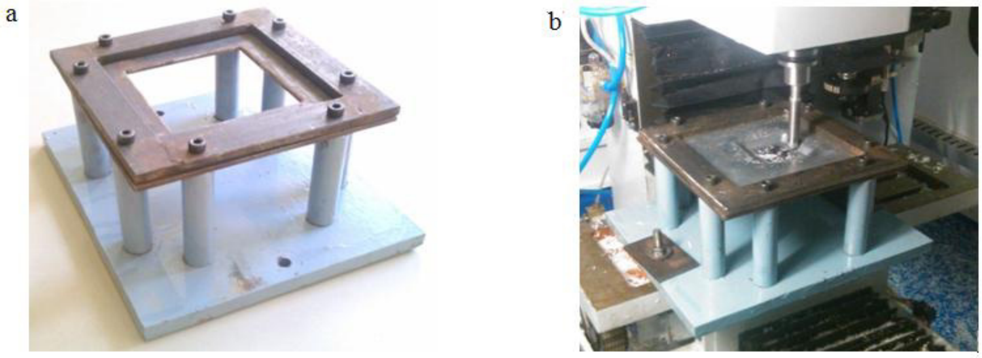

Fig. 2(a) Fixture to hold sheet metal and (b) fixture with sheet metal mounted on CNC machine

Fig. 3 Cone formed by increment forming process

A high speed hemispherical end tool of 12 mm diameter is used to perform the experiments. The experiments were carried out at room temperature. The Ra and t at the formed area of each workpiece was measured. Reading was repeated three times for better results. Values are taken at different regions and the average was calculated and tabulated.

3. Experimental Design and Response Surface Modeling

Design of Experiments (DOE) is a method, used to reduce the number of experiments to obtain the maximum optimum conditions. Response Surface Methodology (RSM) explores the relationships between the primary variables and one or more output response variables. Central Composite Design (CCD) tool is used to determine the number of experiments required to study the responses [15-16]. The purpose of the analysis of variance is to investigate which forming parameters significantly affect the Ra and t. The Fisher's ratio is used to determine whether the parameter has a significant effect on the output characteristics by comparing the F test value with T table value ($F_{0.05}$) at 5% significance level. If the F test value is greater than $F_{0.05}$, the forming parameter is considered significant [17].

The forming parameters and response parameters were modeled using response surface method. The aim is to obtain the optimal response of the inputs to the output through a quadratic model. This design consists of the following three portions: a) a complete 2k factorial design, where k is the number of variables whose factors level are coded as -1 and 1, b) axial portion of 2k points arranged in a manner such that two points are chosen at a distance of α from the design center and c) n_o center points. Thus the total number of design points in a CCD is $n = 2^k+2k+n_o$. The minimum possible number of experiments (N) can be determined from the following equations.

$$N = n_f + n_a \tag{1}$$

Where $n_f = 2^k$ and $n_a = 2k$, n_f defines the number of factorial points and n_a defines the number of axial points or star points [18]. The factors and levels used in the factorial design were given in table 2.

Table 2 Factors and levels used in factorial design

Forming parameter	Factor	Unit	Low Level	Medium Level	High Level
Spindle speed	V	mm/min	1500	2000	2500
Feed	F	mm/rev	500	650	800
Step size	S	mm	0.25	0.5	0.75

A five level central composite experimental design with categorical factor was employed to optimize the surface roughness and t in sheet metal during incremental forming. The design was composed of five levels and a total of 20 experiments were carried out to optimize the input variables. In this study, three parameters (8 factorial points and 6 axial points) and their output (Ra and sheet thickness) were studied.

