Empirical Modeling and Analysis of Process Parameters in Laser Beam Cutting Process

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***Abstract*—The research has been originated based on the persuasive applications of Lasers in the field of various engineering industries, i.e., Aerospace, Automobile, Electronic and Heavy manufacturing industries to machine a variety of metals and alloys. Out of all the machining processes available, Laser Beam Machining is considered to be the best one, because of the following advantages, i.e., quick material removal, non-contact, non-wearing tool, involves highly localized heat input to the work piece, reduces distortion, and offers no tool wear, diminishes tendency of cracking. The present paper focused mainly on developing the empirical relationships between the input process parameters and the output responses in Laser beam cutting process. Laser power, Cutting Speed, Gas pressure and Focal distance are the input process parameters. The output responses considered are related to the quality of cut. Surface roughness is the first output responses considered and the second one is Burr height. Total number of experiments carried out is 27 based on the Taguchi Design of Experiments. Haste alloy C276 is the work material. Response Surface Methodology is applied for the Experimental data of 31 samples to derive the empirical relationships. Later ANOVA analysis is also carried out to check the adequacy of the derived equations. Based on the ANOVA analysis, the models are classified as significant or not significant. Further the significant models can be used for optimizing the Laser beam cutting process. Once the process is optimized, it can be automated, so that the process can be run very efficiently and economically.**

***Keywords*—ANOVA analysis, empirical modeling, laser beam cutting, response surface methodology**

I. INTRODUCTION

Thermal separation is the process that is used to the laser machining process. A wide range of materials, particularly those that have low reflectivity, thermally and electrically conducting or non-conductive, and that cannot be machined by other unconventional machining techniques like Wire Electrical Discharge Machining (WEDM), Ultrasonic Machining (USM), Electrical Discharge Machining (EDM), Electro Chemical Machining (ECM), Plasma Arc Machining (PAM), etc., can be processed using laser machining. One of the most reliable sophisticated manufacturing techniques for industrial processes is laser cutting, which has changed significantly since its introduction in the 1970s. The following describes how a laser is generated and how to regulate its beam so that it can cut a workpiece's surface. A glass tube with mirrors at both ends produces a laser beam [1]. A turbine disperses the laser gas once it has been introduced into the glass. Helium, nitrogen, and carbon dioxide make up the laser gas. Typically, this mixture of laser gas is referred to as a CO_2 laser. An external power source, such as Radiofrequency (RF generator) or Electrical Power (DC power), is used to excite the atoms in the laser gas and release the excited atoms into the mixture of laser gas. A photon of seventeen lights is released by the excited gas atoms in the laser. More photons are released when this photon excite other atoms. This takes the shape of a domino effect. The generated photons travel between the glass tube's two mirrors until some of them break free through the partially reflected mirror. High productivity and the greatest cut quality are achieved when the laser beam is focused onto the workpiece to be cut by adjusting the laser's focal length to the cut's depth [2].

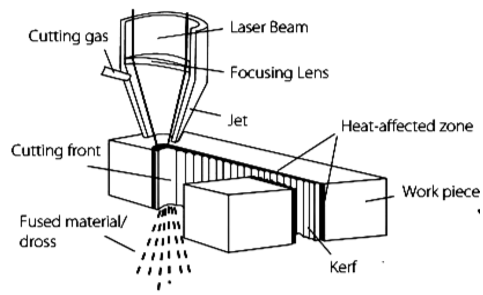

Fig. 1. Laser cutting principle.

The principle of laser cutting is shown in Fig 1. The efficiency of the overall process in terms of productivity, cut quality, and cost is determined by a number of characteristics that make laser cutting an unpredictable operation. The key concerns for producers are minimising costs, cutting quality, and increasing productivity. Theoretical and practical knowledge will aid in the methodical selection of laser process parameters [3], which are often selected using values from handbooks. Setting the ideal cutting parameters helps to accomplish a desired outcome. A poor choice of cutting parameters

