International Journal of Physical Sciences Vol. 7(16), pp. 2422 - 2430, 16 April, 2012
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS12.109
ISSN 1992 - 1950 ©2012 Academic Journals

Full Length Research Paper

Comparative modeling of CO_2 laser cutting using multiple regression analysis and artificial neural network

Miloš Madić* and Miroslav Radovanović

Department of Production Engineering, Faculty of Mechanical Engineering, University of Niš, Niš, Serbia.

Accepted 2 April, 2012

In this paper, empirical modeling of surface roughness in CO_2 laser cutting of mild steel using the multiple regression analysis (MRA) and artificial neural network (ANN) was presented. To cover wider range of laser cutting parameters such as cutting speed, laser power and assist gas pressure as well as to obtain experimental database for MRA and ANN model development, Taguchi's L_{25} orthogonal array was implemented for experimental plan. The average surface roughness was chosen as a measure of surface quality. The mathematical models of surface roughness developed by MRA and ANN were expressed as explicit nonlinear functions of the selected input parameters. The comparison between experimental results and models predictions showed that ANN model provided more accurate predictions when compared with the MRA model. The use of MRA for surface roughness prediction in CO_2 laser cutting was of limited applicability and reliability. Powerful modeling ability of the ANNs justified the use of the ANN models for accurate modeling of the complex processes with many non-linearities and interactions such as CO_2 laser cutting. Finally, based on the derived ANN equation, the effects of the laser cutting parameters on surface roughness were examined.

Key words: Surface roughness, CO_2 laser cutting, multiple regression analysis, artificial neural networks.

INTRODUCTION

Laser cutting is a thermal energy based advanced machining process in which the material is removed by melting, vaporization and chemical degradation (Noor et al., 2011). Among various machining processes, laser cutting is one of the most popular processes with many applications in various manufacturing industries. The wide spectrum of industrial application of the laser cutting is due to its: convenience of operation, small heat-affected zone, minimum deformity (Yang et al., 2011), high cutting speed, high precision, high product quality (Choudhury and Shirley, 2010), low level of noise (Kurt et al., 2009), flexibility, ease of automation etc. As a non-contact process, it is well suited for advanced engineering materials such as difficult-to-cut materials, brittle materials, electric and non-electric conductors, and soft and thin materials (Chen et al., 2011). For the aforementioned reasons, laser cutting has become an area of great interest for research. Considerable research studies were carried out to examine laser cutting process with some of the findings summarized in recent comprehensive review papers (Dubey and Yadava, 2008; Meijer, 2004).

The laser cutting is a complex process characterized by a number of process parameters which in turn determine efficiency of the whole process in terms of productivity, quality and costs. When the cut quality is considered, in most reported studies, kerf width, surface roughness and size of the heat affected zone, were commonly used as cut quality characteristics (Radovanović and Madić, 2011). However, surface roughness is very important indicator of cut quality (Chen et al., 2011) and one of the main criteria of a product (Dhokia et al., 2008).

The parameters leading to the surface roughness formation in laser cutting are complex. Great practical importance of the surface roughness and its complex

*Corresponding author. E-mail: madic@masfak.ni.ac.rs. Tel: +381 18500687. Fax: +381 588244.

nature attracted attention of a great number of researchers. The work of researchers considering surface roughness analysis in CO_2 laser cutting is indicated as follows.

Kurt et al. (2009) investigated the effect of the laser cutting parameters such as the assist gas pressure, cutting speed and laser power on the dimensional accuracy and surface roughness in cutting engineering plastic materials. It was observed that the surface roughness decreased at higher cutting speeds and assist gas pressure. However, as the cutting speed increased together with the assist gas pressure, the increase of the surface roughness was insignificant.

Choudhury and Shirley (2010) developed a model equation for relating the surface roughness and the laser cutting parameters (laser power, cutting speed and assist gas pressure) for cutting of three polymeric materials. Based on the model, it was observed that the surface roughness decreased with an increase in the cutting speed, laser power and assist gas pressure. Also, it was observed that the effects of the cutting speed and assist gas pressure were more pronounced than the effect of the laser power.

Rajaram et al. (2003) indicated that the low cutting speed resulted in good surface roughness when cutting 4130 steel. As noted by the authors, this apparent contrast was due to the place of the range of cutting speeds used in the study with respect to the optimum cutting speed. When the order of magnitude was considered, the cutting speed had a major effect on the surface roughness while the laser power had a small effect. Additionally, it was observed that the effect of the laser power on the surface roughness was more significant at low laser power levels.