Design Expert provides prediction equations in terms of actual units and coded units. The coded equations are determined first, and the actual equations are derived from the coded. To get the actual equation each term in the coded equation is replaced with its coding formula.

$$X_{coded} = \frac{X_{actual} - \bar{X}}{(X_{Hi} - X_{Low})/2} \tag{2}$$

The experimental results from the forming trials performed according to the matrix by central composite full factorial design are tabulated in Table.3. These results are given as input in Design Expert software for further analysis. The most commonly used quadratic equation to fit the experimental data and to determine the output response is given by,

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 AB + \beta_5 AC + \beta_6 BC + \beta_7 A^2 + \beta_8 B^2 + \beta_9 C^2 \tag{3}$$

Table 3 Study of experimental variables in coded units

Std	Run	Factor 1 A:V mm/min	Factor 2 B:F mm/rev	Factor 3 C:S mm	Response 1 Ra micro m	Response 2 t mm
1	15	-1	-1	-1	4.38	0.726
2	19	1	-1	-1	3.78	0.671
3	1	-1	1	-1	3.47	0.739
4	17	1	1	-1	3.85	0.697
5	7	-1	-1	1	3.37	0.732
6	16	1	-1	1	3.89	0.691
7	14	-1	1	1	3.29	0.726
8	12	1	1	1	3.94	0.701
9	2	-1.682	0	0	5.06	0.716
10	5	1.682	0	0	5.28	0.648
11	9	0	-1.682	0	3.54	0.711
12	11	0	1.682	0	3.32	0.738
13	6	0	0	-1.682	2.41	0.741
14	18	0	0	1.682	1.92	0.745
15	10	0	0	0	2.81	0.754
16	4	0	0	0	2.81	0.754
17	13	0	0	0	2.81	0.754
18	8	0	0	0	2.81	0.754
19	3	0	0	0	2.81	0.754
20	20	0	0	0	2.81	0.754

4. Result and Discussion

4.1. Statistical Analysis

The optimal conditions for Ra and t of AA5052 aluminium alloy sheet metal formed by incremental forming were determined by means of central composite design using response surface methodology. The obtained ANOVA for response surface quadratic models are tabulated in the tables 4 and 5. The quality of the fitted model was given by the coefficient of determination, R^2. This gives the proportion of the total deviation in the predicted response and a high R^2 is desirable (close to 1). Considering the determination coefficient R^2(adj) = 98.91% for Ra and R^2(adj) = 99.58% for t, the equation demonstrates that the model is well fitted. Model terms were evaluated by the F probability value with 95% confidence level. The P values were used to check the significance of each coefficient. The P values less than 0.05 indicates that the model and model terms were statistically significant [19]. By dividing the difference between the maximum predicted response and the minimum predicted response by the average standard deviation of all predicted responses adequate precision measures signal to noise ratio was computed. Ratios greater than 4 are desirable. In case of Ra the value was 38.593 and in case of t the value was 56.094 which were well above 4, which indicated adequate signals to use this model to navigate the design space.

Table 4 ANOVA for Response Surface Quadratic Model (response: Ra in μ m)

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F	
Model	13.27882	9	1.475	100.574	< 0.0001	Significant
A-V	0.127583	1	0.127	8.696	0.0146	
B-F	0.112587	1	0.112	7.674	0.0198	
C-S	0.240969	1	0.240	16.425	0.0023	
AB	0.154013	1	0.154	10.498	0.0089	
AC	0.241513	1	0.241	16.463	0.0023	
BC	0.082012	1	0.082	5.590	0.0397	
A^2	10.60282	1	10.602	722.754	< 0.0001	
B^2	0.847922	1	0.847	57.799	< 0.0001	
C^2	0.603751	1	0.603	41.155	< 0.0001	
Residual	0.1467	10	0.014			
Lack of Fit	0.1467	5	0.029			
StdDev	0.12		R^2		0.9891	
Mean	3.42		Adjusted R^2		0.9792	
C.V%	3.54		Predicted R^2		0.9066	
PRESS	1.25		Adequate Precision		39.593	

Table 5 ANOVA for Response Surface Quadratic Model (response: t in mm)

