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Linear Model for Turning Al6061 using Least Absolute Shrinkage and Selection Operator (Lasso)

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Abstract: *Machining Aluminium to produce low cost and high quality products is the order of the day and the same has seen intense research over the years. Formation of built-up edge has an opposing effect on quality of the workpiece and it can be avoided by careful tuning of the machining parameters. This paper focuses on the optimisation of process parameters such as speed, feed, and the depth of cut in order to minimize the cutting forces and maximise the surface finish of the work piece. A full-factorial approach was used to conduct experimentation and a mathematical model was developed using Least Absolute Shrinkage and Selection Operator to understand the effect of the mentioned process parameters on the required target variables.*

Keywords: *Al6061, Design of Experiments, Lasso, Cutting Force, Surface finish.*

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I. Introduction

Modern machining strives to high quality and high quality while dealing with surface finish and dimensional accuracy. The quality of a surface is a significant factor in estimating the productivity of machine tool and machined parts while the surface roughness of machined parts has critical effects on some functional attributes of parts, such as, contact causing surface friction, wearing, light reflection, ability of distributing, and. load bearing capacity.

Kannan Nair M R and ShyamSundar[1] experimented with turning operations along with finite thermal analysis to understand that the cutting speed was main variable affecting the chip-tool interface temperature. SohailAkram[2] determined the sensitivity of residual stresses to cutting speed and feed rate using finite element method. The simulation results showed that residual stresses were insensitive to changes in cutting speed, however, residual stresses were clearly affected by a change in feed rate NitinSawarkar&Ghanshyam[3] concluded that graphical analysis of residual stress vs machining parameters can be done, from which decision about selection of optimum machining process, to improve component life can be made. Robert Tibshirani[4] introduced Least Absolute Shrinkage and Selection Operator (Lasso) to improve the prediction accuracy and interpretability of regression models using feature selection. The regression model was generated using Lasso and a semi-empirical formula was developed that represented the relationship between the process parameters and the output variables.

II. Experimental Methodology

2.1 Design of Experiments

Three process parameters with two levels are taken into consideration while performing the experiment and are shown in table 1.A two level full factorial design of experiments was adopted for calculating the main and the interaction effects of the three factors at two levels; 2^3=8 experiments were conducted to fit an equation. The design plan with high and low limits as indicated is utilized looking into practical considerations of the turning operation and are tabulated in table 1.

Table 1 – Process Parameters And Levels

Factors	Units	Designation	Test levels		Average	Variation interval
			Low	High		
Speed	rpm	N	715	1210	960	245
Feed	mm/rev	f	0.1	0.2	0.15	0.05
Depth of Cut	mm	d	0.1	1	0.55	0.45

Table 2 – Design Matrix For Experimentation

Trial No.	1	2	3	4	5	6	7	8
Speed (rpm)	715	1210	715	1210	715	1210	715	1210
Feed (mm/rev)	0.1	0.1	0.2	0.2	0.1	0.1	0.2	0.2
Depth of Cut (mm)	0.1	0.1	0.1	0.1	1	1	1	1

2.2 Experimentation

Al6061 work piece is obtained from Die casting process. From the acceptable range of values, a specimen with the highest yield strength was chosen by using Taguchi L8 array and the same is tabulated in table 3.

Table 3 – Optimum Composition Of Al6061

Component	Aluminium	Magnesium	Silicon	Iron	Copper	Zinc	Manganese	Chromium
Percentage	98.46	0.8	0.4	0.05	0.15	0.05	0.05	0.04

Experimentation iscarried out on Hindustan Machine Tool HMT NH 22 (Fig. 2) using HSS single point cutting tool according to the design matrix.

Fig. 1 – A: Casting Process, B: Casting, . 2 – Experimental Setupc: Finished Workpiece, D: Workpiece After Machining

The cutting forces are measured during the experimentation using a piezoelectric dynamometer and the surface finish is measured using TALYSURF (Fig. 3).

