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Original scientific paper

Comparative Regression and Neural Network Modeling of Roughness and Kerf Width in CO_2 Laser Cutting of Aluminium

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Abstract: Laser cutting is the most promising thermal-based unconventional manufacturing process which can cut complex shapes on different materials. Surface roughness and kerf width are the important characteristics that determine the product quality and rely on the rational selection of the input parameters. The present work focuses on comparing surface roughness and the kerf width predicted using regression and artificial neural network model intended for cutting aluminium by CO_2 laser. The independent parameters like laser power, assist gas pressure and cutting speed are varied up to three levels and the proposed Box-Behnken design constitutes 17 experiment runs for data acquisition and further modeling. The coefficient of correlation and the absolute mean error percentage are used for the study and comparison of regression and artificial network models. The artificial neural network has a lower mean absolute percentage error (MAPE) than the regression models. In addition, the *R*-value of the artificial neural network is greater than those of the regression models. The regression modeling methodology has been shown to be inadequate in predicting desired parameters while more reliable results have been obtained with the use of artificial neural network.

Keywords: ANN; kerf width; laser aluminium cutting; regression; surface roughness

1 INTRODUCTION

Laser cutting is nowadays widely used in modern industries because of several advantages like no complex fixtures and jigs to hold the workpiece create complex and accurate shapes on almost all the categories of materials and not cause any mechanical forces. The responses investigated mostly are the roughness and the kerf width which depends on the independent laser cutting parameters like laser power, assist gas pressure and cutting speed. The aim of this work is to perceive the correlation between the independent laser cutting parameters on the dependent kerf width and roughness while CO_2 laser cutting of aluminium. Box-Behnken experimental design with 17 experiments is conducted and feed-forward backpropagation ANN algorithm is used for predicting the roughness and kerf width.

2 LITERATURE REVIEW

Different methodologies are used nowadays to predict the surface quality, such as roughness and kerf width in CO_2 laser cutting. Many researchers employed classical regression modeling and nowadays artificial intelligence techniques are employed for modeling the laser cutting. Ivan Peko et al. [1] analyzed the kerf width of plasma arc machining by ANN. Tamilarasan and Rajamani [2] proposed multi-response optimization method using the desirability approach of Box-Behnken and response surface methodology for minimizing kerf taper during Nd: YAG laser cutting of titanium superalloy sheet. Anamal Hossain et al., [3] used the Mamdani Fuzzy Model to predict kerf width during laser beam machining of PMMA and obtained good results correlating with experimental data. Adalarasan et al. [4], used Taguchi to optimize the roughness and kerf width of the aluminium composite during laser cutting. Arun Kumar Pandey and Avanish Kumar Dubey [5] proposed hybrid neural network with genetic algorithm approach for modeling and optimization of the surface roughness and kerf taper during Nd: YAG laser cutting of titanium alloy sheet. Vinayagamoorthy et al., [6] validated by comparing the central composite model with fuzzy model and obtained only minimal error. Palanisamy Angappan et al., [7] utilized Taguchi and grey relational analysis to develop the regression model and optimize the machining parameters. Anamal Hossain et al., [8], utilized Mamdani Fuzzy Model to predict the kerf width during the laser beam machining of PMMA and obtained good results that were consistent with the experimental values. Rupesh Goyal and Avanish Kumar Dubey [9] developed empirical models and optimized the laser parameters using GA to achieve good geometrical characteristics. Parthiban et al. [10], examined the influence of laser cutting parameters using ANOVA on the upper and lower kerf widths of AISI316L during CO_2 laser cutting and found that the significant parameters can up to by response surface methodology (RSM). Arindam Ghosal and Alakesh Manna [11] developed mathematical model to optimize taper using RSM. A. K. Chaudhary et al. [12], used CATFMO methodology to optimize surface roughness and kerf width. Milos Madic and Miroslav Radovanovic [13] compared artificial neural network with the regression model for cutting mild steel using CO_2 laser. They found that the ANN model could effectively predict the surface quality. Chaki and Ghosal [14] developed simulated annealing hybrid with ANN model for predicting the quality of cut during laser cutting of mild steel plates and concluded that optimization using this hybrid simulated annealing with ANN optimization yields good accuracy. Yang et al. [15] combined Taguchi with ANN model for the prediction of responses in laser cutting and confirmed that the training samples can be reduced by this hybrid approach. Syn et al. [16] utilized fuzzy logic for predicting the dross and surface roughness and found that the fuzzy model exhibits a good correlation with the experimental results. Pandey and Dubey [17] combined Taguchi and fuzzy logic for optimizing kerf quality for cutting duralumin sheet using laser. Milos Madic and Miroslav Radovanovic [18] utilized RCGA (Real coded genetic algorithm) to obtain optimal values of biases and weights in ANN model training to predict the kerf width and surface roughness. They concluded that the implementation of RCGA biases and weights provides reliable ANN training and can predict good results. Arun