Stournaras et al. (2009) investigated the cut quality for the aluminum alloy AA5083 with the use of a pulsed laser cutting system using nitrogen as assist gas. The results showed that the laser power, cutting speed and pulsing frequency were the major influencing parameters, whereas the influence of the assist gas pressure on the surface roughness was negligible. However, combined effect of high cutting speed with high-pressure assist gas removed the molten material more effectively and faster, which resulted in smoother surface. Also, it was observed that the increase in the laser power decreased the surface roughness.

Syn et al. (2011) presented an approach for the prediction of cut quality in cutting Incoloy(R) alloy 800 by employing fuzzy expert system. Based on the results of the prediction runs of the model, it was shown that there are high interaction effects between the assist gas pressure, cutting speed and laser power on the surface roughness.

From what was said, it was seen that numerous parameters and their complex influences have an essential role on the surface roughness obtained in CO_2 laser cutting of a given material and thickness. The mechanism behind the surface roughness formation is further complicated considering the interaction effects between the laser beam, process parameters and workpiece properties. Also, the order of magnitude of a given parameter on the surface roughness is dependent on the values of other parameters and their interactions.

A fishbone diagram showing the various parameters influencing the surface roughness in CO_2 laser cutting is shown in Figure 1. There are several ways to describe the surface roughness among which the average surface roughness which is often represented with the symbol R_a, is mostly used. It is defined as the arithmetic value of the departure of the profile from the centerline along sampling length (Kurt et al., 2009).

Surface roughness affects fatigue life, corrosion, thermal conductivity, friction and wear and tear of parts (Choudhury and Shirley, 2010; Kurt et al., 2009). Hence, it is of great importance to exactly quantify the functional relationship between the surface roughness and the laser cutting parameters so as to predict its value for any cutting condition. Actually, surface roughness modeling has become not just a special defying business but an area of great interest for research (Pontes et al., 2010). The mechanism behind the formation of the surface roughness is very complicated and process dependent, and along with the numerous uncontrollable factors that influence the phenomena, make surface roughness prediction difficult (Benardos and Vosniakos, 2003). Development of the mathematical models to predict the values surface roughness is important in order to have a better understanding of the machining process (Zain et al., 2011). Literature reveals that different methodologies have been employed for predicting the surface roughness in CO_2 laser cutting, such as: multiple regression analysis (MRA) (Rajaram et al., 2003; Stournaras et al., 2009), response surface method (RSM) (Choudhury and Shirley, 2010) and fuzzy expert system (Syn et al., 2011). However, although the application of artificial neural networks (ANNs) for predicting surface roughness in conventional machining processes is wide (Dhokia et al., 2008; Pontes et al., 2010), to the authors knowledge, no work has been reported in the literature on developing mathematical models for surface roughness based on ANNs in CO_2 laser cutting.

MRA and ANNs are two important competitive data mining techniques widely used for development of predictive empirical models for surface roughness with the ultimate aim of relating process parameters (inputs) and process performance (responses, outputs). Both methodologies were successfully applied for surface roughness modeling, however when compared to one another, different conclusions were drawn. Çaydas and Hasçalik (2008) founded that the MRA model yielded slightly superior results for surface roughness prediction than the ANN model. On the other hand, for Asiltürk and Çunkaş (2011) and Paulo Davim et al. (2008), ANN modelling offers several advantages over MRA such as

