Laser Cutting Quality Control of Melamine Using Artificial Neural Networks

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Abstract - *Experimental analysis has been carried out to seek the optimum combination (cutting speed, laser power, assist pressure of air and standoff distance) of input controllable variables in the process of laser cutting in order to improve the laser cutting quality on non-metallic such as Urea formaldehyde (Melamine). Furthermore, the values of edge quality, kerf widths, percent overcut and material removal rate were measured for calculating quality. Taguchi method was used in experimental design using orthogonal array. The effect of input parameters on output quality variation was assessed by analysis of variance to determine the optimum combination of input. Artificial neural network can measure and improve the quality of cutting by training on aggregation data, using feed-forward back-propagation to predict overall cutting quality. Simulation of aggregated function can be used for better optimization than ANOVA technique because it provides the overall quality prediction, as against single quality prediction.*

Keywords: *Artificial Neural Network, Simulation, Cutting quality, analysis of variance, back-propagation and aggregation*

1. INTRODUCTION

Laser cutting is one of the latest technologies in machining materials through thermal cutting processes. The use of laser technology is justified as the laser machining process is reliable and produces better quality products, even though it has a high cost, which is constantly reducing. Utilization of cutting of plastic materials increases to achieve a finer product quality, together with robust process solution. The motivation of this study is to cut non metallic material such as Urea Formaldehyde (Melamine) using CO_2 laser cutting. Extensive information on the effect of input controllable variables on output attributes such as edge quality, kerf width, overcut and material removal rate measurements were taken into account for overall process optimization.

The problem can be resolved by the existing techniques such as transfer function, curve fitting and Taguchi methods, or by training of experimental data to provide sufficient knowledge for Laser cutting machine input parameters adjustment for efficient cutting. The combined use of Target Performance Measurement (TPM), Noise Performance Measurement (NPM) and Artificial Neural Networks (ANN) is used to measure the output quality of the work-piece.

The development of transfer function is not an easy task because of variations in four variables. It is difficult to plot four input and one or four output quality parameters.

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The usage of Taguchi Method's Orthogonal Arrays (OA) can reduce the number of observations from 81 to 9, hence reducing time and cost of experiment. This method also accounts for all types of noises, but is time consuming, lengthy and statistical. It was also used for the solution of laser engraving problem (Tan et al. 2003). The overall quality was measured in the paper using data mining technique (DMT) and taking aggregation on the basis of geometric mean and variance instead of signal to noise ratio (Phillips and Kim, 1999).

The ANN is used to predict the orthogonal array model. The training of experimental data by ANN is an easier task as compared to other graphical and modeling techniques. ANNs can be used in the problem areas of setting of laser cutting and milling parameters.

1.1 LASER

LASER is an electromagnetic radiation with the property of coherent and monochromatic beam that propagates with insignificant divergence in the same direction and having a broad range of frequency, power (mW to kW), laser beam density in continuous or pulsed power and hence it finds wide applications in normal to scientific use, in medical and defense areas. The Laser application for metallic and non metallic processes is widely categorized into four areas such machining, surface, welding and laser assisted forming. It can be divided into change of phase or require high energy to induce the phase change. This study is concerned with laser cutting of melamine sheets which is an application of material processing (Majumdar & Manna, 2003) with the objective of achieving quality in the cutting process.

The rising applications material processing of laser is due to requirement of high productivity, quality, material utilization, reduction of finishing operation, processing cost and heat affected zone and non-contact processing such as by CO_2 and Nd–YAG lasers Majumdar & Manna, (2003). Laser cutting is a common industrial application for organic compounds, metals, ceramics, polymers composites and wood materials irrespective of their hardness. Although several successful stories have been reported, laser cutting of wood (organic material) has not usually been acknowledged by the manufacturer (Yusoff et al. 2008). CO_2 laser cutting of wood is discussed in this experiment to control the process variables of fireboard (medium density). It was pointed out that laser beam cutting process impart energy on the work piece which breaks the chemical bonds and results in cutting. This paper explains the effect of input parameters on the cutting quality of soft and hard wood. The quality improves by applying assist gas pressure with different pressure and nozzle design. Laser cutting speed is of vital importance in achieving better productivity. The shield gas may cause unknown variation due to reduction in pressure when less gas remains in cylinder. The standoff distance changes the beam width due to focal length which affect the cutting quality (Yusoff et al. 2008).

