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Development of Regression Model Using Lasso And Optimisation of Process Parameters in Metal Spinning

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ABSTRACT:- Metal Spinning is a concept of describing the forming of metal into seamless, axisymmetric shapes by a combination of rotational motion and force. Sheet metal spinning is one of the metal forming processes, which a flat metal blank is rotated at a high speed and formed into an axisymmetric part by a roller which gradually forces the blank on to a mandrel, bearing the final shape of the spun part. Over the last few decades, sheet metal spinning has developed significantly and spun products have been used in various industries. Nowadays the process has been expanded to new horizons in industries, since tendency to use minimum tool and equipment costs and also using lower forces with the output of excellent surface quality and good mechanical properties. The automation of the process is of greater importance, due to its wider applications like decorative household's goods, rocket nose cones, gas cylinders etc. The objective of the current work is to develop the mathematical model for the spinning process with surface roughness as response and the input parameters as Mandrel speed (rpm), geometry of the Roller and Thickness of sheet (mm). Type of mandrel (EN8 Material) considered in the spinning process has the geometrical profile of parabola and single roller and double roller tools (EN8 Material) are used to deform the Al2024-T3 sheet metal paper aims to understand the process parameters that affect the surface finish of the spun component. Full factorial Design of Experiments technique is used to find the minimum number of experimental trials that are required to develop the regression model. A regression model using Least Absolute Shrinkage and Selection Operator (Lasso) is developed to further deepen the understanding between the input parameters and the surface roughness. The model was optimised using Sequential Quadratic Programming.

Keywords:- DoE, Lasso, Metal Spinning, Sequential Quadratic Programming, Surface Roughness.

I. INTRODUCTION

Metal spinning has been one of the oldest chipless forming techniques. However, with the passage of time, automation has taken a foothold in the manufacturing industry and a statistical model to understand the behaviour of the input parameters on the responses has become quintessential. Sheet metal spinning is one of the metal forming processes, where a flat metal blank is formed into an axisymmetric part by a roller which gradually forces the blank onto a mandrel, bearing the final shape of the spun part. As shown in Figure 1, during the spinning process, the blank is clamped between the mandrel and back plate; these three components rotate synchronously at a specified spindle speed. Materials used in the spinning process include non-alloyed carbon steels, heat-resistant and stainless steels, non-ferrous heavy metals and light alloys. The process is capable of forming a work piece with a thickness of 0.5 mm to 30 mm and diameter of 10 mm - 5 m.

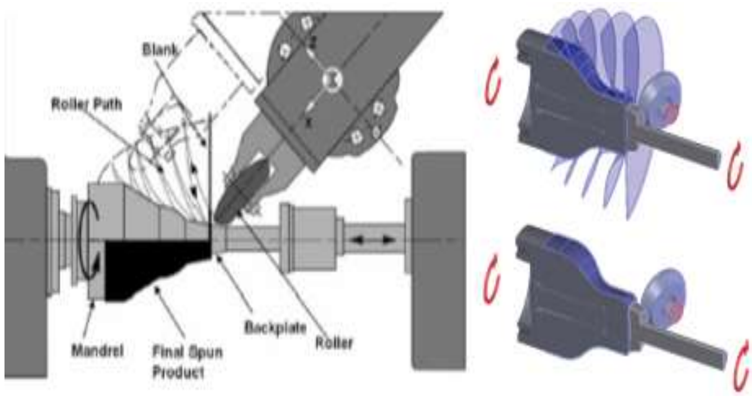

Fig. 1: Metal Spinning Process

II. METHODOLOGY AND EXPERIMENTATION

A mathematical model is developed using Lasso to understand the relationship between the input parameters and the target variable. The optimisation of the model was done using an iterative method for non-linear optimisation. Aluminium 2024-T3 alloy was chosen for the study and the chemical composition of the material is tabulated in table 1.

Table 1 : Composition of Al2024-T3

Element	Al	Cu	Mg	Si	Cr	Mn	Fe	Ti	Zn
Percentage (%)	90-94.7	3.8-4.9	1.2-1.8	Max 0.5	Max 0.1	0.3-0.9	Max 0.5	Max 0.15	Max 0.25

The process parameters shown in table 2 were taken into consideration and a full-factorial approach was adopted to perform the experiment.

