Response Surface Method and Neural Network to Determine Surface Roughness for Laser Cutting on Acrylic Sheets

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Abstract
This paper presents the use of response surface method (RSM) and neural network to study surface roughness for laser beam cutting on acrylic sheets. Box-Behnken design based on response surface method and multilayer perceptions neural network were used to predict the effect of laser cutting parameters. These parameters include power requirement, cutting speed and tips distance on surface roughness during the machining of acrylic sheets. It is found out that the predictive models are able to predict the longitudinal component of the surface roughness close to those readings recorded experimentally with a 95% confident interval. The result obtained from the predictive model was also compared using multilayer perceptions with back–propagation learning rule artificial neural network. The first order equation revealed that power requirement was the dominant factor which was followed by tip distance, and cutting speed. The cutting parameter predicted by using neural network was in good agreement with that obtained by RSM. This observation indicates the potential of using response surface method in predicting cutting parameters thus eliminating the need for exhaustive cutting experiments to obtain the optimum cutting condition to enhance the surface roughness.

1. INTRODUCTION

Laser light differs from ordinary light due to it has the photons of same frequency, wavelength and phase. Thus, unlike ordinary light laser beams are high directional, have high power density and better focusing characteristics [1,2]. These unique characteristics of laser beam are useful in processing of materials. The laser beams are widely used for machining and other manufacturing processes such as cutting, drilling, micromachining, marking, welding, sintering and heat treatment. Lear beam machining (LBM) is a thermal energy based advanced machining process in which the material is removed by melting, vaporization and chemical degradation. When a high energy density laser beam is focused on work surface the thermal energy is absorbed which heats and transforms the work volume into a molten, vaporized and chemically changed state that can be easily be removed by flow of high pressure assist gas. LBM can be applied to a wide range of materials such as metals and non-metals. Laser surface texturing may be an ideal technology for applications in mechanical face seal, as well as in various components in engine such as piston ring and cylinder and thrust bearings, involving creation of an array of micro dimples or channels artificially distributed on the mating surface with a pulsed laser beam [3,4]. The most widely used lasers for sheet cutting are continuous wave (CW), CO_2 and pulsed Nd:YAG [5]. Pulsed Nd:YAG laser cutting becomes an excellent cutting process because of high laser beam intensity, low mean beam power, good focusing characteristics, and narrow heat affected zone (HAZ) [6,7]. Processing regimes for pulsed laser cutting can be established based on pulse energy and cutting speed for a given material–thickness combination [8]. Study have found that the laser-assisted turning (LAT) of silicon nitride ceramics economically reduces the surface roughness and tool wear in comparison to only conventional turning process. The study reveals that low pulse frequencies and high peak powers were found to be favourable for higher cutting speeds [9].

In any manufacturing process it is always desired to know that the effect of variation of input parameters on process performance in order to achieve the goal of better product quality. LBM being a non-conventional machining process requires high intensity and offers poor efficiency. Therefore, high attention is required for better utilization of resources. The values of process parameters are determined to yield the desired product quality and also to maximize the process performance. In LBM, there are various variables including beam power, cutting speed and tips distance which affect the surface roughness. Surface roughness value reduces on increasing cutting speed and frequency, and decreasing the laser power and gas pressure. In addition, nitrogen gives better surface finish than oxygen [10]. The laser power and cutting speed has a major effect on surface roughness as well as striation frequency [11]. Artificial Neural Networks (ANNs) are excellent tools for complex manufacturing processes that have many variables and complex interactions. Neural networks have provided means of excellent controlling of complex processes [12]. In the past, many researchers have reported the application of neural network models in monitoring tool condition and predicting the tool wear and tool life. An exclusive review of the current literature has been presented [13].

Researchers have used neural networks to predict surface roughness in milling operations by including machining parameters such as spindle speed, feed, depth of cut, and vibration ‘‘intensity’’ per revolution [14]. Their neural networks have been executed in real time. For the same purpose, hybrid techniques (neural networks combined with fuzzy logic) have been employed by the same authors [15].

The aim of this work is to present and discuss about the experimental investigations using response surface method and Neural Network (NN) and acrylic sheets in order to predict the significant factors and their effects on quality characteristics for better cutting performance and showing the effect relationship between process variables and performance characteristics.