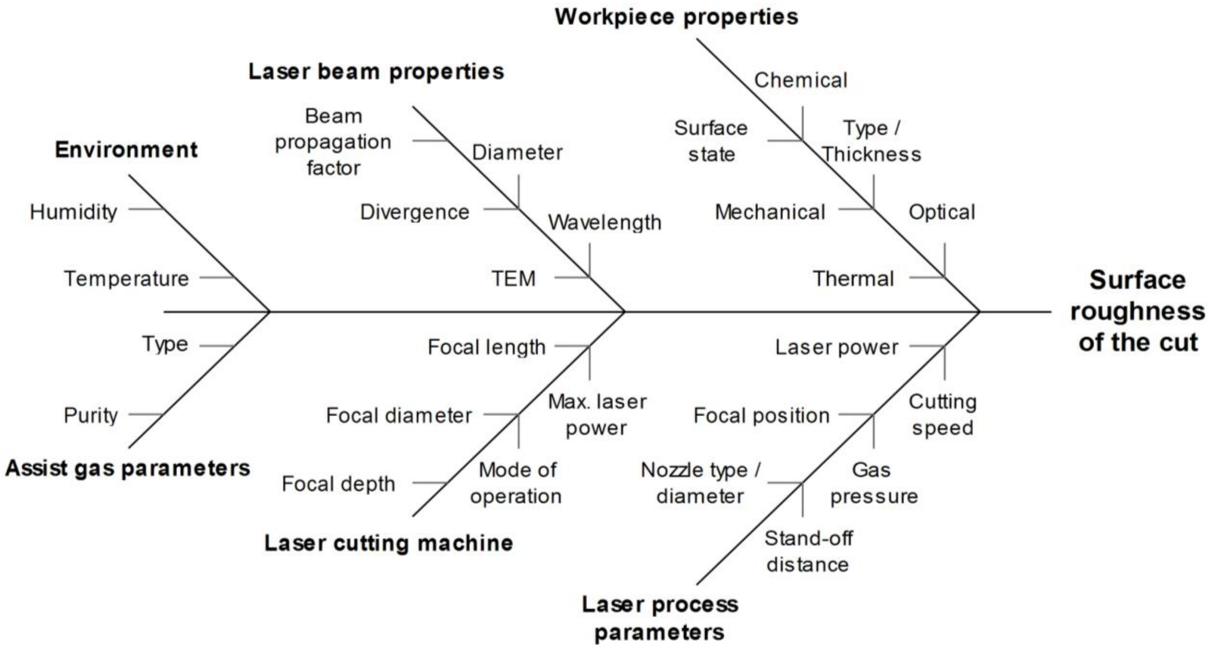


Figure 1. A fishbone diagram for the surface roughness in CO_2 laser cutting.

simplicity, speed and modeling complex nonlinearities and interactions. Furthermore, as noted by Fredj and Amamou (2006) and Stournaras et al. (2009), MRA models established using design of experiments (DOE) techniques may overestimate or underestimate the experimental data. However, applying ANNs for surface roughness prediction is not without some reported shortfalls such as lack of systematic design methods for ANNs (Dhokia et al., 2008) and more computational effort and time for development of an ANN model (Çaydas and Hasçalik, 2008).

Motivated by the lack of model equations relating CO_2 laser cutting parameters with response like surface roughness, an attempt was made to develop such models. In an initial attempt, MRA was employed for development of the surface roughness model in terms of three laser cutting parameters, namely, the cutting speed, laser power and assist gas pressure. In addition, mathematical model of the surface roughness was developed using ANN, so as to evaluate and compare these methods for developing the empirical surface roughness models for CO_2 laser cutting. To obtain data for MRA and ANN models development, the laser cutting experiment was conducted according to Taguchi's L_{25} orthogonal array (OA) experimental layout plan.

MATERIALS AND METHODS

CO_2 laser cutting modeling

In laser cutting, the process performance change drastically with the laser cutting parameters. For effective utilization of the laser cutting processes, it is very much important to find out the optimal combinations of process parameters to achieve enhanced machining performance with high dimensional accuracy (Samanta and Chakraborty, 2011).

To select optimal conditions of the process parameters for different machining processes, various classical and meta-heuristic optimization techniques were proposed. However, an effective application of these techniques requires accurate mathematical models. Analytical solutions based on the physics of the process involve simplifications and approximations in relation to the real laser cutting process and hence generally do not guaranty results accurate enough for practical usage. In the present study, two attempts were made to model such complex and stochastic process, one is by traditional MRA, and the other one is by ANN approach. For both approaches, the use of distinct data sets for the model development and testing (Montgomery et al., 2008) was applied so as to evaluate and compare the performance of MRA and ANN models when exposed to new data.

Experimentation

Taguchi experimental design provides an efficient plan to study the entire experimental region of interest for the experimenter, with the minimum number of trials as compared with the classical DOE, therefore it was chosen for performing the laser cutting experiment. Furthermore, since it was assumed that the effects of the laser cutting parameters on the surface roughness were complex and nonlinear, the experiment was set up with parameters with more number of levels. To this aim, Taguchi's L_{25} orthogonal array with 3 input parameters and 5 levels was used so as to cover wider range of the laser cutting parameters that are controlled by the operator.

The laser cutting experiment was performed by means of ByVention 3015 (Bystronic) CO_2 laser cutting machine delivering a maximum output power of 2.2 kW at a wavelength of 10.6 µm, operating in CW mode. The cuts were performed with a Gaussian distribution beam mode (TEM_{00}) on 2 mm thick mild steel S355J2G3 (EN). In consideration of the numerous parameters that

Table 1. Laser-cutting conditions.