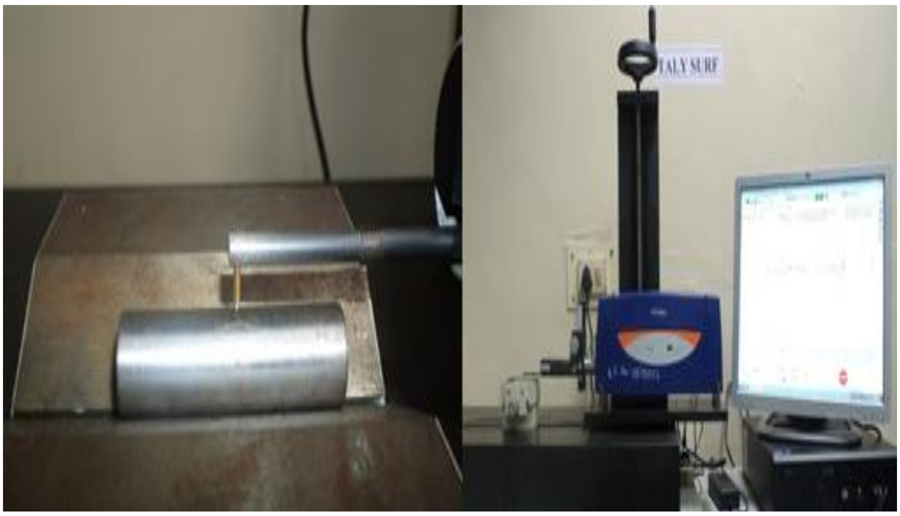

Fig. 3 – measurement of surface finish using talysurf

2.3 Regression Analysis

The data from the design matrix along with the observations made during the experimentation were taken as the training data to perform regression analysis using Lasso. Least Absolute Shrinkage and Selection Operator (Lasso) is a sparsity operator that performs regularised regression with an L1 norm penalty. Lasso's ability to perform subset selection relies on the form of the constraint and has a variety of interpretations including in terms of geometry, Bayesian statistics, and convex analysis. It minimises the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant. Because of the nature of this constraint, it tends to produce some coefficients that are exactly zero and hence gives interpretable models.It is preferred over ordinary least squares (OLS) [5] as it offers better bias and a lower variance. Its ability to obtain sparse coefficients makes it more suitable over Ridge Regression[6], which performs regression using an L2 norm penalty.

The variance or the cost function used to perform Lasso regression is outlined below:

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

$$t = regularization\ parameter$$
$$\beta = Coefficients$$
$$y = output$$
$$X = Input$$

The same is written in the Lagrangian form as:

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

$$N = Number\ of\ samples$$
$$y_i = Response$$
$$x_{ij} = Input\ parameters$$
$$w_j = Coefficients$$

The value of λ determines the amount of regularisation and its behaviour is outlined below:

$\lambda = 0$ $(Same\ coefficients\ as\ OLS)$

$\lambda = \infty$ $(All\ coefficients\ are\ reduced\ to\ zero)$

$0 < \lambda < \infty$ $(Coefficients\ between\ zero\ and\ that\ of\ OLS)$

The model is validated using various metrics that include Coefficient of Determination[7], Median Absolute Deviation[8], and Mean Square Error. The regression analysis using Lasso is performed in Python 3.6.1 with Numpy, Pandas, Scikit-Learn, and Matplotlib libraries. The following code shows the general Lasso Class in Python using Scikit-Learn to generate the regression coefficients and the intercept.

```
## Fits the training data using LASSO
# X – Input parameters
# y – Response
# alpha – Regularization parameter
classLinearModel():

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)
returnclf.coef_, clf.intercept_, pred
```

III. Results And Conclusions

The observations made for the trials during the experimentation are tabulated in table 2 and the dynamometer readings for cutting forces and surface finish readings from Talysurf are shown in Fig. 4.

Table 4 - Observations

Trial Number	Resultant Force (N)	Surface Roughness (Ra)
1	50.33	2.163
2	49.89	1.079
3	70.26	4.773
4	78.88	5.565
5	147.98	9.873
6	203.82	10.182
7	213.58	12.12
8	463.23	4.997