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leads to excessive manufacturing expenses, poor product quality, and waste; conversely, a good choice of these parameters improves the quality of the final product. Therefore, it is even more important to accurately assess using mathematical models the relationship between laser cutting parameters and cutting performance [4], and then utilise optimisation techniques to determine the ideal or nearly optimal cutting parameters [5]. The manufacturing process parameters, machine specifications, creation of efficient optimisation conditions, empirical equations to develop realistic constraints, and proficiency with numerical and mathematical optimisation techniques are all necessary for the modelling and optimisation of processes, which are typically very challenging tasks. A vast array of optimisation strategies have been developed by researchers, who have also addressed numerous models of parameter optimisation problems and talked about the Design of Experiment (DOE) [6] and other methods used to predict empirical models [7]. Predicting the parametric equations between the input process variables and the output responses is the primary goal of the proposed effort. The empirical models are predicted using the experimental data. Using the Response Surface Methodology approach, two models are predicted for the kerf width and surface roughness. Using the ANOVA analysis, the projected models are also evaluated for appropriateness [8]. The created formulas can also be utilised to streamline the laser beam cutting procedure, which can then be automated [9].

II. Experimental Work

The experiments were conducted on a 3 axes CNC controlled CO_2 laser cutting machine which is available in Meera Laser Solutions, Ambattur, Chennai. The maximum average power produced at laser is 100 W. The experiments are carried out on Hastelloy C-276 with a thickness of 2 mm. Square profiles are cut on the workpieces. The machine and the samples are presented in Fig. 2.

Fig. 2. Laser cutting profiles.

Haste alloy C276 is chosen as the work piece because of the following advantages, i.e., high resistance to uniform attack, outstanding localized corrosion resistance, excellent stress corrosion cracking resistance, and ease of machining, welding and fabrication. A total of 31 experiments were carried out on the LBC apparatus by varying the input variables, i.e., Laser power, Cutting speed, focal distance and the Gas pressure. Based on Taguchi [10], the experimental plan is prepared. Based on the trail experiments, the ranges for each process parameters are found out. The minimum value of laser power is 1.7 and maximum value is 1.9 KW. Cutting speed is varied between 3 and 6 mm/sec. The third parameter focal distance is adjusted between 0.4 and 0.6 mm, whereas the fourth and the last parameter, i.e., gas pressure is adjusted between 2 and 3 bar. The Minitab software [11] is used to prepare the experimental plan. The output responses measured are Burr height and the Surface roughness. The experimental data is presented in Table I.

TABLE I. Experimental Data

Exp No	Laser Power [KW]	Cutting Speed [mm/sec]	Focal Distance [mm]	Gas Pressure [bar]	Surface Roughness [μm]	Burr Height [μm]
1	1.750	3.750	0.500	2.250	3.575	0.815
2	1.850	3.750	0.500	2.250	4.640	1.880
3	1.750	5.250	0.500	2.250	3.543	0.783
4	1.850	5.250	0.500	2.250	3.803	1.043
5	1.750	3.750	0.700	2.250	3.539	0.779
6	1.850	3.750	0.700	2.250	3.548	0.788
7	1.750	5.250	0.700	2.250	3.548	0.788
8	1.850	5.250	0.700	2.250	3.697	0.937
9	1.750	3.750	0.500	2.750	3.050	0.290
10	1.850	3.750	0.500	2.750	3.879	1.119
11	1.750	5.250	0.500	2.750	3.308	0.548
12	1.850	5.250	0.500	2.750	3.398	0.638
13	1.750	3.750	0.700	2.750	3.646	0.886
14	1.850	3.750	0.700	2.750	3.551	0.791
15	1.750	5.250	0.700	2.750	3.317	0.557
16	1.850	5.250	0.700	2.750	3.127	0.367
17	1.700	4.500	0.600	2.500	3.210	0.450
18	1.900	4.500	0.600	2.500	4.589	1.829
19	1.800	3.000	0.600	2.500	4.425	1.665
20	1.800	6.000	0.600	2.500	3.440	0.680
21	1.800	4.500	0.400	2.500	3.256	0.496
22	1.800	4.500	0.800	2.500	4.245	1.485
23	1.800	4.500	0.600	2.000	3.070	0.288
24	1.800	4.500	0.600	3.000	3.789	1.029
25	1.800	4.500	0.600	2.500	3.345	0.456
26	1.800	4.500	0.600	2.500	3.968	1.208
27	1.800	4.500	0.600	2.500	3.635	0.875
28	1.800	4.500	0.600	2.500	3.595	0.835
29	1.800	4.500	0.600	2.500	3.471	0.711
30	1.800	4.500	0.600	2.500	3.223	0.463
31	1.800	4.500	0.600	2.500	3.210	0.489

III. Empirical Modeling and Analysis

The experimental data shown in above section is used to develop the empirical models between the input process parameters and the output responses. For all the manufacturing industries, automation is the prime requirement due to the fact that the manufacturing output is increased with the reduction in the manufacturing cost.