K. Pandey & Avanish K. Dubey [19] optimized multiple responses during laser cutting of difficult to cut material (duralumin) using grey-fuzzy methodology. Madić et al., [20] determined optimum laser cutting parameters to minimize perpendicularity using RSM and GA. Although different modeling techniques were used for laser cutting process, a comparative study of different modeling techniques for the prediction of responses is not much available. Hence, an attempt is done for comparing the performances of the regression model with the ANN model to predict the surface roughness and kerf width while CO_2 laser cutting of aluminium 6351.

3 EXPERIMENTAL DETAILS

Experiments are conducted using AMADA LCG3015 and the specification of the laser cutting machine is given in Tab. 1. For the present study, Aluminium 6351 is chosen as the work material as it is used extensively in the aerospace, automotive and food industry.

Table 1 Specification of machine

Model	Amada LCG3015
Laser type	Carbon dioxide (CO_2)
Mode	Continuous Wave (CW)
Power	3500 W
Assist gas	Nitrogen

The sheet dimensions are 350 × 300 mm with thickness of 2 mm. The cutting operation carried out on workpiece with the profile is shown in Fig. 1. The shape of cut on the workpiece allows the measurement of kerf width and roughness in a simple and accurate way.

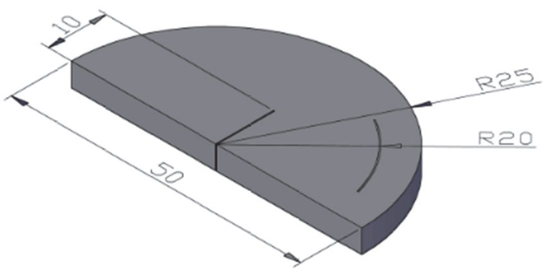

Figure 1 Photo image of the profile (after cut)

Table 2 Specification of surface roughness tester

Equipment Name	Surf test
Make	SJ-210-MITUTOYO
Measuring range	17.5 mm
Measuring speed	0.25-0.75 mm/sec
Cut of length	0.08, 0.25, 0.8, 2.5 mm
Sampling length	0.08, 0.25, 0.8, 2.5 mm
Stylus tip radius	2 µm
Type of indenter	Diamond
Power supply	Battery and AC adapter
Mass	500g

Table 3 Specification of tool makers microscope

Equipment name	Tool makers microscope
Make	BSPIL - MTR-03003
Magnification	2×-30× standard Magnification
Measuring stage	Measuring stage
Eye piece protractor	1° Graduation 360° Rotation 2 minutes least count for vernier
Illumination	6 V-20 W Halogen light

Surf test SJ-210 profilometer is used to measure the average roughness along the cut and the kerf width of the straight cut is measured using tool makers microscope at 15× magnification. The specification of the roughness tester and the tool makers microscope is given in Tabs. 2 and 3.

3.1 Experimental Design

Dubey and Yadava [21] found that DOE approach is used in most laser processing of materials. Pengpeng Qiu et al., [22] found that Box-Behnken design minimizes the number of experiments better than traditional factorial design without decreasing the optimization accuracy. The independent laser cutting parameters like laser power, kW; cutting speed, m/min; assist gas pressure, bar, are varied up to three levels as shown in Tab. 4 and the Box-Behnken design requires 17 experiment runs.