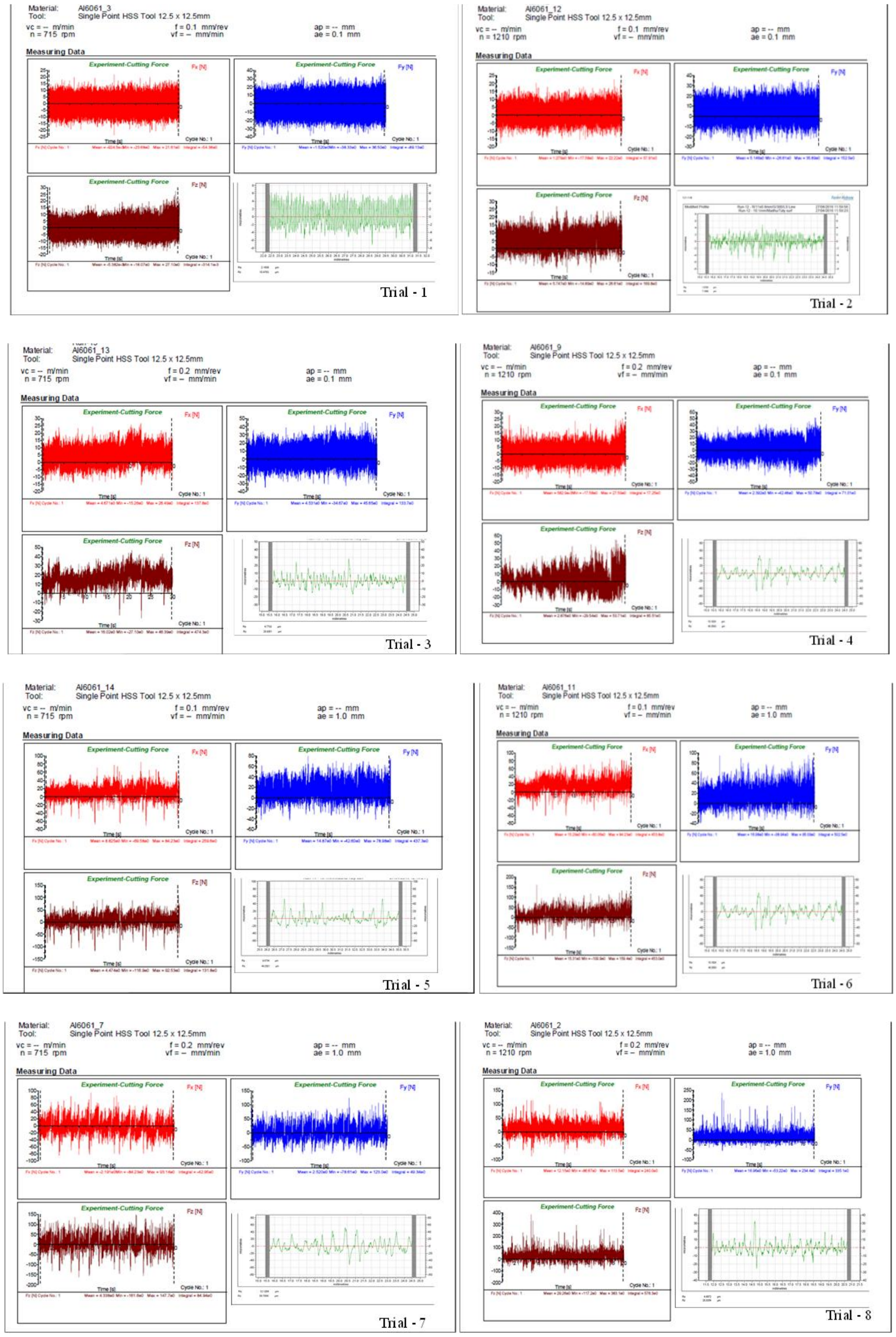

Fig. 4 – cutting forces and surface roughness for all trials

3.1 Regression model for Resultant Cutting Force

The coefficients of the linear model for cutting force are recorded in table5.

Table 5 – Regression Coefficients For Cutting Force

Variable	Intercept	N (Speed)	f (Feed)	d (DoC)	Nf	Nd	fd	Nfd
Coefficient	1.73	0.017	0	0	0.086	-0.028	0	1.73

The final equation:

Y = 7.788 + 0.017(N) + 0.086(Nf) – 0.028(Nd) + 1.73(Nfd)

Validation metrics:

Coefficient of Determination: 0.97

Median Absolute Error: 14.382

Mean Square Error: 496.372

3.2 Regression model for Surface Finish

The coefficients of linear model for the surface finish of the material are recorded in table 6.

Table 6 – Regression Coefficients For Surface Finish

Variable	Intercept	N (Speed)	f (Feed)	d (DoC)	Nf	Nd	fd	Nfd
Coefficient	6.693	-0.01	0	5.65	5.65	0.043	0.01	0

The final equation:

Y = 6.693 – 0.01(N) + 5.65(d) + 0.043(Nd) + 0.01(Nf) – 0.067(Nfd)

Validation metrics:

Coefficient of Determination: 0.85

Median Absolute Error: 0.98

Mean Square Error: 2.1

3.3 Variation of responses with respect to feed

An increase in feed showed an increase in resultant force (Fig. 5). However, there was a conflicting result with surface finish (Fig. 6).