In the process non-metallic materials like carbon, plastic and wood, the laser beam boils the surface and creates a keyhole. It basis a fast absorption due to multiple times beam reflection and starting point gets deeper resulting in cut (Majumdar & Manna, 2003). As laser cutting is a non-contact cutting method, use of laser cutting for radioactive materials is an important application. Diamond cutting is ten times slower than laser in case of Textiles and hard brittle ceramics. These materials can be cut by the combination of fusion, vaporization and chemical degradation processes (Caiazzo et al. 2005). Processing is automated for speed, power, standoff distance and gas pressure by neural networks, and high quality surface finish has been achieved.

1.2 Orthogonal Array

Taguchi Method uses design of experiment based on Orthogonal Arrays (OA). It is one of the better methods to reduce cost of experiment, get better quality, and minimize design and development interval.

Dr. Taguchi had designed a method based on OA experiments resulting in controlling variations for the experiment with optimum settings of input controllable variables (Mustafa and Amin, 2010, Tan et al. 2008). OA gives sets of well balanced (minimum) experiments. In this experiment four-three level orthogonal array $L_9(3^4)$ i.e. a full factorial design (3x3x3x3) of 81 sets of experiments was reduced to 9 runs. Taguchi method uses the Signal to Noise (S/N) ratio of dependent quality as quality parameter for optimization. It is utilized in data variation and prediction of optimum results, these signal to noise expressions are used in (Mustafa and Amin, 2010).

$$\textit{Nominal the best} = 10\log 10\left(\bar{X}^2/\sigma^2\right) \quad (1)$$
$$\textit{Smaller the better} = -10\log 10(\sigma^2 + \bar{Y}^2) \quad (2)$$
$$\textit{Larger the better} = -10\log_{10}\{1/\bar{Y}^2\ (1 + 3\,\sigma^2/\bar{Y}^2)\} \quad (3)$$

Analysis Of Variance (ANOVA) used by Taguchi method to estimate quantitatively the relative contribution of each input control variable on the quality of the work-piece. In this paper, three replications reduce uncontrolled error factors and human error by taking the arithmetic mean. Controllable factors with the largest effect have higher weighting effect on the cutting quality. ANOVA makes possible the study of known and unknown errors for achieving better quality.

1.3 Artificial Neural Networks

ANN is based on an information-processing model of densely interconnected, parallel structure of simple processing units motivated by the human brain and neuron processes information system. In this model, a large number of interconnected processing elements are connected together with weighted connections that are analogous to neuron synapses. The benefit of ANN is in learning of 9 observations and on its basis it can simulate on the entire possible 81 values and more. By using the trained network, we can reduce the machine setting time and human error on the new work-piece. The neural network processes in parallel. The ANN function is built by the connections among the elements.

The selection of network model is based on the data processing technique. They are also distinguished by the method of training used; supervised and unsupervised training. In supervised learning, inputs are applied and output response obtained, which is compared with the desired output. The training algorithm adjusts the connection weight values to minimize the error i.e. the difference between desired output. When an input is applied to a trained neural network the response indicates the class of quality.

1.4 Feedforward back-propagation ANN

The simplicity and effectiveness of Feed-forward backpropagation neural networks makes it a widely used neural network architecture model, with successful application in areas such as pattern recognition, classification, expert systems and process control. It is a supervised learning model with an input, output layers with multiple hidden layers. This architecture enables complex functions to be modeled by the neural network. Error back propagation algorithm is used to train such networks. This model is adopted in the work presented in this paper.

The training data is compiled from calculations on the experimental values. The trained network is then able to predict other unknown values of inputs which are useful in outputting better overall quality and in the tolerance range.

