International Conference on Recent Advances in Materials, Minerals & Environment
(RAMM'09), 1~3 Jun, Bayview Beach Resort, Batu Ferringhi, Penang, Malaysia,
ISBN 978-983-3986-57-6, 2009.

Artificial Intelligent Model to Predict Surface Roughness in Laser Machining

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Abstract

Light Amplification Stimulation Emission of Radiation or the common name is Laser. The laser light differs from ordinary light due to it has the photons of same frequency, wavelength and phase. Advantages of using laser beam cutting (LBC) are materials with complex figures can easily be cut by incorporating computer numerical control (CNC) motion equipment, LBC has high cutting speed, Low distortion, very high edge quality and most important thing is LBC has a minimal heat affected zone (HAZ).This paper discussed the development of Radian Basis Function Network (RBFN) to predict surface roughness when laser cutting acrylic sheet. The main objectives of this paper are to find the optimum laser parameters (power, material thickness, tip distance and laser speed) and the effect of these parameters on surface roughness. The network was trained until it predict closer to the experimental values. It observed that some of good surface roughness specimen fail in terms of structure when investigate under microscope.

KEYWORDS: laser beam cutting, Radian Basis Function Network (RBFN), surface roughness, Power requirement

1. Introduction

Unlike ordinary light laser beams are high directional, have high power density and better focusing characteristics [1, 2, 3]. 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. Several authors [4, 5, 6, 7, 8] reporting on laser cutting of polymeric materials, have shown that the processing parameters have an essential role on the quality of the surface obtained. Caiazzo et al. [9] investigated the CO_2 laser cutting of polymeric materials, specifically applied to polyethylene (PE), polypropylene (PP) and polycarbonate (PC) in order to provide potential future industrial users of this technology with exhaustive information on optimum power levels and cutting velocities as well of the quality of the surfaces. According these authors the laser cutting workability of the three polymers under investigation is as follow: PC high, PP high/medium and PE lower. Devim et al.

[10] conclude that CO_2 laser cutting of polymers/composites is widely used on industrial applications.

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 [11,12]. 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) [13, 14]. Lei et al. [15] 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.

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 tip distance which affect the surface roughness. Surface roughness value reduces on increasing cutting speed and frequency, and decreasing the laser power and gas pressure. Also nitrogen gives better surface finish than oxygen [16]. The laser power and cutting speed has a major effect on surface roughness as well as striation frequency [17]. The aim of this work is to present and discuss about the experimental investigations using response surface method 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.

Recently, artificial neural networks and neuro-fuzzy techniques have been intensively studied and are the most frequently chosen methods of Artificial Intelligence (AI) for feature fusion [18 - 21]. 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 [22]. 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 by Dan and Mathew [23].

A neural network is an adaptable system that can learn relationships through repeated presentation of data and is capable of creating a new, previously unseen data. Some networks are supervised, in that a human determines what the network must learn from the data. In this case, where the network is provided with a set of inputs and the corresponding desired outputs, the network tries to learn the input-output relationship by adapting its free parameters. Other networks are unsupervised, i.e. the information is hard-coded into their respective architectures [24].

Koren et al. [25] have proposed a model-based approach to sense tool wear and breakage. Algorithms and on-line training of the model-based approach by using artificial intelligence methods have been suggested by Koren et al. [25]. Tarng and Lee [26] have proposed the use of average and median force of each tooth in the milling operation. Measured by sensors, the average and median forces of each tooth have been used as input values. An appropriate threshold has been subsequently built to analyse information and detect the tool conditions.

Ko et al. [27] have introduced an unsupervised, self-organised neural network combined with an adaptive time-series AR modelling algorithm to monitor tool breakage in milling operations. The machining parameters and average peak force have been used to build the AR model and neural network. Lee and Lee [28] have used a neural network-based approach to show that by using the force ratio, flank wear can be predicted within 8% to 11.9% error and by using force increment, the prediction error can be kept within 10.3% of the actual wear. Choudhury et al. [29] have used an optical fibre to sense the dimensional changes of the work-piece and correlated it to the tool wear using a neural network approach. Dimla and Lister [30] have acquired the data of cutting force, vibration and measured wear during turning and a neural network has been trained to distinguish the tool state.

Tsai Yu-Hsuan et al. [31] 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. 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 [32]. Similarly, fuzzy Petri nets have been used in the same context [33]. Acoustic emission data during machining have been taken into account in [34] along with a self-organising network for real-time estimation of surface roughness. The dynamic characteristics and chattering have been considered to be the most important factor for poor surface quality and reduced tool life [35]. The effect of learning parameters and rules on a neural network's ability to generalise has been examined in [36] in the context of milling 4140 steel and monitoring signals of spindle vibration, cutting force and machining.

The focus of the paper is to develop surface roughness prediction model using RBFN when machining with CO_2 laser beam.