Parameter	
Constant	
Workpiece material	Mild steel S355J2G3 (EN)
Material thickness (mm)	2
Laser	CO_2
Operating mode	CW
Max. power (kW)	2.2
Lens focal length (inch)	5 (127 mm)
Focal point position (mm)	0 (sheet top surface)
Nozzle	Conical shape, ∅ = 1 mm
Stand-off distance	0.7 mm
Type of assist gas	O_2, purity ≥ 99.95%
Variable	
Cutting speed *v* (m/min)	3, 4, 5, 6, 7
Laser power *P* (kW)	0.7, 0.9, 1.1, 1.3, 1.5
Assist gas pressure *p*, (bar)	3, 4, 5, 6, 7

influence cutting process and finally the cut quality, that is, surface roughness, some of the process parameters were kept constant through the experimentation. On the other hand, the main cutting parameters such as cutting speed (v), laser power (P) and assist gas pressure (p) were taken as the variable input parameters. The laser cutting conditions are summarized in Table 1.

The value range for each parameter was chosen such that wider experimental range is covered, full cut for each parameter combination is achieved and by considering the manufacturer's recommendations for parameter settings. Two straight cuts each of 60 mm in length were made in each experimental trial to ascertain surface finish. Experiment trials were conducted in random order to avoid any systematic error.

The surface roughness of the cut was measured in terms of the average surface roughness (R_a) using Surftest SJ-301 (Mitutoyo) profilometer. The sampling length of each measurement was set at 4 mm. Each measurement was taken along the cut at approximately the middle of the thickness and the measurements were repeated three times to obtain averaged values.

Experimental data were divided into two data sets: 20 data for the model development (training data) consisting of 80% of the entire available data and 5 data for the model testing (testing data) consisting of 20% of the entire available data. The selection of data for training and testing was made by random method. For both approaches, the goal was to find the simplest model that has both bias and variance (the total error) considerably low. To facilitate the comparative analysis of the predictive performance of surface roughness prediction models, the same input parameters (the cutting speed, laser power and assist gas pressure) were used in both MRA and ANN models.

RESULTS AND DISCUSSION

MRA model

To establish the surface roughness prediction model, MINITAB 15 statistical software package was used to perform the MRA using the available data. The second order MRA model (full quadratic regression model with interactions) relating the laser cutting parameters and the surface roughness was obtained as:

$$R_a(\mu m) = -1.704 + 1.495v + 5P - 1.13p - 0.72vP + 0.091vp + 0.842Pp - 0.136v^2 - 2.495P^2 \quad (1)$$

More detailed results of MRA with all the corresponding coefficients and P-values are shown in Table 2.

Note that insignificant model term p^2 was automatically eliminated by the software since it was highly correlated with other variables. The adequacy of the proposed MRA model was checked based on coefficients of multiple determinations R^2 and R^2 (adj.). The R^2 value indicates that the cutting parameters explain 97.8% of variance in surface roughness. This value indicates that the developed model fits the data very well. Analysis of variance (ANOVA) for the MRA model is given in Table 3. The F-ratio from statistical table is 4.74 for a level of confidence of 99%. Referring to F-ratio of 60 in Table 3, which is greater than that of statistical table value, yields a statistically significant MRA model.

ANN model

To establish the mathematical relationship between the laser cutting parameters and the surface roughness, a multilayer perceptron type ANN was selected. To develop ANN surface roughness model, the same twenty sets of experimental data considered for obtaining MRA model were taken for training the ANN by using MATLAB Neural Network Toolbox. Three neurons at the input layer (for each of the laser cutting parameter), one neuron at the output layer for calculating the surface roughness and only one hidden layer were used to define ANN architecture. Hyperbolic tangent sigmoid and linear activation functions were used in hidden layer and output layer respectively. The number of hidden neurons was selected by considering the following: (*i*) too few neurons in hidden layer can lead to underfitting, whereas too many neurons can contribute to overfitting (Karnik et al., 2008); (*ii*) the more the hidden neurons the more the expressive power of the ANN; (*iii*) the upper limit of number of hidden neurons can be determined considering that the total number of weights and biases in the ANN does not exceed the number of data for training. As noted by Sha and Edwards (2007), in a case where the number of the connections to be fitted is larger than the number training data, ANN can be still trained, but the case is mathematically undetermined.

Table 2. The MRA model for surface roughness.