Table 2 : Process Parameters

Factor	**Units**	**Designation**	**Test Level**	
			Low	**High**
Speed	rpm	N	283	485
Thickness of Sheet	mm	t	0.8	1
Roller Type	-	R	Single Roller	Double Roller

Eight trials were conducted according to the design matrix in table 3. The single-roller was represented with ‘1’ while the double-roller was represented with ‘2’ to maintain numeric consistency in the statistical model. The experiments were carried out on a Capstan Lathe Machine (Fig. 2) using EN8 Spinning Tool (Roller).

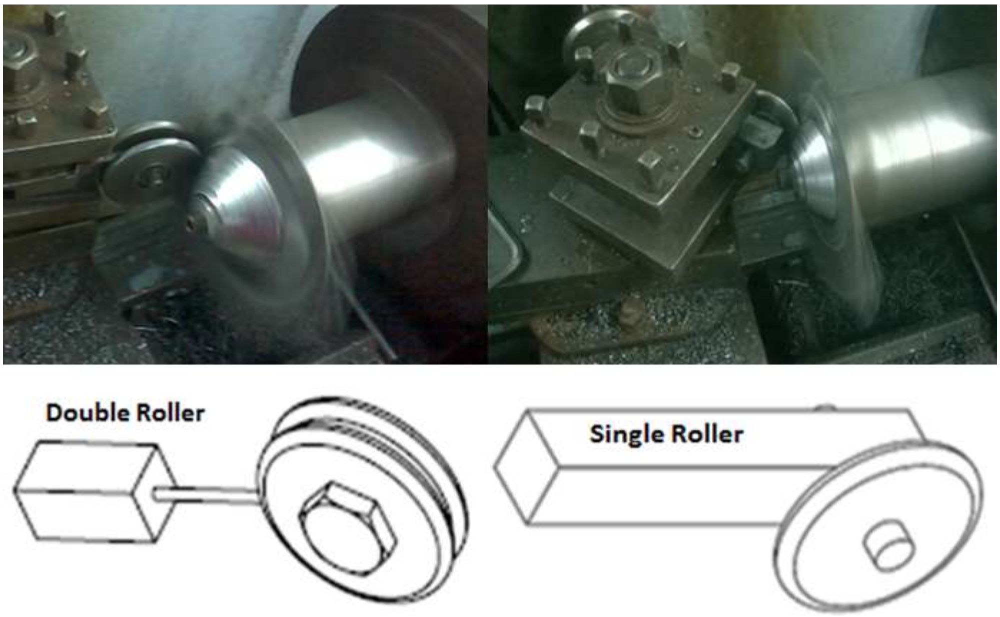

Fig. 2: Experimentation

Table 3: Design Matrix

Trial No.	1	2	3	4	5	6	7	8
Speed (rpm)	283	485	283	485	283	485	283	485
Thickness of Sheet (mm)	1.0	1.0	1.0	1.0	0.8	0.8	0.8	0.8
Roller Type	1	1	2	2	1	1	2	1

The design matrix in the table 3 was taken as the input data for regression analysis while value of surface roughness was taken as the output parameter. Least Absolute Shrinkage and Selection Operator is developed to generate sparse solutions of the Ordinary Least Squares (OLS) problem. Lasso offers better bias and lower variance. Moreover, Lasso’s ability to generate simpler models makes it a better alternative to Ridge Regression (Regularised Regression with L2 norm penalty).

$$\arg\min\left\{\frac{1}{N}\parallel y - X\beta \parallel^2\right\} \textit{ subject to } \parallel \beta \parallel_1 \leq t$$

The same is written in the Lagrangian form as:

$$\min\left\{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \sum_{j=0}^{M} w_j x_{ij}\right)^2 + \lambda\sum_{j=0}^{M}|w_j|\right\}$$

The L1 norm in the cost function allows for sparse solutions and can be adjusted by tweaking the regularisation parameter. It is a mathematical tool that balances between the model fit and the complexity of the model. The behaviour to the cost function with various values of regularisation parameter is outlined below:

$$\lambda = 0 \rightarrow \textit{Same coefficients as OLS}$$
$$\lambda = \infty \rightarrow \textit{All coefficients are reduced to zero}$$
$$0 < \lambda < \infty \rightarrow \textit{Coefficients between zero and that of OLS}$$