As LBC process is a very complex process involving many number of input process parameters to be controlled correctly to achieve quality output, it becomes very difficult for the manufacturing people to judge and set the correct parameter at the correct level. He never achieves the optimal output if such trial and error methods are employed. Hence there is a need to develop the methodology which gives us the optimal settings. In order to optimize the process, one should establish the relationships between the input process parameters and the output responses. In this work, the main priority is given for finding the empirical relationships. Response Surface methodology [12] is the method which is used here to find the empirical relationships.

A. Response Surface Methodology (RSM)

For building of empirical models, the Response surface methodology is used for empirical modeling. By conducting experiments and applying regression analysis [13], a model of response to some independent variables can be obtained. In RSM it is possible to represent independent process parameters in quantitative form as:

$$Y = f(X_1, X_2, X_3, \ldots, X_n) \pm \varepsilon \tag{1}$$

In this case, Y represents the response, f denotes the response function, ε is the experimental error, and the independent parameters are X_1, X_2, X_3, Xn, etc. Plotting Y's anticipated response yields a surface that is referred to as the response surface. It is uncertain what form f takes and it could be exceedingly complex.

RSM thus seeks to approximate f in some region of the independent process variables by an appropriate lower order polynomial. The function Y mentioned in the above Eq. (1) can be rewritten, if the answer can be accurately represented by a linear function of the independent variables:

$$Y = C_0 + C_1X_1 + \ldots + C_nX_n \pm \varepsilon \tag{2}$$

However, if a curvature appears in the system, then a higher order polynomial such as the quadratic model may be used and is given as

$$Y = C_0 + \sum_{i=1}^{n} C_iX_i + \sum_{i=1}^{n} d_iX_i^2 \pm \varepsilon \tag{3}$$

In addition to examining the reaction across the whole factor space, the goal of Response Space Mapping (RSM) is to identify the region of interest where the response approaches or exceeds its ideal value. It is possible to determine the response surface model—the set of variables that produces the optimal response—by closely examining the data.

For the present research, Design Expert software is used to find the empirical models based on the RSM method. The data collected from distinctive experiments pertaining to output responses, Surface roughness and Burr height from Table I are used to implement the proposed RSM methodology. The need in developing the mathematical relationships is to relate the measured output responses Surface Roughness and the Burr height to the input process parameters such as Laser power (x_1), Cutting speed (x_2), Focal distance (x_3), and Gas Pressure (x_4) thereby facilitating the optimization of the cutting process. Design Expert 10, statistical analysis software [8], is used to compute the regression coefficients of the proposed models. The following empirical models are obtained

$$\textit{Surface Roughness} = 23.46 - 59.71\, x_1 + 2.98\, x_2 + 39.91\, x_3 + 9.62\, x_4 - 2.49\, x_1 x_2 - 29.62\, x_1 x_3 - 4.23\, x_1 x_4 + 0.41\, x_2 x_3 - 0.08\, x_2 x_4 + 3.08\, x_3 x_4 + 21.81\, x_1^2 + 0.14\, x_2^2 + 3.45\, x_3^2 - 0.73\, x_4^2 \tag{4}$$

$$\textit{Burr Height} = 25.79 - 65.00\, x_1 + 2.92\, x_2 + 39.47\, x_3 + 9.55\, x_4 - 2.49\, x_1 x_2 - 29.62\, x_1 x_3 - 4.23\, x_1 x_4 + 0.41\, x_2 x_3 - 0.08\, x_2 x_4 + 3.08\, x_3 x_4 + 30.18 x_1^2 + 0.14\, x_2^2 + 3.82\, x_3^2 - 0.71\, x_4^2 \tag{5}$$

Predictions on the response for specific amounts of each element can be made using the equations above, which are expressed in terms of coded factors. The factors' high values are automatically typed as +1, and their low levels are coded as −1. By comparing the factor coefficients, the coded equation can be used to determine the relative impact of the components. Also to understand the trends between the input process parameters and the output rsponses, using the Design Expert software, two dimentsonal plots are plotted. Fig. 3 shown below is the plot between the inputs, i.e., power, cutting speed, focal distance and the gas pressure versus the surface roughness, The plot shows that the surface roughness tends to increase with the increase in the power and the focal distance, wheras the surface roughenss decreases with the increase in the cutting speed and the gas pressure.