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F	
Model	0.017679	9	0.001964	262.7464	< 0.0001	Significant
A-V	0.005633	1	0.005633	753.449	< 0.0001	
B-F	0.000572	1	0.000572	76.55038	< 0.0001	
C-S	4.12E-05	1	4.12E-05	5.513814	0.0408	
AB	0.000105	1	0.000105	14.06102	0.0038	
AC	0.00012	1	0.00012	16.06735	0.0025	
BC	0.000153	1	0.000153	20.48127	0.0011	
A^2	0.009944	1	0.009944	1330.084	< 0.0001	
B^2	0.001821	1	0.001821	243.6271	< 0.0001	
C^2	0.000319	1	0.000319	42.60903	< 0.0001	
Residual	7.48E-05	10	7.48E-06			
Lack of Fit	7.48E-05	5	1.5E-05			
StdDev	2.734E-3		R^2		0.9958	
Mean	0.73		Adjusted R^2		0.9920	
C.V%	0.38		Predicted R^2		0.9680	
PRESS	5.674E-4		Adequate Precision		56.094	

PRESS stands for ‘Prediction Error Sum of Squares’ and it is a measure indicates how well the model for the experiment is likely to predict the responses in new experiments. Small values of PRESS are desirable. In case of Ra the value was 1.25 and in case of t the value was 5.674E-4. Model fitting with the help of Design-Expert software suggested that a quadratic model provided the best fit, and the model was found to have insignificant lack of fit. Based on the fig. 4(a) and (b) a correlation response equation for Ra and t with respect to the input parameters in terms of coded factors are given by the following equation (4) and (5).

$$Ra = 2.81 + 0.097A - 0.091B - 0.13C + 0.14AB + 0.17AC + 0.10BC + 0.86A^2 + 0.2B^2 - 0.20C^2 \tag{4}$$

$$t = 0.75 - 0.02A + 6.474x10^{-3}B + 1.737x10^{-3}C + 3.625x10^{-3}AB + 3.875x10^{-3}AC$$
$$-4.375x10^{-3}BC - 0.026A^2 - 0.011B^2 - 4.702x10^{-3}C^2 \tag{5}$$

Figure 4(a) and (b) shows the graph for Ra and t plotted against experimental and predicted values. The points are well distributed and closer to the straight line (R^2 = 98.91 and R^2 = 99.58) which gives an excellent relationship between the experimental and predicted Ra values and t.

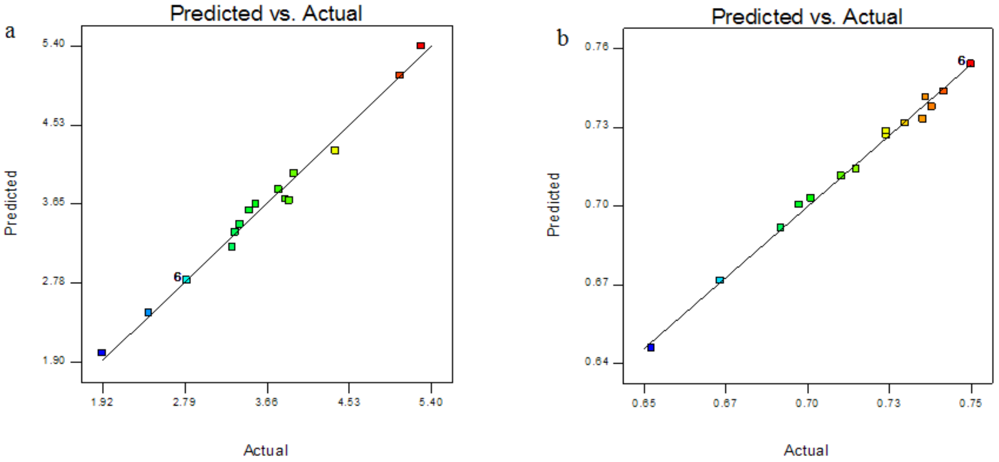

Fig. 4 Plot for (a) Ra and (b) t by experimental and predicted responses.

