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AN ARTIFICIAL INTELLIGENCE APPROACH FOR THE PREDICTION OF SURFACE ROUGHNESS IN CO_2 LASER CUTTING

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Abstract

In laser cutting, the cut quality is of great importance. Multiple non-linear effects of process parameters and their interactions make very difficult to predict cut quality. In this paper, artificial intelligence (AI) approach was applied to predict the surface roughness in CO_2 laser cutting. To this aim, artificial neural network (ANN) model of surface roughness was developed in terms of cutting speed, laser power and assist gas pressure. The experimental results obtained from Taguchi's L_{25} orthogonal array were used to develop ANN model. The ANN mathematical model of surface roughness was expressed as explicit nonlinear function of the selected input parameters. Statistical results indicate that the ANN model can predict the surface roughness with good accuracy. It was showed that ANNs may be used as a good alternative in analyzing the effects of cutting parameters on the surface roughness.

Keywords: CO_2 laser cutting, Surface roughness, Artificial neural networks.

1. Introduction

Laser cutting is thermal, noncontact and effective method of cutting a wide range of materials with a high degree of accuracy and low costs. Of particular interest to manufacturers using laser cutting are the maximization of the productivity and the subsequent quality of components made by the laser cutting process [1]. To maintain a high production rate and an acceptable level of quality for the cut parts, it is important to select the optimum combination of process parameters [2]. With a limited theoretical and practical background to assist in systematical selection, these parameters are usually set by previous experience. Above all, optimal cutting parameter settings for achieving good cut quality are not guaranteed. Considerable research studies were carried out to examine laser cutting

Nomenclatures

B_1	Biases of the hidden neurons
B_2	Bias of the output neuron
N	Number of data
o_i	i-th ANN predicted value of average surface roughness, µm
P	Laser power, W
p	Assist gas pressure, bar
R	Correlation coefficient
R_a	Average surface roughness, µm
t_i	i^{th} target (experimental) value of average surface roughness, µm
v	Cutting speed, mm/min
W_1	Weights between input and hidden layer
W_2	Weights between hidden layer and output layer
X	Input vector to ANN

Greek Symbols

η	Learning rate
μ	Momentum

Abbreviations

ANN	Artificial neural network
BP	Back propagation
DOE	Design of experiments
GA	Genetic algorithm
MAPE	Mean absolute percentage error
MSE	Mean squared error
OA	Orthogonal array

process previously. Comprehensive review papers of laser cutting are available [3-5]. Numerous CO_2 laser cutting experimental studies concerned with the analysis of the effects of cutting parameters on the cut quality were reported and review paper is available [6].

Rajaram et al. [1] studied the cut quality (kerf width, surface roughness, striation frequency and the size of heat affected zone) in laser cutting of 4130 steel at different combinations of cutting speed and laser power. They observed that the cutting speed has a major effect on surface roughness and striation frequency and that the laser power has a small effect on surface roughness and no effect on striation frequency. Systematic investigation about the effect of gas composition in laser cutting of mild steel was carried out by Chen [7]. The author founded that a high purity of oxygen is required for the high-performance CO_2 laser cutting of 3 mm mild steel. Only a tiny oxygen impurity (1.25%) reduces the maximum cutting speed by 50 %. In [8], Chen analyzed the effects of high-pressure assist gas (up to 10 bars) in high-power laser cutting of mild steel. The effects of cutting speed, laser power, assist gas and gas pressure on laser cut quality (kerf width, striation formation and dross adhesion) were investigated. The author noted that using oxygen or air as assist gas produces wider kerf while the use of inert gas produces the smallest kerf. Also, it was observed that higher cutting speeds have positive influence on surface finish. Tirumala Rao and Nath

[9] reported a study on laser cutting of mild steel with oxygen as an assist gas. The dependence of melt film thickness on assist gas pressure, cutting speed and work piece thickness was estimated and compared with experimental results. It was found that the melt film thickness was influenced to a greater extent by the change in cutting speed than the variation in the cutting nozzle gas pressure.

Nevertheless, due to dynamic nature of very complicated mechanism behind laser cutting it is very difficult to predict laser-cutting quality [1, 10]. Consequently, there is a need to describe the relation between laser cutting parameters and cutting performance through mathematical modelling. Modelling studies in laser cutting process are the scientific ways to study the system behaviours and helps us to get a better understanding of this complex process [11]. As noted by Dubey and Yadava [3] few researchers concentrated on modelling and optimization of laser cutting through artificial intelligence (AI) based techniques such as artificial neural network (ANN), fuzzy logic and genetic algorithm (GA). Some of the work of other researchers is indicated below.