2. RESPONSE SURFACE METHOD

Response surface method is a collection of statistical and mathematical methods that are useful for the modelling and optimization of the engineering problems. In this technique, the main objective is to optimize the responses that are influencing by various parameters. RSM also quantifies the relationship between the controllable parameters and the obtained response. In modelling of the manufacturing processes using RSM, the sufficient data is collected through designed experimentation. In general, a second order regression model is developed because of first order models often give lack-off fit [16]. The study uses the Box-Behnken design in the optimization of experiments using RSM to understand the effect of important parameters. Box-Behnken design is normally used when performing non-sequential experiments. That is, performing the experiment only once. These designs allow efficient estimation of the first and second – order coefficients. Because Box-Behnken design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box-Behnken design does not have axial points, thus we can be sure that all design points fall within the safe operating. Box-Behnken design also ensures that all factors are never set at their high levels simultaneously [17-19].

3. MULTILAYER PERCEPTIONS NEURAL NETWORK

In the current application, the objective is to use the supervised network with multilayer perceptions and train with the back-propagation algorithm (with momentum). The components of the input pattern consist of the control variables used in the machining operation (the cutting speed, power requirement and tip distance), whereas the components of the output pattern represent the responses from sensors (surface roughness). During the training process, initially all patterns in the training set were presented to the network and the corresponding error parameter (sum of squared errors over the neurons in the output layer) was found for each of them. Then the pattern with the maximum error was found which was used for changing the synaptic weights. Once the weights were changed, all the training patterns were again fed to the network and the pattern with the maximum error was then found. This process was continued till the maximum error in the training set became less than the allowable error specified by the user. This method has the advantage of avoiding a large number of computations, as only the pattern with the maximum error was used for changing the weights. Fig.1 shows the neural network computational mode with 3-7-1 structure. There were 45 data had been used to train the neural network.

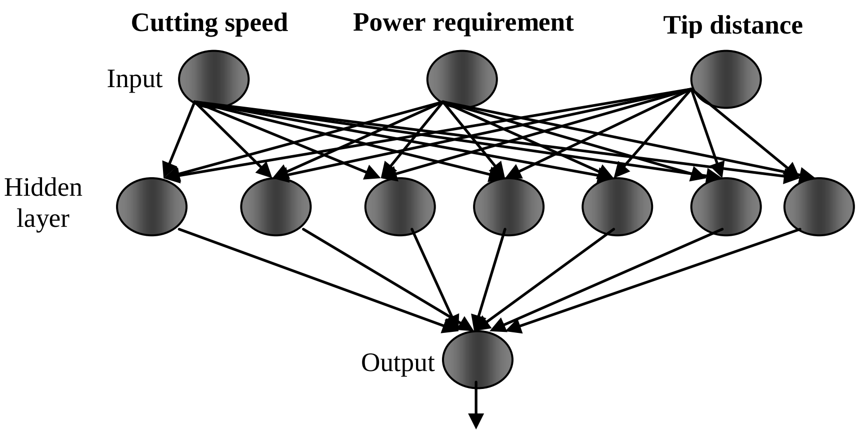

Figure 1: Neural network with 3-7-1 structure

4. EXPERIMENTAL SET-UP

The experiment was performed on a 30W pulsed CO_2 laser beam system with CNC work table. The oxygen is used as an assist gas. The variable process parameters taken are: beam power, cutting speed and tip distance. Focal length of the lens used is 50 mm, nozzle diameter 1.0 mm and nozzle tips distance 1.0 mm, were kept constant throughout the experiments. The fifteen experiments were carried out using the laser machine, which is shown in Fig. 2. Acrylic sheet of thickness 3.0 mm, 30.0 mm width and 40.0 mm long was taken as specimen. Acrylic sheet was cut into rectangular size to measure the surface roughness. The dimension of acrylic sheet specimen is shown in Fig 3. Four sides were measure to get the average roughness. Surface roughness tester was used to measurement of roughness. The material properties of the work piece are listed in Table 1. After the preliminary investigation, the suitable levels of the factors are used in the statistical software to deduce the design parameters for acrylic sheets, which is also listed in Table 2.The 15 experiments were repeated for 3 times to get accurate results. The lower and higher speed values were selected of 700 pulses/s and 1100 pulses/s respectively. The higher and lower value of power requirement of 95% and 90% are considered. The range of tip distance is 3 mm to 9 mm.