Sequential Quadratic Programming (SQP) is an iterative algorithm that is used for the nonlinear optimisation of an objective function that is twice continuously differentiable. The function is minimised by calculating the Jacobian and the Hessian to determine the appropriate search direction over the convex (largely) function. The iteration step with one bound equality constraint is shown below:

$$\min \quad f(x_k) + \nabla f(x_k)^T d + \frac{1}{2} d^T \nabla_{xx}^2 \mathcal{L}(x_k, \lambda_k) d$$
$$s.t. \quad c(x_k) + \nabla c(x_k)^T d = 0$$

$$f(x) = \textit{objective function}$$
$$c(x) = \textit{constraint}$$
$$d \textit{ is the search direction}$$
$$\mathcal{L} \textit{ is the Lagrangian}$$
$$\lambda \textit{ is the Lagrange multiplier}$$
$$k \textit{ is the iteration value}$$

It was used to optimise (minimise surface roughness) the equation generated from the regression analysis and the same was validated with the experimental minimum.
The model was developed in Python 3.6.1 using Numpy, Pandas, Scikit-Learn libraries while the optimisation was performed using Scipy library.

```
## Fits the training data using LASSO
# X – Input parameters
# y – Response
# alpha – Regularization parameter
class LinearModel():
        def __init__(self, X, y, alpha):
                self.X = X
                self.y = y
                self.alpha = alpha
        def lasso(X, y, alpha):
                clf = linear_model.Lasso(alpha = alpha)
                clf.fit(X, y)
                pred = clf.predict(X)
return clf.coef_, clf.intercept_, pred
# SQP Optimisation
fun = lambda x: ‘‘‘ regression equation ’’’
bnds = ((283,485), (0.8,1.0), (1,2))= Scipy.optimize.minimize(fun, (‘‘‘random variables’’’), method = “SLSQP”, bounds = bnds)
 print (res)
```

The observations made during the experimentation are recorded in table 4 and the specimen is shown in Fig. 3.

Fig. 3: Surface roughness measurement of specimen

Table 4: Observations

Trial No.	Experimental Values			Response Parameter
	Speed (rpm)	Thickness of Sheet (mm)	Roller Type	Surface Roughness (Ra)
1	283	1.0	Single Roller (1)	7.05
2	485	1.0	Single Roller (1)	3.64
3	283	1.0	Double Roller (2)	3.60
4	485	1.0	Double Roller (2)	1.78
5	283	0.8	Single Roller (1)	5.62
6	485	0.8	Single Roller (1)	8.04
7	283	0.8	Double Roller (2)	6.78
8	485	0.8	Double Roller (2)	4.11

Regression analysis was performed and the coefficients of the linear model using Lasso are outlined in table 5.

Table 5: Regression Coefficients

Coefficient	Value
Intercept	7.72
N	0.027
t	0
R	0
Nt	-0.029
NR	-0.005
tR	0

A model was selected after comparing the R-Squared and the Adjusted R-Squared of models with various complexities ranging from simple linear equation to a third-degree polynomial. In this study, the following model showed the best relationship and has been selected for further optimisation.
The final equation is: **$Y = 7.72 + 0.027N - 0.029Nt - 0.005NR$**

The regression model developed was validated with various validation metrics and the results are recorded in table 6.

Table 6: Validation Metrics

Metric	Value
R-Squared	0.765
Mean Square Error (MSE)	0.939
Median Absolute Deviation (MAD)	0.81

The output from the optimisation of the regression model using SQP is tabulated in table 7 and is found to be in close approximation with the actual output, which further validates the mathematical model.

Table 7: Variation between the Optimised Value and the Actual Value

Speed (rpm)	Thickness of Sheet (mm)	Roller Type	Function Value (Ra)	Experimental Value (Ra)	Absolute Deviation (mm)
485	1.0	2 (Double Roller)	1.90	1.78	0.12

III. RESULTS AND CONCLUSIONS

Plots between the process parameters and the surface finish are shown from Fig. 4 to Fig. 6. Level 1 indicates that all the other process parameters other than the ones under study are in the lower level and Level 2 indicates that these are in the higher level.