Table 4 Laser cutting parameters and its levels

Parameters	−1 Level	+1 Level
Power / kW	3	3.2
Speed / m/min	5	5.4
Gas Pressure / bar	6	8

The proposed Box-Behnken design and the collected experimental data given in Tab. 5 can further be used for regression and ANN modeling.

Table 5 Box-Behnken design

Exp. No.	Power	Speed	Pressure	Roughness / µm	Kerf width / mm
1	3.2	5.2	8	2.532	0.270
2	3.1	5.2	7	2.674	0.320
3	3.1	5.4	6	2.546	0.286
4	3.2	5.0	7	2.693	0.341
5	3.1	5.2	7	2.704	0.323
6	3.1	5.0	6	2.835	0.360
7	3.2	5.4	7	2.494	0.260
8	3.1	5.2	7	2.711	0.322
9	3.0	5.2	6	2.607	0.284
10	3.1	5.4	8	2.604	0.279
11	3.1	5.2	7	2.693	0.321
12	3.0	5.0	7	2.666	0.315
13	3.0	5.2	8	2.550	0.272
14	3.1	5.2	7	2.656	0.317
15	3.0	5.4	7	2.493	0.282
16	3.2	5.2	6	2.548	0.281
17	3.1	5.0	8	2.711	0.330

4 MATHEMATICAL MODELING

4.1 Regression Modeling

Response surface methodology can be used to evaluate the effect of independent variables on the responses. Mathematical models, relating to the responses and their factors are generated for facilitating the optimization. The mathematical or the regression model for the responses Y can be represented as

$$Y = \psi(P, S, p) + \varepsilon \tag{1}$$

where P is laser beam power, S is cutting speed and p is assist gas pressure and ε is error, which is distributed normally about the observed machining response Y.

Let $\psi(P, S, p) = \eta$ (2)

η is called the response surface and represents the surface. The second-order polynomial model i.e the quadratic model is given by

$$Y_u = b_0 + \sum_{i=1}^{n} b_i x_{iu} + \sum_{i<j}^{n} b_{ij} x_{iu} x_{ju} + \sum_{i=j}^{n} b_{ii} x_{ju}^2 \quad (3)$$

where Y_u is the proposed expected response on higher-order polynomial; x_i represents process variables like laser power, cutting speed and assist gas pressure respectively and b represents the regression coefficients which are to be obtained by multiple regression analysis.

Table 6 Comparison of experimental and regression predicted roughness and kerf width

Exp. No.	Experimental		Regression Predicted		Absolute error Percentage	
	Roughness (*Ra*)	Kerf width	Roughness (*Ra*)	Kerf width	Roughness (*Ra*)	Kerf width
1	2.532	0.270	2.546	0.269	0.546	0.224
2	2.674	0.320	2.687	0.321	0.502	0.194
3	2.546	0.286	2.550	0.286	0.145	0.123
4	2.693	0.341	2.683	0.341	0.382	0.079
5	2.704	0.323	2.687	0.321	0.613	0.737
6	2.835	0.360	2.833	0.357	0.080	0.863
7	2.494	0.260	2.478	0.258	0.654	0.953
8	2.711	0.322	2.687	0.321	0.869	0.428
9	2.607	0.284	2.593	0.285	0.543	0.227
10	2.604	0.279	2.606	0.282	0.074	1.128
11	2.693	0.321	2.687	0.321	0.207	0.118
12	2.666	0.315	2.682	0.318	0.599	0.800
13	2.550	0.272	2.538	0.269	0.487	1.049
14	2.656	0.317	2.687	0.321	1.183	1.142
15	2.493	0.282	2.503	0.282	0.399	0.081
16	2.548	0.281	2.560	0.284	0.474	1.031
17	2.711	0.330	2.707	0.330	0.149	0.120

Design expert software was used to establish second-order response surface equations for roughness and kerf width.

The square values of the regression coefficient are 0.975 and 0.994 respectively, which indicated high association of the regression coefficients with variances in the predictor values. The adjusted square values of the regression coefficients are 0.943 and 0.987. This indicated variance is high, making the models stronger. The p-value from analysis of variance (ANOVA) for roughness and kerf width is less than 0.0001 which confirms the accuracy of the mathematical model.