Fig. 2: Laser machine

Table 1: Material properties of specimen

Properties	Value	Unit
Density	1170	kg/m^3
Yield Tensile Strength	52.1	MPa
Processing temperature	156	°C
Modulus of elasticity	2.31	GPa

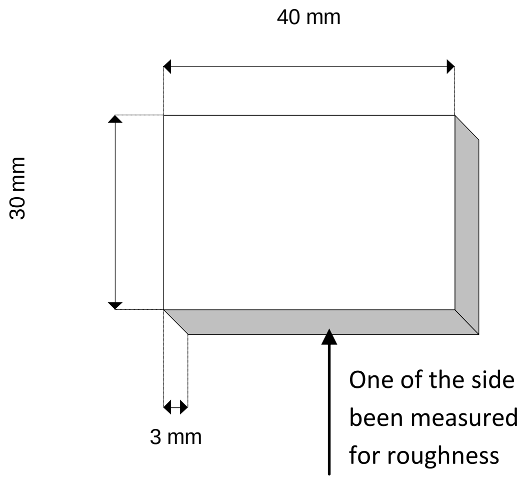

Fig 3: Dimensions of the specimen

Table 2: Level of design variables

Design Variables	Coding of levels		
	lowest	**middle**	**highest**
Power requirement (%)	90	92.5	95
Cutting speed (pulse/s)	700	900	1100
Tip distance (mm)	3	6	9

5. RESULTS AND DISCUSSION

After conducting the 15 cutting experiments, the surface roughness readings are used to predict the parameters appear in the postulated first model, which are expressed as Eq. (1). In order to calculate these parameters, the least square method was used to determine these parameters with the help of statistical software. The first linear and quadratic equation used to predict the surface roughness, which is expressed as Eq. (1).

$$Ra^{(1)} = -0.7059 + 0.0124\,\mathrm{Pr} - 0.0000265 C_{speed} + 0.016 GD \tag{1}$$

where *Ra* is surface roughness, Pr is the power requirement, C_{speed} is cutting speed and *TD* is the tip distance.

From this linear equation, one can easily notice that the response surface roughness is affected significantly by the power requirement, followed by tip distance and cutting speed. Eq. (1) shows that combination of high power and tip distance produce a rough surface. On other hand, high cutting speed produces a very smooth surface. Similar to the first-order model, by examining the coefficients of the first-order terms, the tip distance (*TD*) has the most dominant effect on the surface roughness. The contribution of power requirement (Pr) is the least significant. Also, owing to the P-value of interaction is 0.092 (>0.05), one can easily deduce that the interactions of distinct design variables are not significant. In other words, the most dominant design variables *TD* and Pr have the minimum interaction with others in the current context. As seen from Fig. 4 and Table 3, the predicted surface roughness using the second order RSM model is able to produce values close to those with experimental, and, as it should be the case, it exhibits better agreement as compared to those from the first-order RSM model. The ANOVA analysis shown in Tables 4 and 5, those indicate that the model is adequate as the P-value of the lack-of-fit is not significant (> 0.05).

Table 3: RSM models prediction for surface roughness

No. Exp	Power requirement (%)	Cutting speed (pulse/s)	Tip distance (mm)	Surface roughness (µm)	1st order-RSM	NN prediction for surface roughness
1	90	900	9	0.826	0.543	0.826
2	95	900	9	0.23	0.605	0.230
3	90	1100	6	0.241	0.488	0.241
4	92.5	900	6	0.423	0.526	0.539
5	95	700	6	0.525	0.564	0.525
6	90	900	3	0.277	0.447	0.277
7	92.5	900	6	0.794	0.526	0.539
8	92.5	700	9	0.398	0.581	0.398
9	92.5	700	3	0.496	0.484	0.496
10	92.5	1100	3	0.291	0.471	0.291
11	90	700	6	0.852	0.502	0.852
12	95	900	3	0.451	0.509	0.451
13	95	1100	6	1.238	0.55	1.238
14	92.5	900	6	0.399	0.526	0.539
15	92.5	1100	9	0.448	0.568	0.448

Table 4: Analysis of variance (ANOVA) for first-order equation

Source of variation	Degree of freedom	Sum of squares	Mean squares	*F*-ratio	*P*-value
Regression	3	0.02676	0.00892	0.09	0.964
Linear	3	0.02676	0.00892	0.09	0.964
Residual Error	11	1.09008	0.099098		
Lack-of-Fit	9	0.992	0.110222	2.25	0.346
Pure Error	2	0.09808	0.04904		
Total	14	1.11684			