2. EXPERIMENTAL MEASUREMENT, ANALYSIS AND DISCUSSION

The research was carried out by performing experiment by low power CO_2 laser. The specification of CO_2 laser were

- 500W maximum output power
- 125 mm/second Maximum cutting speed
- Gas mixture of around 65% He, 28% N2 and 7% CO2

The laser cutting machine used was the Zech Carbon Dioxide Laser Machine ZL1010, operated in continuous wave mode. Measurements of work-piece before and after cutting were taken using a digital caliper. The cutting parameters can be distinguished between constant and variable factors. Controllable factors are mentioned with levels in Table 2 and some of the parameters are considered constant factors such as

Nozzle Diameter: 2mm	Delay Time: 5 seconds
Thickness: 2.5 mm	Assist Gas: Compressed Air
Corner Power: 70%	Actual Sideline Length: 40 mm

Table 2: Input factors levels

Input Factors	*Ordinal Levels*			
	Level 1	*Level 2*	*Level 3*	*Units*
Laser Power A	100	300	500	Watt
Cutting speed B	0.2	0.7	1.2	m/min
Assist gas Pressure C	0.5	2.5	4.5	bars
Standoff distance D	1	5	10	mm

Measurements were recorded to calculate edge quality (mm) directly and kerf width (mm), overcut in percentage and material removal rate in m^3/minute. Furthermore, the experiment investigates the variation in quality based on controllable input parameters for each quality characteristic separately and also predicts the optimum input data set.

2.1 Analysis of Performance of quality variables

Table 1: TPM for edge quality

TPM	A	B	C	D
Level 1	0.005	0.004	0.004	0.005
Level 2	0.004	0.005	0.004	0.004
Level 3	0.004	0.004	0.005	0.004
Range	0.001	0.001	0.000	0.001
Rank	2	3	4	1
Optimum	A3	B3	C2	D3

Table 2: NPM for edge quality

NPM	A	B	C	D
Level 1	46.336	47.923	47.608	46.756
Level 2	47.200	46.738	47.677	47.437
Level 3	48.533	47.944	47.009	48.648
Range	2.197	1.205	0.668	1.892
Rank	2	3	4	1
Optimum	A3	B3	C2	D3

Table 3: TPM for kerf width

TPM	A	B	C	D
Level 1	0.476	0.874	0.803	0.498
Level 2	0.814	0.707	0.689	0.731
Level 3	0.862	0.617	0.751	1.145
Range	0.386	0.257	0.113	0.647
Rank	2	3	4	1
Optimum	A1	B3	C2	D1

Table 4: NPM for kerf width

NPM	A	B	C	D
Level 1	6.448	1.670	2.330	6.045
Level 2	2.167	3.767	4.096	3.092
Level 3	1.884	4.370	2.886	-1.180
Range	4.565	2.700	1.767	7.224
Rank	2	3	4	1
Optimum	A1	B3	C2	D1

Table 5: TPM for Overcut

TPM	A	B	C	D
Level 1	0.312	1.333	0.950	0.479
Level 2	1.192	1.023	1.021	0.981
Level 3	1.390	0.650	1.228	1.995
Range	1.078	0.683	0.278	1.516
Rank	2	3	4	1
Optimum	A1	B3	C1	D1

Table 6: NPM for Overcut

NPM	A	B	C	D
Level 1	10.813	1.131	3.688	7.588
Level 2	-0.500	1.382	2.032	1.475
Level 3	-1.665	3.796	-1.015	-6.028
Range	12.478	2.665	4.703	13.616
Rank	2	3	4	1
Optimum	A1	B3	C1	D1

After the calculation of Total Performance Measurement (TPM) and Noise Performance Measurement (NPM), it becomes possible to see the effect of level variation of inputs controllable characteristics such as Laser power A, cutting speed B, assist gas pressure of air C and standoff distance D independently on all quality characteristics, as shown in Table 1 to Table 8.