The equations in terms of the actual factors of the independent variables for roughness and kerf width were:

$$\begin{aligned} Roughness = & -89.34170 + 67.82475 \cdot Power - \\ & -2.83950 \cdot Speed - 1.23218 \cdot Pressure - \\ & -0.32500 \cdot Power \cdot Speed + 0.10250 \cdot Power \cdot Pressure + \\ & +0.22750 \cdot Speed \cdot Pressure - 10.79250 \cdot Power^2 + \\ & +0.17062 \times Speed^2 - 0.020425 \times Pressure^2 \end{aligned} \quad (4)$$

$$\begin{aligned} Kerf\ width = & -30.68558 + 21.11225 \cdot Power - \\ & -0.55762 \cdot Speed + 0.04245 \cdot Pressure - 0.6 \cdot Power \cdot Speed + \\ & +2.5E-003 \cdot Power \cdot Pressure + 0.02875 \cdot Speed \cdot Pressure - \\ & -2.90500 \cdot Power^2 + 0.19875 \cdot Speed^2 - \\ & -0.014800 \cdot Pressure^2 \end{aligned} \quad (5)$$

In order to verify if a developed regression polynomial still predicts the response of a system well enough, the adequacy test is carried out. The predicted dimensional deviation values were obtained using Eq. (4) and Eq. (5) compared with the measured values and percentage of error for each experiment is given in Tab. 6. It is evident that in most cases, the error in prediction is smaller than 10%. The average error observed was 0.465% and 0.547%.

4.2 Artificial Neural Network Model

Artificial neural network (ANN) also called neural network mimics a biological nervous system in which the neural network can be trained by varying the weights between the neurons to perform a particular function. The output and the target are compared and the network is adjusted until the target matches the network output. Matlab Neural Network Toolbox was used to model the neural network structure. The considered neural network model consists of three input neurons in the input layer (laser power, speed and gas pressure) one hidden layer with ten neurons and two output neuron in the output layer (roughness and kerf width) as shown in Fig. 2. Out of 17 experimental data, the training and testing samples taken are 12 and 5 respectively based on the ratio of 70% : 30%. The network is trained using a feed forward backpropagation algorithm by assigning random weights and biases to the interconnected neurons. The feed-forward backpropagation algorithm is a gradient descent method in which the weights are varied until the mean squared error between network target values and training values converges until the network output matches the target. Then the testing data can be fed to the trained network for predicting the output.

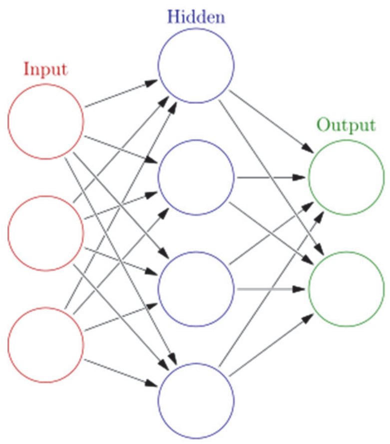

Figure 2 ANN Model

The hidden and the output layer utilizes logsig and tansig activation function to map the roughness and kerf width values. The training and the learning function are traingdx and learngd. The performance of the developed network is examined by mean squared error and the correlation coefficient (R). The mean squared error must be less and the correlation coefficient which is a measure of the closeness between the output and the target values must be closer to 1. The mean squared error was $2.8622e^{-5}$ and the value of R was 0.9995 as shown in Figs. 3 and 4 indicating that the experimental data and model predicted values are in good correlation.