6. COMPARISON BETWEEN TWO TECHNIQUES

After determining the surface response method equations of all the response variables and also neural network program, the prediction by both techniques was compared. The prediction from the neural network was compared with the prediction from the model developed by response surface method (RSM). Fig.4 shows the comparison between the predicted values for surface roughness obtained by neural network (NN) and experimental data. Both the values are in close agreement with each other. Fig.5 shows the error percentage by neural network and response surface method. From these figures it is clear that the response surface method is quite close to the prediction value of the neural network. Neural network predicted more accurate compared with RSM. The error for both techniques can be accepted and the model of the response surface method can be accepted. Fig. 6 shows the MSE (mean square error) of the neural network for predicting surface roughness.

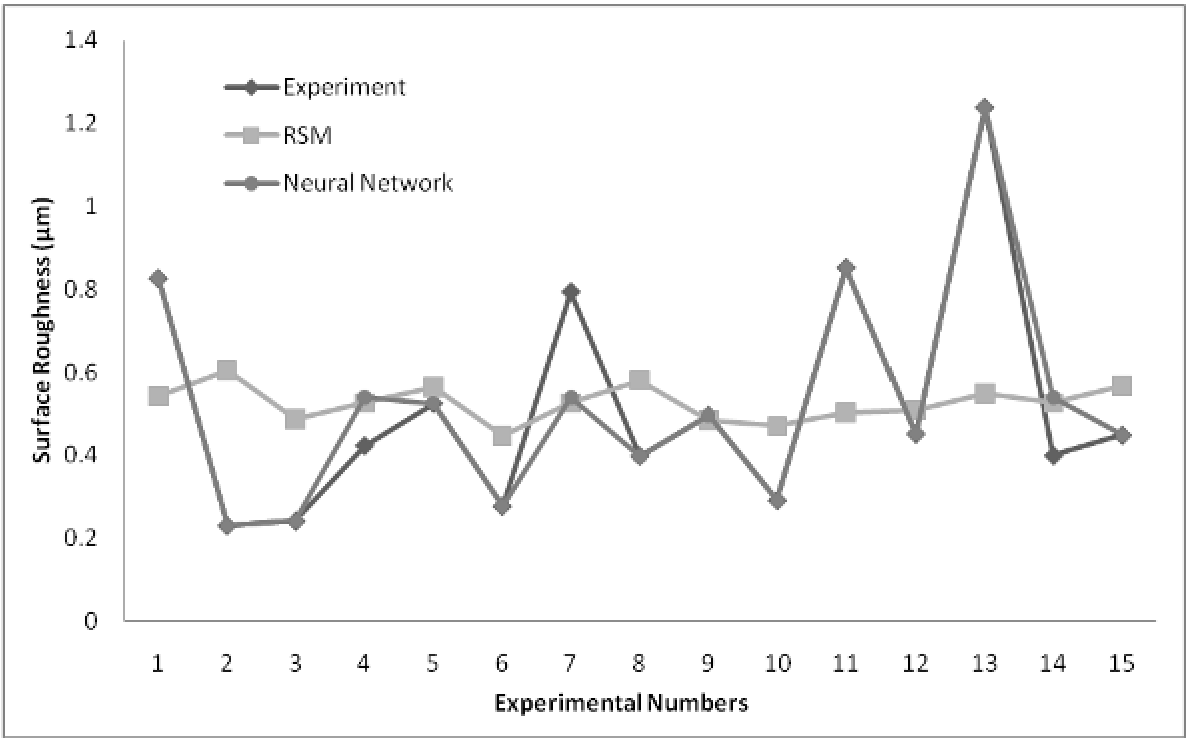

Fig.4: Comparison of RSM models against experimental values

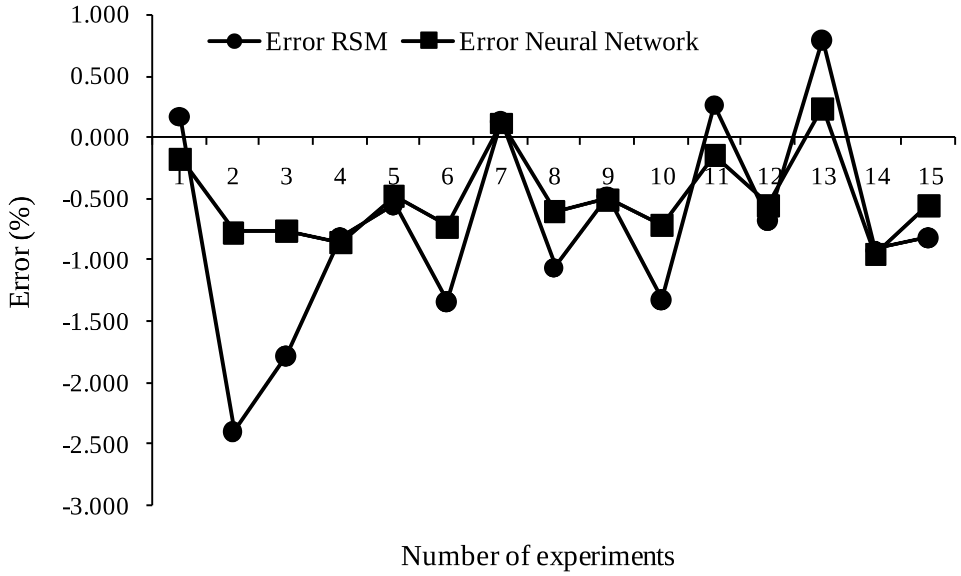

Fig.5: Error percentage by neural network and response surface method

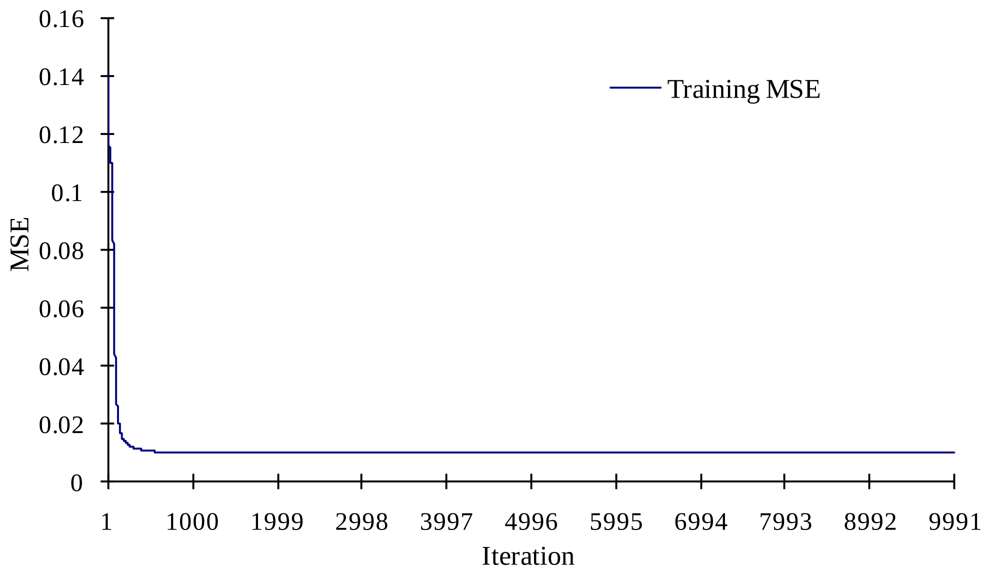

Fig.6: MSE (mean square error) of the neural network (NN) for predicting surface roughness

7. CONCLUSIONS

In the current work, the response surface methodology and neural network have been proven to be a successful technique to perform the trend analysis of surface roughness with respect to various combinations of three design variables. By using the least square method, the first-order models have been developed based on the test conditions in accordance with the Box–Behnken design method. The models have been found to accurately representing the surface roughness values with respect to those experiment values. The equations have been checked for their adequacy with a confidence interval of 95%. Both models reveal that the power requirement and tip distance is the most significant design variable in determining the surface roughness response as compared to the others. In general, within the working range of the power requirement and tip distance considered, the surface roughness increases as the both variables increases. The models have been found to be accurately representing surface roughness values with respect to experimental results. Both RSM and neural network models reveal that power requirement is the most significant design variable in determining surface roughness response as compared to other parameters. With the model equations obtained, a designer can subsequently select the best combination of design variables for achieving optimum surface roughness. This eventually will reduce the machining time and save the cutting tools.

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