Table 7: TPM for Material removal rate

TPM	A	B	C	D
Level 1	$3.5x10^{-7}$	$4.4x10^{-7}$	$1.5x10^{-6}$	$8.6x10^{-7}$
Level 2	$1.3x10^{-6}$	$1.2x10^{-6}$	$9.2x10^{-7}$	$1.2x10^{-6}$
Level 3	$1.3x10^{-6}$	$1.2x10^{-6}$	$4.7x10^{-7}$	$8.6x10^{-7}$
Range	$9.5x10^{-7}$	$8.0x10^{-7}$	$1.0x10^{-6}$	$3.4x10^{-7}$
Rank	4	2	3	1
Optimum	A1	B1	C3	D1

Table 8: NPM for Material removal rate

NPM	A	B	C	D
Level 1	84.686	127.691	119.535	123.250
Level 2	119.373	118.906	121.302	120.297
Level 3	119.089	76.552	82.311	79.600
Range	34.688	51.139	38.991	43.650
Rank	2	3	1	4
Optimum	A2	B1	C2	D1

2.2 ANN Simulation

The above experimental data can be explained on the basis of curve fitting or Response Surface Methodology (RSM) or some other mathematical modeling techniques but this can also be discussed for single quality parameter by ANN. Back-propagation network has been used for the training of data and solution of the problem. The Network design needs the input and target data to be mapped. The existing data can be trained and is able to predict the values of single quality characteristic. However, the problem of overall quality can be achieved by aggregation of all quality parameters. The solution is to give equal importance or weightage to all parameters normalization of dependent variables in range of 0 to 1. Aggregation of normalized data can be 0 to 4. It is again normalized and trained with input dataset. The size of input dataset is very small but the values do not contain noise and balanced orthogonal design data sets of experimental observations. For the purpose of modeling, the ANN universal approximater maps the network by adjusting its weights during the training session and establishes relationship between the inputs and outputs. The formula for Normalized aggregation is

$$\text{Sum of all qualities} = \text{Normalized (Edge quality)} + \text{Normalized (Kerf width)} + \text{Normalized (Overcut)} + (1 - \text{Normalized (Material removal rate)}) \quad (4)$$

$$\text{Normalized Aggregation} = \text{Normalized (Sum of all qualities)} \quad (5)$$

From the dataset in Table 9, 20% were for use in validation, 20% for test and 60% for training the model. Figure 1 shows sorted data of experimental normalized aggregation and simulated data predicted by the ANN. The overall regression coefficient of training, validation and test data was 1, which is good for using the factorial design dataset for simulations. The difference between the target and output values as a percentage was 7.88×10^{-9} minimum and 0.0032 maximum.

Table 9: Normalized aggregated data for Training

Run	A (Watts)	B (m/min)	C (bars)	D (mm)	Normalized Aggregation
1	100	0.2	0.5	1	0.529
2	100	0.7	2.5	5	0.478
3	100	1.2	4.5	10	0.000
4	300	0.2	2.5	10	1.000
5	300	0.7	4.5	1	0.578
6	300	1.2	0.5	5	0.347
7	500	0.2	4.5	5	0.884
8	500	0.7	0.5	10	0.710
9	500	1.2	2.5	1	0.320

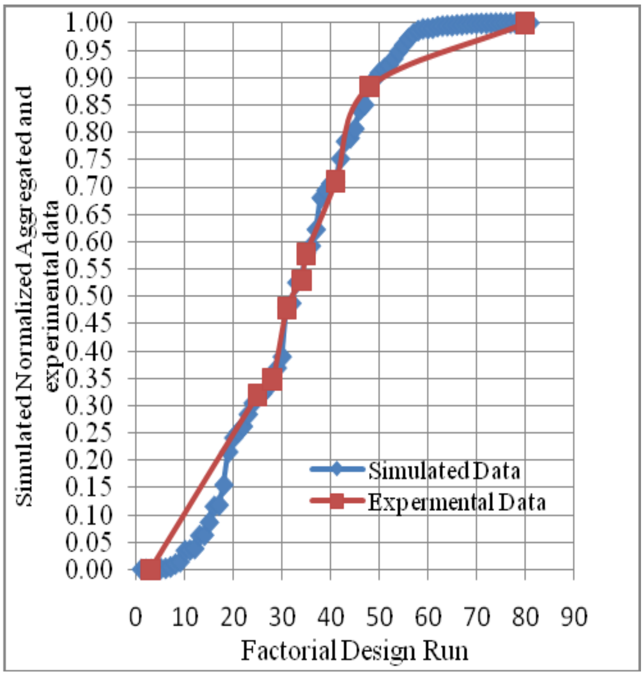

Figure 1: Sorted data of experimental normalized aggregation and predicted by the ANN