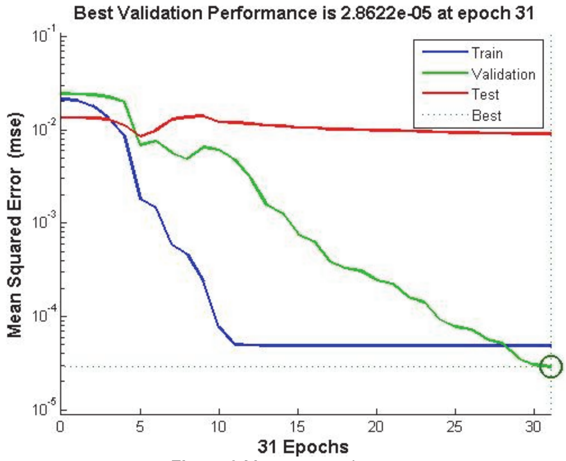

Figure 3 Mean squared error

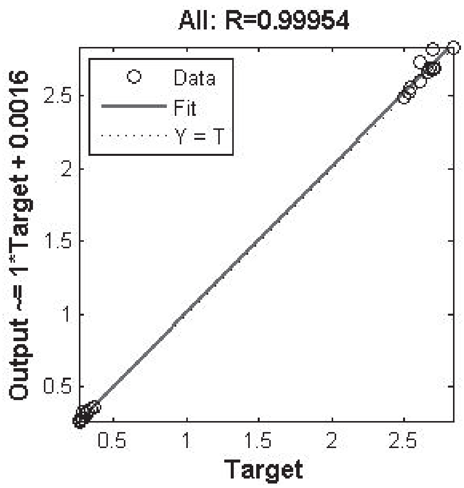

Figure 4 Correlation coefficient (R)

Table 7 Comparison of experimental and ANN predicted roughness and kerf width

Exp. No.	Experimental		ANN Predicted		Absolute error Percentage	
	Roughness (Ra)	Kerf width	Roughness (Ra)	Kerf width	Roughness (Ra)	Kerf width
1	2.532	0.270	2.532	0.270	0.000	0.000
2	2.674	0.320	2.696	0.322	0.834	0.522
3	2.546	0.286	2.556	0.284	0.393	0.577
4	2.693	0.341	2.826	0.344	4.935	0.771
5	2.704	0.323	2.696	0.322	0.285	0.412
6	2.835	0.360	2.835	0.360	0.004	0.031
7	2.494	0.260	2.494	0.260	0.004	0.054
8	2.711	0.322	2.696	0.322	0.542	0.102
9	2.607	0.284	2.673	0.293	2.549	3.275
10	2.604	0.279	2.604	0.279	0.000	0.000
11	2.693	0.321	2.696	0.322	0.123	0.209
12	2.666	0.315	2.666	0.315	0.000	0.000
13	2.550	0.272	2.515	0.264	1.376	3.125
14	2.656	0.317	2.676	0.322	0.764	1.473
15	2.493	0.282	2.526	0.289	1.336	2.525
16	2.548	0.281	2.612	0.287	2.524	2.146
17	2.711	0.330	2.756	0.336	1.675	1.825

The ANN predicted values are compared with the measured values and the percentage of error for each experiment is given in Tab. 7. It is evident that in most cases, the error in prediction is smaller than 10%. The average error observed was 1.020% and 1.003%.

5 CONCLUSION

In this work, an attempt has been made to develop and compare the mathematical models of roughness and kerf width during CO_2 laser cutting of aluminium using regression and ANN. The conclusions are:

- Both the regression and ANN model provide accurate results for the prediction of roughness and kerf width.
- The time taken and effort is found to be less for the regression model when compared with the ANN model.
- The average absolute percentage of error for roughness and kerf width for regression is 0.465% and 0.547% whereas for ANN it is 1.020% and 1.003%
- The coefficient of correlation for roughness and kerf width using regression is 0.975 and 0.994 whereas using ANN the co-efficient of correlation of roughness and kerf width is 0.9995.
- Based on the statistical performance criteria i.e., average absolute error percentage and the coefficient of correlation indicate that the ANN model showed the best prediction results and can be used for the prediction of surface roughness and kerf width during CO_2 laser cutting of aluminium.
- Using the RSM and ANN model, the value of the surface roughness and kerf width can be predicted for a given set of laser input parameters. This will help the laser industries in setting the machining parameters for a particular machining condition. Hence, the outcome of the model developed will facilitate the setting of laser machining parameters to accomplish the objective.

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