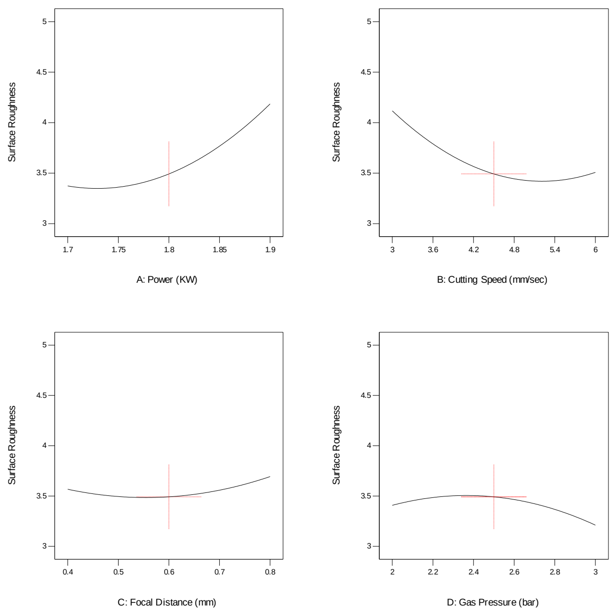

Fig. 3. Effect of Input parameters on surface roughnesss.

Fig. 4 is the plot between the inputs, i.e., power, cutting speed, focal distance and the gas pressure versus the burr height. The graph shows that the burr height is increasing with the increase in the power and the focal distance, wheras the burr height decreases with the increase in the cutting speed and the gas pressure.

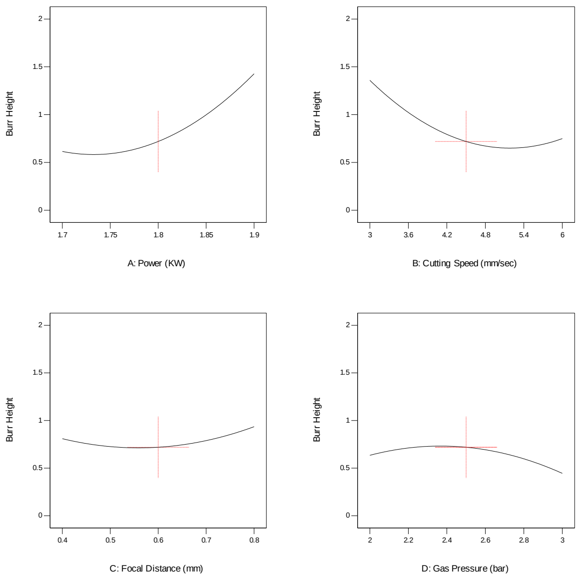

Fig. 4. Effect of Input parameters on burr height.

IV. Test for Adequacy Using ANOVA

The empirical models shown above are s are tested for their adequacy using the ANOVA analysis [9]. It is carried out for both the models which are shown as equations. The statistics of ANOVA for Surface Roughness and Burr height are given in the Tables II and III respectively.

TABLE II. ANOVA Table for Surface Roughness

Source	Sum of Squares	df	Mean Square	F-value	*p*-value Prob > F
Model	80.52	14	5.75	3.82	0.0126
Power (x_1)	17.60	1	17.60	11.70	0.0051
Speed (x_2)	36.64	1	36.64	24.36	0.0003
Focal Distance (x_3)	1.84	1	1.84	1.22	0.2908
Gas Pressure (x_4)	6.30	1	6.30	4.19	0.0632
$x_1 x_2$	1.82	1	1.82	1.21	0.2934
$x_1 x_3$	2.08	1	2.08	1.38	0.2626
$x_1 x_4$	0.92	1	0.92	0.61	0.4485
$x_2 x_3$	3.52	1	3.52	2.34	0.1521
$x_2 x_4$	0.40	1	0.40	0.26	0.6173
$x_3 x_4$	0.033	1	0.033	0.022	0.8855
x_1^2	2.68	1	2.68	1.78	0.2070
x_2^2	0.12	1	0.12	0.079	0.7829
x_3^2	5.04	1	5.04	3.35	0.0922
x_4^2	1.58	1	1.58	1.05	0.3259
Residual	18.05	12	1.50		
Cor Total	98.57	26			
Std. Dev.	1.23			R-Squared	0.8169
Mean	6.26			Adj R-Squared	0.6033

The model's F-value of 3.82 for surface roughness suggests that it is important. The probability that an F-value this great may be the result of noise is merely 1.26 %. "Prob > F" values less than 0.0500 suggest the significance of the model terms. x_1, x_2 are important model terms in this instance. The model terms are not important if the value is bigger than 0.1000. Model reduction could make your model better if it has a large number of unimportant model terms (apart from those needed to maintain hierarchy).