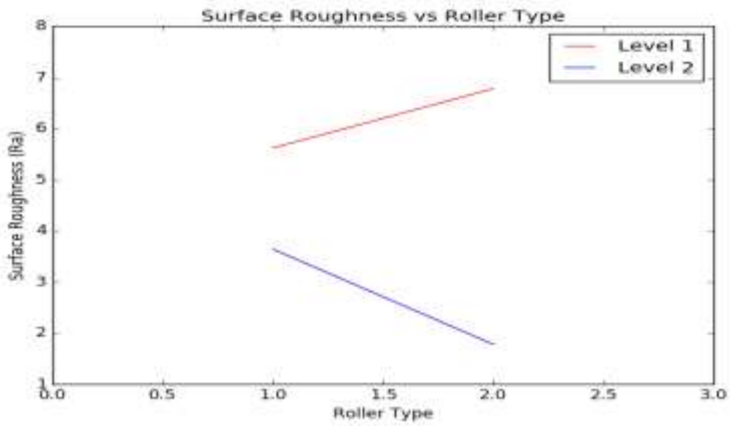

Fig. 4: Surface Roughness vs Roller Type Plot

When the process parameters were at Level 1, change of roller from a single roller to a double roller increased the surface roughness of the component while the same had an adverse effect when the parameters were in Level 2 (Fig. 5).

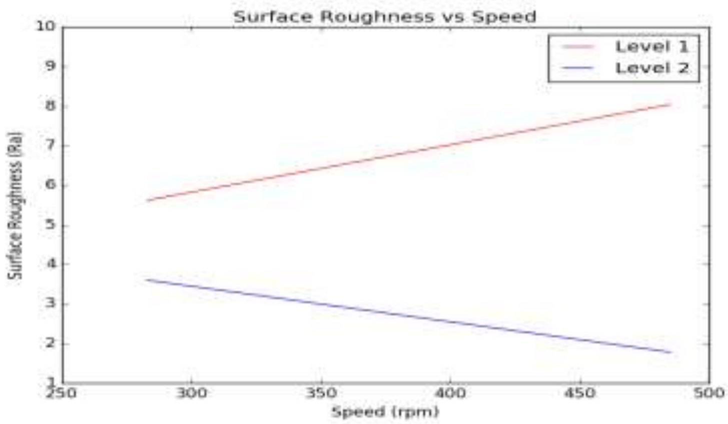

Fig. 5: Surface Roughness vs Speed Plot

The same was the case with surface Roughness and speed (Fig. 5). In Level 1, the component has increase in surface roughness with an increase in speed while the surface roughness reduced when the parameters were in Level 2.

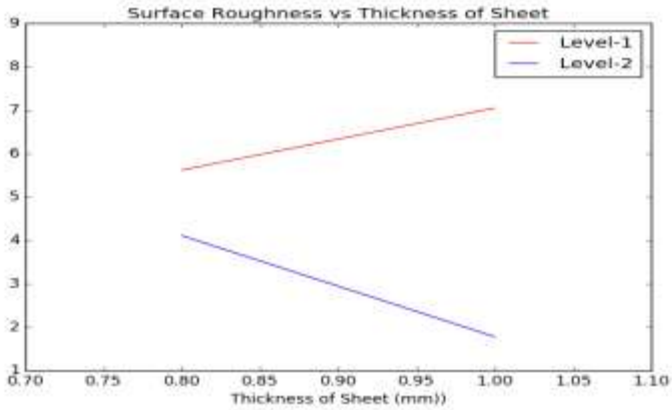

Fig. 6: Surface Roughness vs Thickness of Sheet Plot

Similar relationship can be drawn from the plot between surface roughness and thickness of the sheet (Fig. 6). In this study, the thin sheet showed higher values of surface roughness for both the rollers at both low and high mandrel speeds when compared to the thick sheet. A thick sheet with higher mandrel speed using a double roller needs to be selected to minimise the surface roughness on the spun component.

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