Predictor	Coefficient	SE coefficient	T	P
Constant	-1.7044	0.8251	-2.07	0.063
v	1.4915	0.3379	4.41	0.001
P	5.001	1.901	2.63	0.023
p	-1.1256	0.4959	-2.27	0.044
vP	-0.7176	0.2041	-3.52	0.005
vp	0.09124	0.04778	1.91	0.083
Pp	0.8420	0.2290	3.68	0.004
v^2	-0.13589	0.02978	-4.56	0.001
P^2	-2.4945	0.8238	-3.03	0.011

S = 0.143618; R^2 = 0.978; R^2 (adj.) = 0.961. T, value of Student's distribution; P, probability density.

Table 3. ANOVA results for MRA model for surface roughness.

Source	DF	SS	MS	F	P
Regression	8	9.9001	1.2375	60.00	0.000
Residual error	11	0.2269	0.0206		
Total	19	10.1270			

DF, degree of freedom; SS, sum of squares; MS, mean square; F, value of Fisher's distribution.

Table 4. The weights and biases of the developed ANN model for surface roughness.

	W_1		W_2	B_1	B_2
2.4235	-0.35109	0.60286	-0.22013	-1.2987	-0.0010379
-0.15908	1.4035	-1.4569	-0.40441	0.22615	
1.2296	-1.2203	-1.4707	-0.58464	1.5785	

W_1, weights between input and hidden layer; W_2, weights between hidden and output layer; B_1, biases of the hidden neurons; B_2, bias of the output neuron.

For example, for the single hidden layer ANN architecture with *n* input neurons, *m* hidden neurons and *k* output neurons, the total number of weights and biases can be expressed as:

$$T = m(n + k + 1) + k \qquad (2)$$

It is easy to calculate that for three inputs and one output, the upper limit of the number of hidden neurons is 3 for 20 available training data. Therefore, 3-3-1 ANN architecture was selected for surface roughness modeling.

In order to facilitate the ANN training process, both input and output data was normalized in the range [-1, 1]. In the present study, the ANN training process was carried out using variable learning rate training procedure "traingdx". This procedure was selected since it improves the performance of the classical backpropagation training algorithm by allowing learning rate to change based on complexity of local error surface (Karnik et al., 2008). The mean squared error (MSE) was selected as the performance criterion for the ANN training process. Supervised learning was conducted with a zero as a target error value. The ANN training was stopped when no further improvement in performance was achieved and by considering the well known bias-variance trade-off in model development (Feng et al., 2006).

In order to deal with converge to local minima problem and slow convergence, the ANN training process was repeated several times using different initial weights. The MSE at the end of the training process (155 epochs) was found to be 0.00509298.

Once the ANN training process was finished and the near optimum weights and biases of the ANN were determined (Table 4), one can develop explicit mathematical function for the surface roughness based on ANN. Regarding the data normalization, activation functions used in hidden and output layer and by using the weights and biases from Table 4, the mathematical equation for calculating the surface roughness becomes:

$$R_a(\mu m) = 1.2375 \cdot \left(\left(\left[\frac{2}{1 + e^{-2(X \cdot W_1 + B_1)}} - 1 \right] \cdot W_2 + B_2 \right) + 1 \right) + 0.832 \qquad (3)$$

where X is the column vector which contains normalized values of v, P and p.

Comparison between MRA and ANN surface roughness prediction models

Surface roughness prediction models were developed using MRA and ANN, mathematically represented by Equations 1 and 3 respectively. Using these equations, the surface roughness can be calculated for a given cutting condition.

At this stage, in order to understand whether MRA or ANN models have good generalization capability, the models performance was checked using the test data which were not used in models development stage. Among the various statistical methods for assessing the prediction performance of a mathematical model, absolute percentage error (APE) which is one of the most stringent criteria, was used. It is defined as:

$$\%APE = \left| \frac{\text{Experimental value} - \text{Predicted value}}{\text{Experimental value}} \right| \times 100 \qquad (4)$$

Results of ANN and MRA model predictions were compared with experimental results in Table 5 (data for model development) and 6 for assessing the models generalization capability.

It was found from Table 5 that the average APE for the MRA model was 4.56% and for the ANN model was 3.77%. While comparing the modeling accuracy using the testing data, it was found that the average APE for the MRA model was 21.26% and that of the ANN model was 7.36%.