4.2. 3D Response Surface Plot

The 3D response surface plots which are the graphical representation of the regression equation, are useful to understand both interaction properties between the input and output parameters [20-21]. The ultimate aim of the plot is to predict the optimum values of the variables such the responses is maximized or minimized. Each contour represents an infinite number of combinations of two input variables with the response maintained at zero level. Elliptical contour is considered as a measure of perfect interactions among independent variables. The response surface models for Ra and t are given in the figure 5 (a) to (f). The figure shows the estimated Ra and t as a function of input variables.

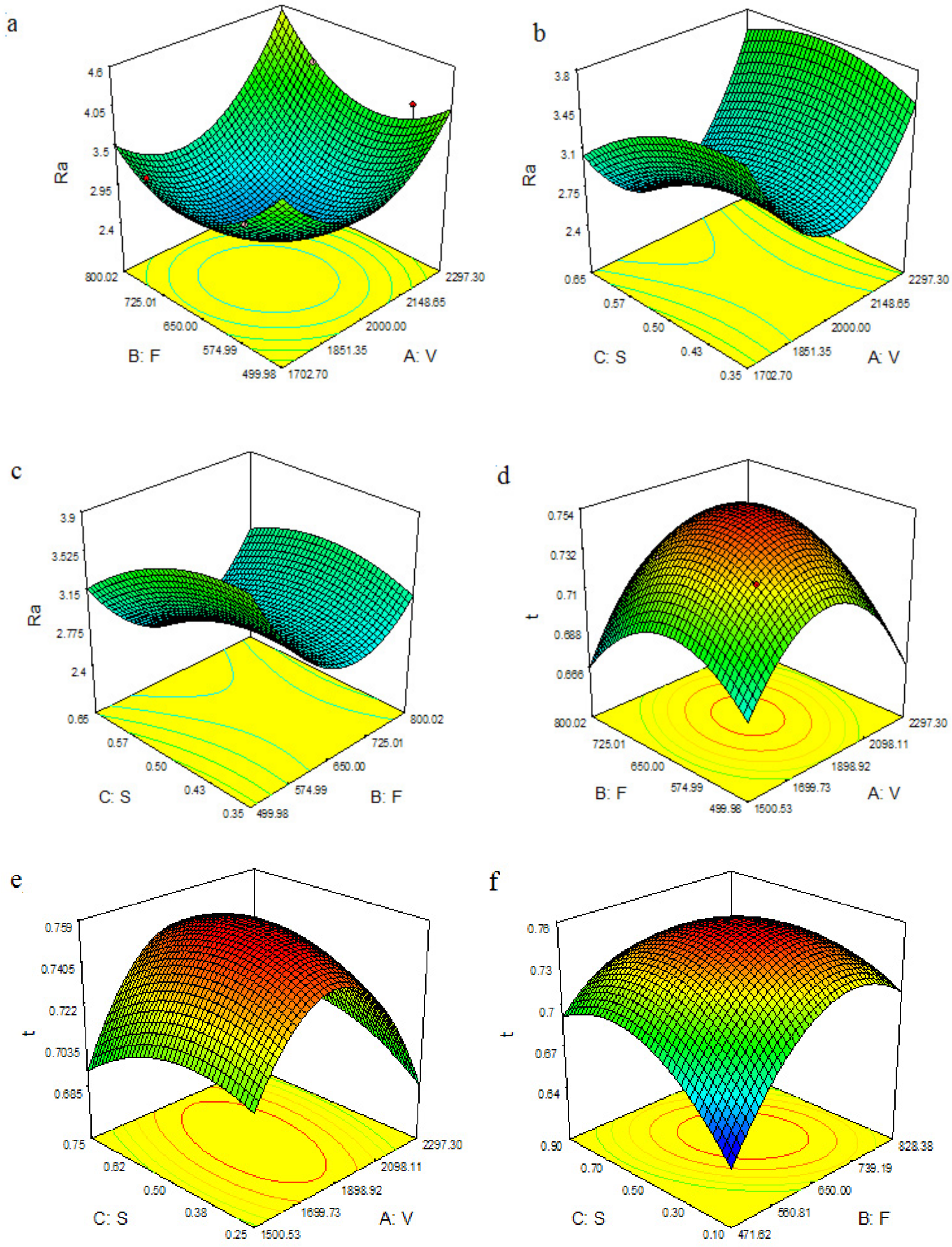

Fig. 5 (a-f) Response surface plot for surface roughness Ra and wall thickness t.