TABLE III. ANOVA Table for Burr Height

Source	Sum of Squares	df	Mean Square	F-value	*p*-value Prob > F
Model	83.72	14	5.98	3.60	0.0081
Power (x_1)	16.67	1	16.67	0.15	0.7014
Speed (x_2)	8.32	1	8.32	1.09	0.3178
Focal Distance (x_3)	7.53	1	7.53	0.98	0.3411
Gas Pressure (x_4)	19.16	1	19.16	2.50	0.1398
$x_1 x_2$	8.13	1	8.13	1.06	0.3233
$x_1 x_3$	4.99	1	4.99	0.65	0.4352
$x_1 x_4$	0.27	1	0.27	0.036	0.8530
$x_2 x_3$	0.57	1	0.57	0.074	0.7897
$x_2 x_4$	5.75	1	5.75	0.75	0.4032
$x_3 x_4$	0.041	1	0.041	5.287E–003	0.9432
x_1^2	3.30	1	3.30	0.43	0.5243
x_2^2	4.41	1	4.41	0.58	0.4624
x_3^2	0.46	1	0.46	0.059	0.8115
x_4^2	0.044	1	0.044	5.807E–003	0.9405
Residual	91.93	12	7.66		
Cor Total	175.66	26			
Std. Dev.	1.23			R-Squared	0.840
Mean	6.26			Adj R-Squared	0.719

From both the ANOVA tables of Surface Roughness and Burr Height, it can observe that the value of "Prob > F" for the models are less than 0.05, which indicates that the models are significant [14]. Hence both the above equations are suitable for further use in the process of optimization [15].

A. *Multiple Regression Coefficient (R^2)*

The multiple Regression Coefficient (R^2) is calculated to see if the fitted models accurately represent the experimental data. The R^2 statistic, which is used to gauge how well a model fits an experimental set of data, is defined as the ratio of variability explained by the model to the total variability in the actual data [12]. The better the model fits the experimental data, the closer R^2 becomes to unity. Stated otherwise, it refers to the percentage of variance in the answer, the dependent variable, that can be accounted for by the factors, or predictors, in the model. R^2 for Surface Roughness is determined to be 0.816 from Table II. This indicates that 81.6% of the variation in Surface Roughness can be explained by the second-order model. Similarly, R^2 for Burr Height is determined to be 0.84 from Table III. This demonstrates that an 84% explanation of the variance in Burr height can be provided by the second-order model.

The goal of the adjusted R^2 is to get a more suitable number for the R^2 estimation. One formula to calculate adjusted R^2 is as follows:

$$1-\frac{[(1-R^2)(N-1)]}{[N-K-1]} \tag{6}$$

where k represents the number of predictors and N is the number of observations [16]. Because the ratio of $(N-1)$ / $(N-K-1)$ will be significantly smaller than 1, there will be a lot larger discrepancy between R^2 and adjusted R^2 when N is small and k is large. In contrast, the ratio of $(N-1)$ / $(N-K-1)$ will approach 1 when the number of observations are more than the number of predictors, meaning that the value of R^2 and adjusted R^2 will be considerably closer.

From Table II, adjusted R^2 for Surface Roughness is found to be 0.6033. It can be observed that the values of R^2 and adjusted R^2 are closer to each other. This means that the developed model can represent the process adequately. From Table III, adjusted R^2 for Burr height is found to be 0.71. It can be observed that R^2 and adjusted R^2 are closer to each other for Surface Roughness and Burr Height. This proves that the developed models [17] can represent the process adequately.