From the results given in Tables 5 and 6, it can be seen that both MRA and ANN models exhibit good prediction performance, however the accuracy of the ANN model was much better when the testing data were used. In other words, the ANN model maintained good prediction accuracy, that is, showed good generalization capability on new data, which cannot be said for the MRA model. Better prediction capability of the ANN than the MRA model for predicting the surface roughness in CO_2 laser cutting process could be explained by the fact that laser cutting is a complex process in which the surface roughness obtained is dependent on many process parameters and their interactions. In that sense, ANNs which are based on matrix-vector multiplications combined with nonlinear (activation) functions, offer powerful modeling ability for complex processes with many non-linearities and interactions and hence outperformed MRA.

Effects of the laser cutting parameters on the surface roughness

The developed ANN model for surface roughness prediction showed better performance than the MRA model with the high degree of accuracy within the scope of cutting conditions investigated in the study. Thus, the ANN model was employed to analyze the effects of the laser cutting parameters on the surface roughness. This was accomplished using Equation 3 and by varying value of one parameter, while keeping the other two parameters constant at low, medium and high level. The effect of the cutting parameters on the surface roughness was represented in Figure 2.

From Figure 2 it can be observed that the surface roughness is highly sensitive to the selected laser cutting parameters. Also, it can be seen that the functional dependence between the surface roughness and the laser cutting parameters is nonlinear, and that the effect of a given parameter on the surface roughness must be considered through the interaction with the other parameters. However, the following can be observed:

(1) An increase in the cutting speed leads to the decrease in the surface roughness. This is due to the fact that as the cutting speed increases, the interaction time between laser beam and workpiece material decreases, hence the thermal energy available at the workpiece surface decreases, which results in minimum side burning of the cut edge.
(2) An increase in the laser power improves the surface roughness. This is because laser cutting is less stable at low power levels (Rajaram et al., 2003). However, at higher laser power levels with increasing the assist gas pressure, the heat generated by the laser power and exothermic reaction is increased, which results in higher surface roughness. Actually, as shown in Figure 2b, for a given cutting speed and assist gas pressure, there exists an optimum laser power which provides good surface finish.
(3) An increase in the assist gas pressure increases the surface roughness, depending on the interaction effect between the cutting speed and laser power, this increase is linear or nonlinear. The assist gas pressure has a negative influence on the surface roughness because the reduced gas pressure minimizes side burning of the cut edge.

Conclusion

In this paper, an attempt was made to develop and compare empirical models for surface roughness prediction in CO_2 laser cutting using MRA and ANN. The conclusions drawn can be summarized by the following points:

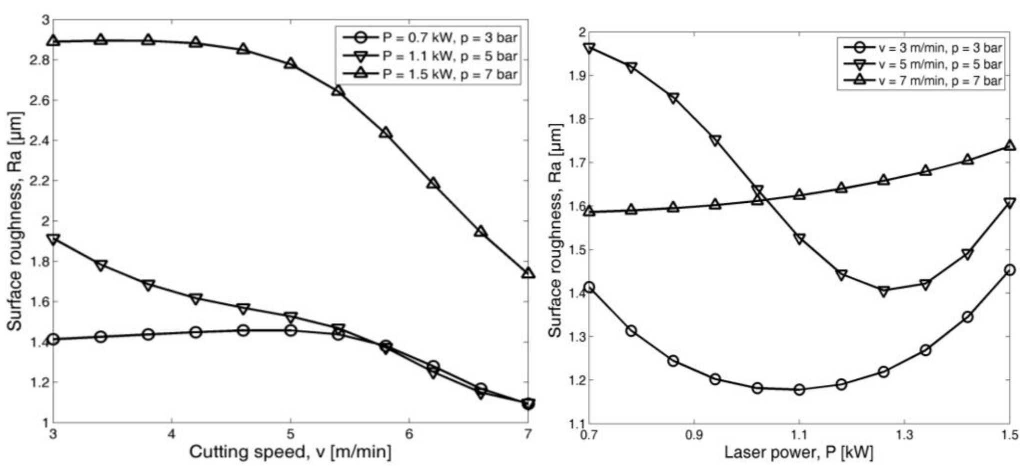
1. Both modeling approaches provide explicit models for the surface roughness prediction. MRA model development

Table 5. Comparison of the experimental and predicted values of the surface roughness using the data for model development.