2. Response Surface Method and RBFN

The 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 do 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 [37 - 39].

Genetic Algorithm (GA) was used to find the optimum weight, momentum and step size to be used in RBFN. Later the optimum weight will be fed to the RBFN. Then, train the network until the R.M.S.E reaches a satisfactory value. The training data acquired from Response Surface

Method to RBFN mode, and the epoch number is 10,000 [40]. After 1,000 iterations, the RBFN is better enough to produce acceptable results. Transfer function used as sigmoid, while for the momentum used is 0.5.

3. Experimental Setup

This study was carryout by the experiment using a 30W pulsed CO_2 laser beam system control by CNC. Design of Experiments (DOE) has been carried out to minimise the number of experiments. The variable process parameters taken are laser beam power, laser cutting speed and laser tip distance. Focal length of the lens used is 50 mm, nozzle diameter 1.0 mm and nozzle tip distance 1.0 mm, were kept constant throughout the experiments. The fifteen experiments were carried out using the laser machine, which is shown in Figure 1. 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 Figure 2. Four sides were measure to get the average roughness. Surface roughness tester Perthometer S2 was used to measurement of roughness. The material properties of the workpiece 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 lower and higher speed values were selected of 700 pulse/s and 1100 pulse/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.

Figure 1: Laser machine

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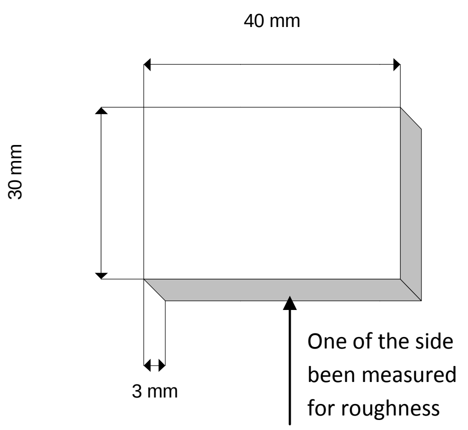

Figure 2: Dimension of the specimen

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

Table 2: Level of design variables

Design Variables	Coding of levels		
	1(lowest)	0(middle)	1(highest)
Power requirement (%)	90	92.5	95
Cutting speed (pulse/s)	700	900	1100
Tip distance (mm)	3	6	9

Results and Discussion

From the experiment result, the surface roughness readings are used to predict the parameters appear in the postulated first and second-order model, which is expressed as Eq. (1) and Eq. (2) respectively. In order to calculate these parameters, the least square method was used to determine these parameters with the help of statistical software. The first and second-order linear and quadratic equation used to predict the surface roughness, which is expressed as Eq. (1) and Eq. (2).

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

$$Ra^{(2)} = 152.618 - 3.23\,\mathrm{Pr} - 0.050 C_{speed} + 2.62 GD + 0.017\,\mathrm{Pr}^2 - 0.022 GD^2 + 0.00053\,\mathrm{Pr}\, C_{speed} - 0.023\,\mathrm{Pr}\, GD \quad (2)$$

where *Ra* is surface roughness, Pr is the power requirement, C_{speed} is cutting speed and *GD* 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 (*GD*) 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 *GD* and Pr have the minimum interaction with others in the current context. As seen from Figure 3 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). Figure 3 shows the comparison of error from the prediction technique. RBFN shows the strong agreement with experimental values. The comparison between the experimental and prediction technique is shown in Figure 4. It is observed that the accuracy of the RBFNN method was slightly superior when compared to the experimental and RSM results on account of Mean Average Error (MAE). Figure 5 show some of the good surface roughness range from 0.2 ~ 0.3μm contain very high burning area when investigate under microscope. These burning areas will reduce the strength of the structure.

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			

Table 5: Analysis of variance (ANOVA) for second-order equation

Source of variation	**Degree of freedom**	**Sum of squares**	**Mean squares**	***F*-ratio**	***P*-value**
Regression	9	0.8524	0.094711	1.79	0.27
Linear	3	0.02676	0.00892	0.17	0.913
Square	3	0.22292	0.074306	1.4	0.344
Interaction	3	0.60273	0.200908	3.8	0.092
Residual Error	5	0.26444	0.052888		
Lack-of-Fit	3	0.16636	0.055453	1.13	0.501
Pure Error	2	0.09808	0.04904		
Total	14	1.11684			