3. DISCUSSION

The results of statistical analysis predict the optimized input data set on the basis of Table 1 to Table 8, summarized in Table 10, for all quality parameters separately. The results show that the prediction by the TPM and NPM are identical for edge quality, kerf width and overcut. In the case of material removal rate the prediction due to cutting speed and standoff distance are similar but differ in case of laser power and assist gas pressure as shown in Table 10. The prediction based on TPM for MRR is justified i.e. $A_1B_1C_3D_1$. The thumb rule is to select and give priority in prediction to NPM (Sarin 1997). However, in the given case signal to noise ratio due to laser power and assist gas pressure in Table 8 is 84.6 for A_1 and 119.4 for A_2 therefore selection of A_1 is also on very high side for the robust design. Similar reason is valid for the selection of C_3.

The need of an alternative technique arises here because customer is concerned with the overall quality of the work-piece, but the predictions in Table 10 show that each predicted data set is different from each other. Therefore the aggregation method is used for overall quality.

Table 10: Summary of optimize input sets

Output Quality Characteristics	Optimum input data set	
	TPM	NPM
Edge quality	$A_3B_3C_2D_3$	Same
Kerf Width	$A_1B_3C_2D_1$	Same
Overcut	$A_1B_3C_1D_1$	Same
Material removal rate	$A_1B_1C_3D_1$	$A_2B_1C_2D_1$

For the prediction of overall quality aggregation of all quality parameters normalized values are added except MRR because it should be “larger the better” as shown in equation (4) and (5). The normalized aggregated values should be “smaller the better”. Therefore (1-Normalized MRR) is added in equation (4). The quality factor can be set as per customer requirement but in this study quality factors are assumed as in Table 11 which can be customized as per individual requirement.

Table 11: Quality Factor

S. No.	Quality Tag	Range
1	Uncut	$x \leq 0$
2	Excellent quality	$0 < x \leq 0.1$
3	Good quality	$0.1 < x \leq 0.25$
4	Unacceptable quality	$0.25 < x \leq 1.0$

The normalized aggregated values and input dataset of Table 9 were used for training. The network consists of two layers of nine neurons in both layers with the sigmoid transfer function and 1000 epoch. The trained data had an overall regression coefficient of 1 which indicates very good training. The sorted simulation results show that the starting three datasets cannot cut the work-piece and the next five can cut with the smallest possible values of quality characteristics with maximum possible material removal rate i.e. excellent cutting. The next “good quality” of Laser cutting is twelve datasets predicted similarly, the remaining are unacceptable. The possibility of one of the unacceptable quality is possible in the aggregated results which can be removed by genetic algorithm. This method predicts overall quality characteristics for systems with multivariable inputs and outputs.

Table 12: Simulated results

Run	A	B	C	D	Norm. Aggregated
1	300	1.2	4.5	10	0.000
2	500	1.2	4.5	10	0.000
3	100	1.2	4.5	10	0.000
4	500	1.2	2.5	10	0.001
5	100	1.2	4.5	1	0.001
6	300	1.2	2.5	10	0.002
7	100	1.2	4.5	5	0.004
8	500	1.2	2.5	5	0.010

4. CONCLUSION

This study has shown that overall optimum quality in laser cutting systems with more than two inputs and more than one output quality characteristics is predictable by an ANN modeling combinations (Power, speed of cutting, assist air pressure and standoff distance) of input parameters. Based on customer requirements, weightage is given to the output quality and the range of the quality tag can be set.

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