Experimental trial	Laser cutting parameter			Experimental	Model prediction		% Error	
	v (m/min)	*P* (kW)	*p* (bar)	R_a (μm)	MRA	ANN	MRA	ANN
1	3	0.7	3	1.487	1.519	1.414	2.19	4.90
3	3	1.1	5	2.073	2.016	1.914	2.77	7.69
4	3	1.3	6	2.477	2.471	2.718	0.24	9.75
5	3	1.5	7	2.937	3.063	2.890	4.31	1.59
6	4	0.7	4	1.780	1.653	1.794	7.13	0.80
8	4	1.1	6	2.337	2.382	2.372	1.95	1.49
9	4	1.3	7	3.307	2.953	3.127	10.69	5.44
10	4	1.5	3	1.190	1.173	1.235	1.44	3.80
12	5	0.9	6	2.017	2.109	2.022	4.60	0.25
13	5	1.1	7	2.603	2.659	2.576	2.14	1.04
14	5	1.3	3	1.173	1.243	1.128	5.95	3.90
15	5	1.5	4	1.380	1.226	1.261	11.16	8.64
16	6	0.7	6	1.660	1.652	1.694	0.48	2.04
19	6	1.3	4	1.007	1.091	1.038	8.33	3.14
20	6	1.5	5	1.143	1.190	1.181	4.04	3.25
21	7	0.7	7	1.587	1.517	1.586	4.38	0.04
22	7	0.9	3	0.832	0.831	0.842	0.17	1.22
23	7	1.1	4	0.903	0.771	0.830	14.69	8.07
24	7	1.3	5	0.880	0.848	0.837	3.61	4.83
25	7	1.5	6	1.073	1.063	1.036	0.93	3.46

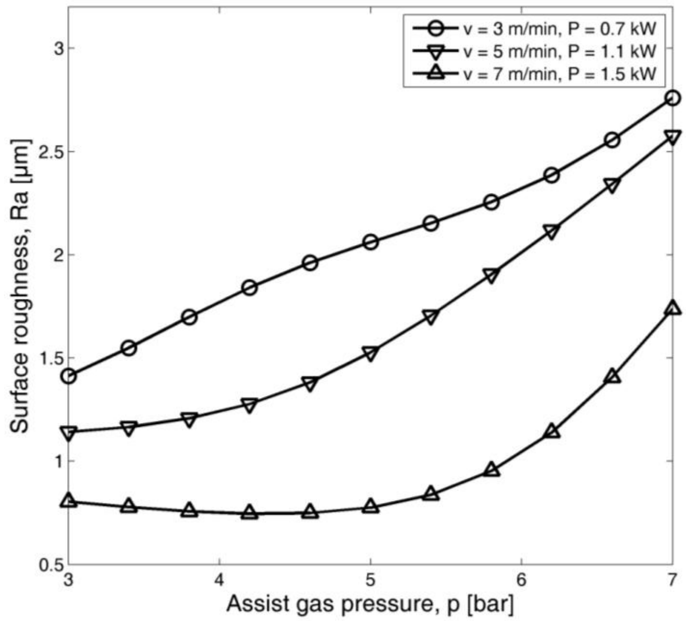
Table 6. Comparison of the experimental and predicted values of the surface roughness using the testing data.

Experimental trial	Laser cutting parameter		Experimental		Model prediction		% Error	
	v (m/min)	*P* (kW)	*p* (bar)	R_a (μm)	MRA	ANN	MRA	ANN
2	3	0.9	4	1.290	1.699	1.469	31.69	13.87
7	4	0.9	5	1.707	1.949	1.860	14.19	8.99
11	5	0.7	5	2.013	1.697	1.965	15.69	2.40
17	6	0.9	7	1.710	2.180	1.759	27.50	2.84
18	6	1.1	3	0.963	1.129	1.047	17.21	8.69



(a) (b)

Figure 2. The effects of the laser cutting parameters on the surface roughness: (a) effect of cutting speed; (b) effect of laser power; (c) effect of assist gas pressure.



(c)

Figure 2. Contd

requires less time and effort than the ANN model development in which one has to take a number of architectural and training parameters in consideration.

2. Quite basic ANN model architecture, trained with “traingdx” procedure using small training data set, proved to be better in predicting the surface roughness than the MRA model considering the prediction accuracy and generalization capability.

3. The use of MRA for surface roughness prediction is of limited applicability and reliability. Complex surface roughness formation mechanism and nonlinear functional dependency between the process parameters in CO_2 laser cutting justifies the use of ANN for reliable modeling of the process.

4. ANNs can be used efficiently as an alternative for analyzing the interdependences between the process parameters and process responses.

5. Development of the ANN model for CO_2 laser cutting also permits optimization of the process parameters on the basis of the desired surface quality, productivity and/or actual operating costs.

6. From the obtained results, the final conclusion drawn from this study is that, ANN models should be preferably used to predict, optimize and improve the CO_2 laser cutting process of each engineering material.