B. *Normal Probability Plots*

The normal probability plot of residuals is to be used to once more assess the validity of the generated mathematical models. To see whether any assumptions are broken and to see if the data are normally distributed, diagnostic plots are created. Thus, Surface Roughness, Burr Height, and the residuals for the responses are displayed using the normal probability plot. Plots of normal probability are used to determine whether data are normally distributed. The statistical process operates under the presumption that there is a normal underlying distribution [14]. Consequently, normal probability plots [18] can either confirm that the assumption is reasonable or flag potential issues with the assumption. Hypothesis tests for normalcy are usually used with normal probability plots in an investigation of normality. If every data point in a normal probability plot is close to the line, then it is plausible to assume that the data is normal [19]. If not, the points will diverge off the line, making it inappropriate to assume normalcy. The normal probability plot of residuals is to be used to once more assess the validity of the generated mathematical models. To see whether any assumptions are broken and to see if the data are normally distributed, diagnostic plots are created. Thus, Surface Roughness, Burr Height, and the residuals for the responses are displayed using the normal probability plot. Plots of normal probability are used to determine whether data are normally distributed. The statistical process operates under the presumption that there is a normal underlying distribution [14]. Consequently, normal probability plots [18] can either confirm that the assumption is reasonable or flag potential issues with the assumption. Hypothesis tests for normalcy are usually used with normal probability plots in an investigation of normality. If every data point in a normal probability plot is close to the line, then it is plausible to assume that the data is normal [19]. If not, the points will diverge off the line, making it inappropriate to assume normalcy.

The normal probability plots of the residuals for the output responses, Surface Roughness and Burr Height are shown in Figs. 5 and 6 respectively. It can be observed that, the residuals are located on straight line, which means that the errors are distributed normally. This represents that the proposed model is satisfactory for the given conditions.

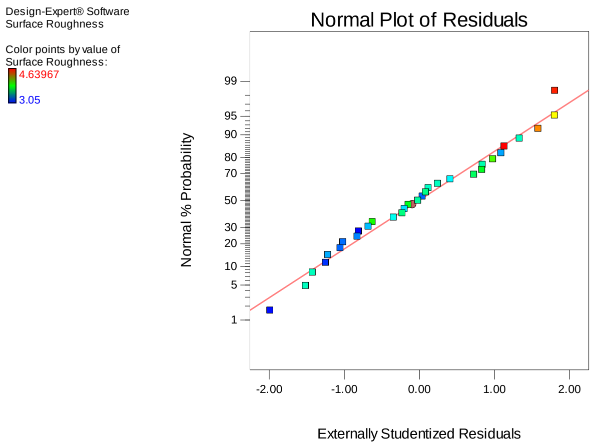

Fig. 5. Normal probability plot of residuals for surface roughness.

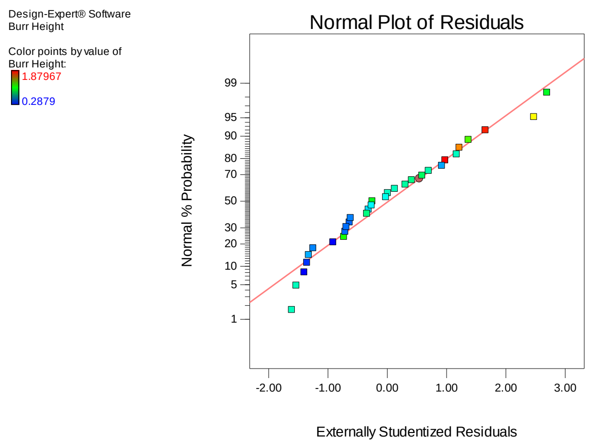

Fig. 6. Normal probability plot of residuals for burr height.

V. Conclusion

In the current research work, Empirical modeling is carried out for the output response of Laser beam cutting process using the Response Surface Method. Experimental data was used to predict the empirical models. Two empirical models are developed one for the Surface roughness and the next one for the burr height. Design Expert software is used successfully to carry out the modeling based on the regression analysis. Also, the empirical models are tested for its adequacy using the ANOVA analysis and also by calculating the multiple regression coefficients. R^2 values are calculated only for the significant equations. R^2 for Surface Roughness is found to be 0.816 means the empirical model can explain the variation in Surface Roughness up to the extent of 81.6%. Similarly, for Burr height, R^2 is found to be 0.84, i.e., the model can explain the variation in Burr height up to the extent of 84%. Overall, the empirical models developed are satisfactory and proved to be significant, which makes them fit to be used for further analysis in the process of optimizing the Laser beam cutting process.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Palleboina Madhava conducted experiments as per the design of experiments; K. Dharma Reddy verified the experimental plan; Palleboina Madhava plotted the two-dimensional plots and developed the empirical models. K. Dharma Reddy verified the empirical models and the regression coefficient values; all authors had approved the final version. All authors had approved the final version.

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