From the analysis of 3D graphs, the major parameters that influence Ra are spindle speed and feed. As far as t is considered, all the three parameters have significant interactions between them.

4.3. Multi Response Optimization

Numerical optimization will optimize any combination of one or more goals. The goals may apply to either factors or responses. The ramp plot was used to analysis the results obtained. The obtained data was optimized numerical for minimum Ra and maximum t. Desirability is an objective function that ranges from zero outside of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. For several responses and factors, all goals get combined into one desirability function. Ramps view shows the desirability for each factor and response, as well as the combined desirability [22]. A highlighted point shows both exact value of the factor or response and how well that goal was satisfied. A ramp plot for desirability of 0.916 was shown in figure 5.

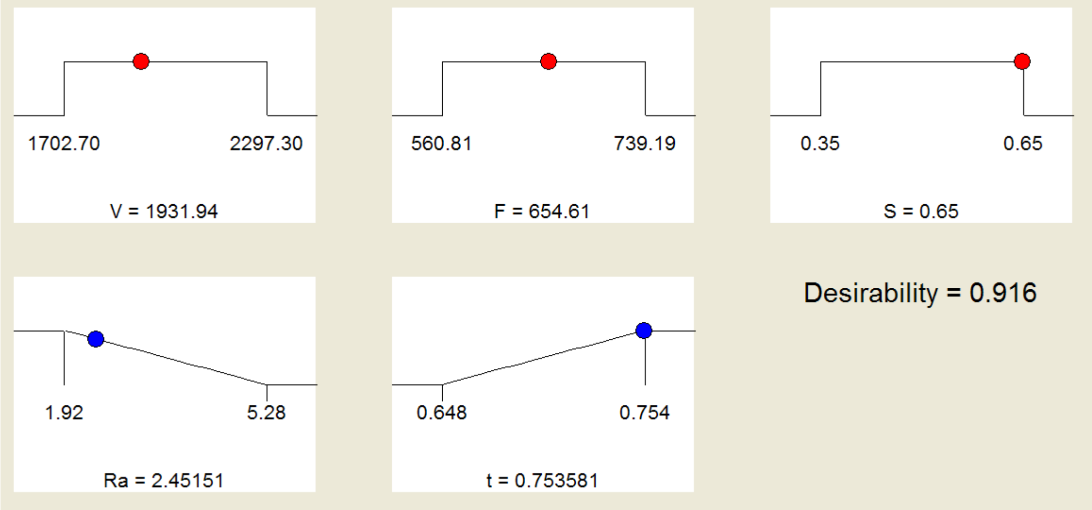

Fig. 6 Ramp function plot for optimized parameters

When spindle speed, feed and step size were 1931.94 rpm, 654 mm/rev and 0.65 mm a minimum Ra of 2.45151 µ m and a maximum t of 0.753 mm can be obtained.

5. Conclusion

Optimization of incremental forming of AA5052 Aluminium alloy sheet was achieved by five factorial full central composite design using response surface methodology in 20 runs. A second-order quadratic model has been obtained to predict the surface roughness (Ra) and wall thickness (t) as function of spindle speed, tool feed and step size variables. A minimum Ra of 2.45 µ m and maximum t of 0.753 mm were obtained at a spindle speed of 1931 rpm with feed 654 mm/rev and step size 0.65 mm. The study also has a higher R^2 value above 0.93 and a lower PRESS value indicating their usefulness in incremental forming. This study will be helpful in characterizing the input variable during incremental forming.

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