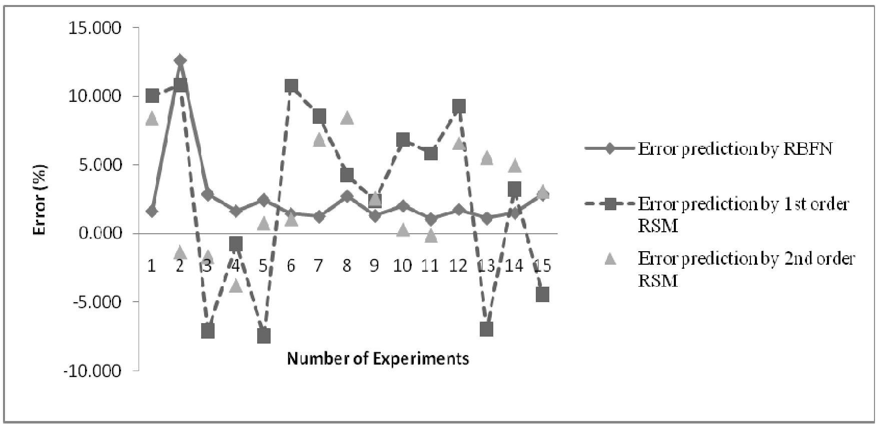

Figure 3: Comparison of error by RBFN, 1st and 2nd order by RSM.

ISBN 978-983-3986-57-6, 2009.

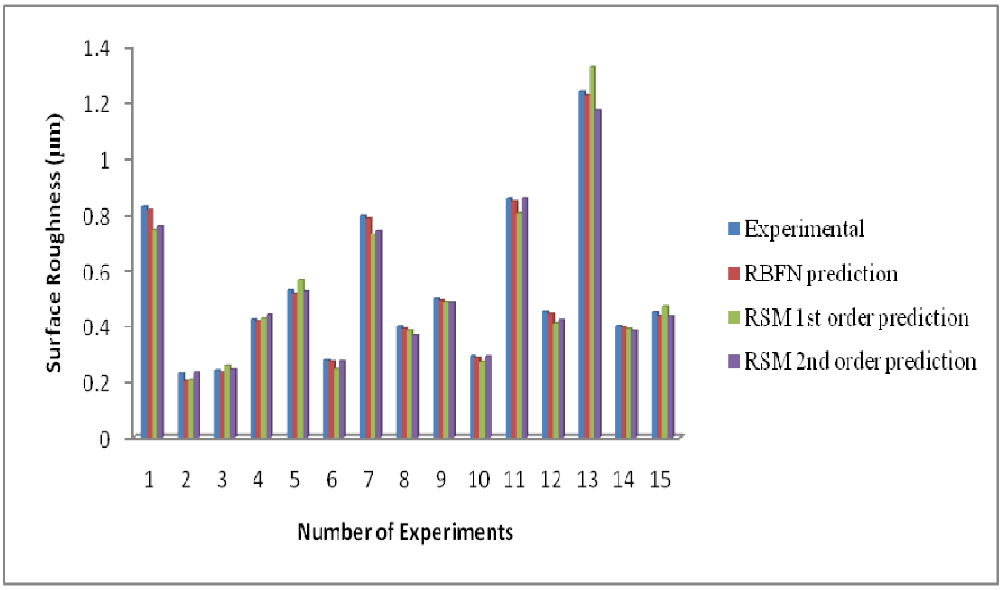

Figure 4: Comparison of experiment and prediction by RBFN, 1st and 2nd order by RSM

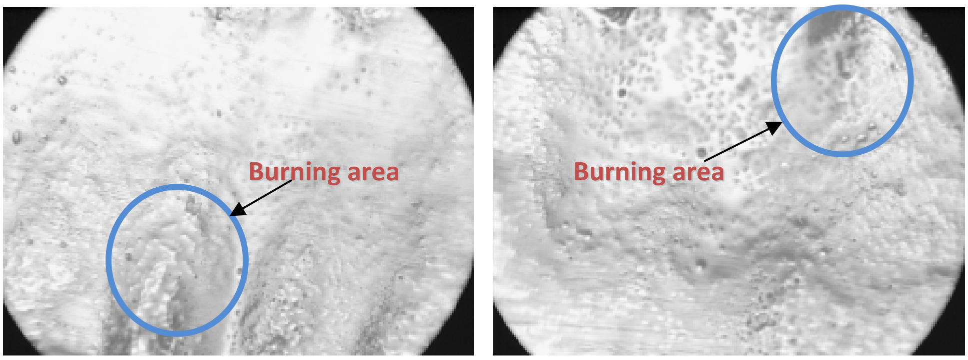

Figure 5: Burning area

Conclusion

RBFN has been found to be the most successful technique to perform trend analysis of surface roughness with respect to various combinations of four cutting parameters (cutting speed, power requirement and tip distance). The models have been found to accurately representing surface roughness values with respect to experimental results. Both RSM and RBFN model reveal that power requirement is the most significant design variable in determining surface roughness response as compared to others. 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.

Acknowledgment

The authors would like to express their deep gratitude to Universiti Malaysia Pahang (UMP) for provided the laboratory facilities and financial support.

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