ACKNOWLEDGEMENT

This work was carried out within the project TR 35034 financially supported by the Ministry of Science and Technological Development of the Republic of Serbia.

REFERENCES

Asiltürk I, Çunkaş M (2011). Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method. Expert Syst. Appl., 38(5): 5826-5832.

Benardos PG, Vosniakos GC (2003). Predicting surface roughness in machining: A review. Int. J. Mach. Tools Manuf., 43(8): 833-844.

Çaydas U, Hasçalik A (2008). A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis method. J. Mater. Process. Technol., 202(1-3): 574-582.

Chen MF, Ho YS, Hsiao WT, Wu TH, Tseng SF, Huang KC (2011). Optimized laser cutting on light guide plates using grey relational analysis. Opt. Laser Eng., 49(2): 222-228.

Choudhury IA, Shirley S (2010). Laser cutting of polymeric materials: An experimental investigation. Opt. Laser Technol., 42(3): 503-508.

Dhokia VG, Kumar S, Vichare P, Newman ST, Allen RD (2008). Surface roughness prediction model for CNC machining of polypropylene. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf., 222(2): 137-157.

Dubey AK, Yadava V (2008). Laser beam machining - A review. Int. J. Mach. Tools Manuf., 48(6): 609-628.

Feng CX, Yu ZG, Kusiak A (2006). Selection and validation of predictive regression and neural network models based on designed experiments. IIE Trans., 38(1): 13-23.

Fredj NB, Amamou R (2006). Ground surface roughness prediction based upon experimental design and neural network models. Int. J. Adv. Manuf. Technol., 31(1-2): 24-36.

Karnik SR, Gaitonde VN, Campos Rubio J, Esteves Correia A, Abrão AM, Paulo DJ (2008). Delamination analysis in high speed drilling of carbon fiber reinforced plastics (CFRP) using artificial neural network model. Mater. Des., 29(9): 1768-1776.

Kurt M, Kaynak Y, Bagci E, Demirer H, Kurt M (2009). Dimensional analyses and surface quality of the laser cutting process for engineering plastics. Int. J. Adv. Manuf. Technol., 41(3-4): 259-267.

Meijer J (2004). Laser beam machining (LBM), state of the art and new opportunities. J. Mater. Process. Technol., 149(1-3): 2-17.

Montgomery DC, Jennings CL, Kulahci M (2008). Introduction to time series analysis and forecasting. Wiley, Hoboken. p. 13.

Noor MM, Kadirgama K, Rahman MM (2011). Particle swarm optimisation prediction model for surface roughness. Int. J. Phys.

Sci., 6(13): 3082-3090.
Paulo Davim J, Gaitonde VN, Karnik SR (2008). Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models. J. Mater. Process. Technol., 205(1-3): 16-23.
Pontes FJ, Ferreira JR, Silva MB, Paiva AP, Paulo Balestrassi P (2010). Artificial neural networks for machining processes surface roughness modeling. Int. J. Adv. Manuf. Technol., 49(9-12): 879-902.
Radovanović M, Madić M (2011). Experimental investigations of CO_2 laser cut quality: A review. Nonconv. Technol. Rev., 15(4): 35-42.
Rajaram N, Sheikh-Ahmad J, Cheraghi SH (2003). CO_2 laser cut quality of 4130 steel. Int. J. Mach. Tools Manuf., 43(4): 351-358.
Sha W, Edwards KL (2007). The use of artificial neural networks in materials science based research. Mater. Des., 28(6): 1747-1752.
Samanta S, Chakraborty S (2011). Parametric optimization of some non-traditional machining processes using artificial bee colony algorithm. Eng. Appl. Artif. Intell., 24(6): 946-957.
Stournaras A, Stavropoulos P, Salonitis K, Chryssolouris G (2009). An investigation of quality in CO_2 laser cutting of aluminum. CIRP J. Manuf. Sci. Technol., 2(1): 61-69.
Syn CC, Mokhtar M, Feng CJ, Manurung YHP (2011). Approach to prediction of laser cutting quality by employing fuzzy expert system. Expert Syst. Appl., 38(6): 7558-7568.
Yang CB, Deng CS, Chiang HL (2011). Combining the Taguchi method with artificial neural network to construct a prediction model of a CO_2 laser cutting experiment. Int. J. Adv. Manuf. Technol., DOI: 10.1007/s00170-011-3557-2.
Zain AM, Haron H, Sharif S (2011). Estimation of the minimum machining performance in the abrasive waterjet machining using integrated ANN-SA. Expert Syst. Appl., 38(7): 8316-8326.