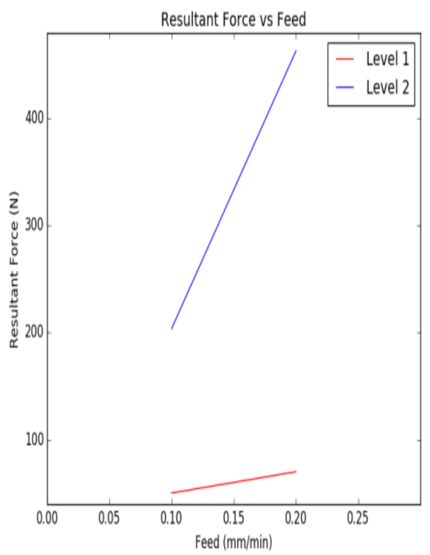

Fig. 5 – resultant force vs feed

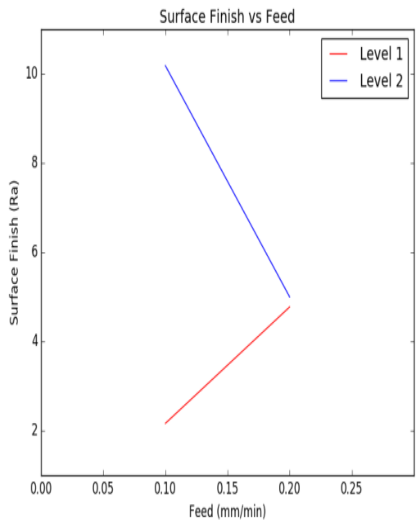

fig. 6 – surface finish vs feed

3.4 Variation of responses with respect to speed

Higher speeds increased the resultant force on the work piece (Fig. 7). However, it had a negative impact on the surface finish of the material (Fig. 8).

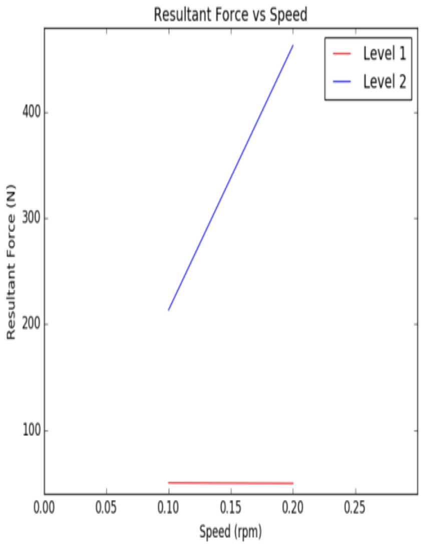

Fig. 7 – resultant force vs speed

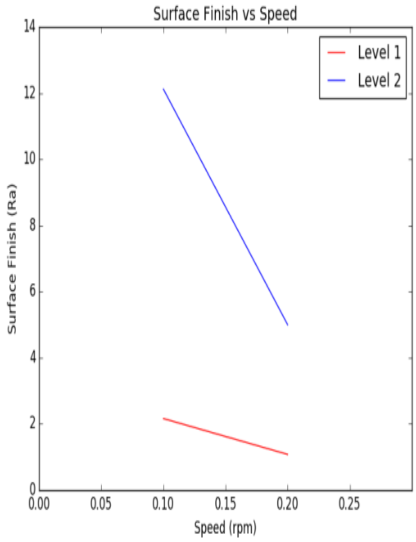

fig. 8 – surface finish vs speed

3.5 Variation of responses with respect to depth of cut

There was an increase in the resultant force with an increase in the depth of the cut (Fig. 9) but a clear relationship could not be obtained in the case of surface finish (Fig. 10).

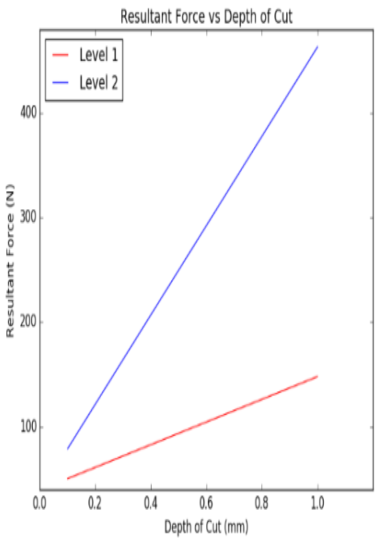

Fig. 9 – surface finish vsdoc

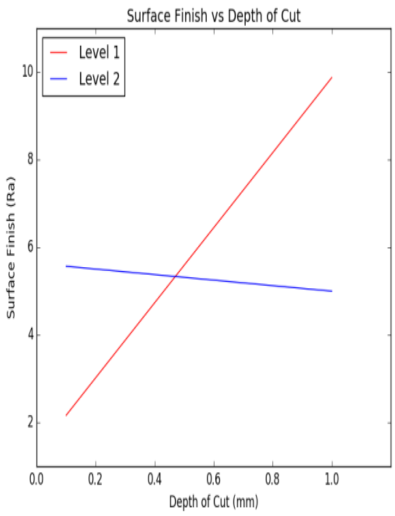

fig. 10 – surface finish vs doc

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