Yousef et al. [12] developed a multi-layered ANN model to predict the level of pulse energy needed to create a dent or crater with the desired depth and diameter in laser micromachining process. Ghoreishi and Nakhjavani [13] used integrated ANN and GA approach for modelling and optimization of cutting parameters in Nd:YAG laser percussion drilling process. The approach proved to be reliable and economical. Tsai et al. [10] utilized a multiple regression analysis, and an ANN to develop a predicting model for the six laser-cutting qualities for cutting quad flat non-lead packages using a diode pumped solid state laser system. GA was applied to obtain the optimal cutting parameters that provide the best cutting qualities. Syn et al. [11] presented an approach to prediction of laser cutting quality by employing fuzzy expert system. The proposed fuzzy logic model proved to be able to accurately predict the surface roughness and dross inclusion in CO_2 laser cutting process of Incoloy alloy 800.

The literature reveals that not much work was reported on prediction of cut quality in CO_2 laser cutting of mild steel using ANNs. The objective of this study is to develop ANN model for predicting the surface roughness in CO_2 laser cutting of mild steel. To this aim, the back propagation (BP) ANN trained with gradient descent with momentum algorithm was applied to construct a mathematical model wherein surface roughness is expressed as explicit nonlinear function of the three selected laser cutting parameters. For conducting the laser cutting experiment, Taguchi's L_{25} orthogonal array (OA) was used where laser cutting parameters, namely cutting speed, laser power and assist gas pressure were arranged. Finally, the 3D response surface plots were generated to study the effect of laser cutting parameters on the surface roughness.

2. Experimental Setup

2.1. Design of experiments

The accuracy of experimentation can be increased by using the scientific experimental design techniques. Design of experiments (DOE) approach is superior from unplanned approach because it is a systematic and scientific way of planning the experiments, collection and analysis of data with limited use of available resources [3]. In engineering applications, among the various DOE (factorial, fractional factorial, central composite design, Placket-Burmann etc.) the Taguchi experimental design is the most widely used experimental design technique [14]. However, literature related to laser material processing showed that most of the experiments were performed without using DOE approach [3]. Although providing 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, the Taguchi experimental design was applied by only few researchers [6]. The classical DOE is sometimes too complex, time consuming and not easy to use [15]. On the other hand, the Taguchi experimental design uses special, highly fractionated factorial designs and other types of fractional designs obtained from orthogonal (balanced) arrays to study the entire experimental region of interest for the experimenter, with the minimum number of trials as compared with the classical DOE, especially with a full factorial design [16].

Therefore, Taguchi's experimental design was chosen in which experiment trials were performed as per standard L_{25} OA (Table 2). This OA allows for studying the effect of three parameters with five levels.

2.2. Experimental details

A 2.2 kW CO_2 ByVention 3015 laser cutting machine provided by Bystronic Inc. was used for conducting the experiment trials. The cuts were performed with a Gaussian distribution beam mode (TEM_{00}) on 2 mm thick StW 22 steel sheet using oxygen as assist gas with purity of 99.95 %. A focusing lens with a focal length of 5 in. (127 mm) was used to perform the cut. The conical shape nozzle (HK10) with nozzle diameter of 1 mm was used. The nozzle-work piece stand-off distance was controlled at 0.7 mm. In the experiment the laser beam was focused on the sheet surface. Focusing lens, focus position, nozzle diameter, nozzle stand-off distance and sheet thickness were kept constant throughout the experimentation.

In the present experimental study, three input parameters, namely, cutting speed (v), laser power (P) and assist gas pressure (p) were considered. The parameter ranges were varied by about 40% above and below their normal operating level as recommended by the machine manufacturer. Table 1 lists the range of levels for cutting speed, laser power and assist gas pressure.

Table 1. Laser Cutting Parameters and Their Levels.

Cutting parameters	Units	Level				
		1	2	3	4	5
Cutting speed, *v*	mm/min	3000	4000	5000	6000	7000
Laser power, *P*	W	700	900	1100	1300	1500
Assist gas pressure, *p*	bar	3	4	5	6	7

Based on the selected parameters and parameter levels, a design matrix was constructed in accordance with the standard L_{25} Taguchi OA. The experimental results are summarized in Table 2.

Table 2. Experimental Design and Results.

Trial	v	P	p	R_a
1	3000	700	3	1.487
2	3000	900	4	1.290
3	3000	1100	5	2.073
4	**3000**	**1300**	**6**	**2.477**
5	3000	1500	7	2.937
6	4000	700	4	1.780
7	4000	900	5	1.707
8	**4000**	**1100**	**6**	**2.337**
9	4000	1300	7	3.307
10	4000	1500	3	1.190
11	5000	700	5	2.013
12	5000	900	6	2.017
13	5000	1100	7	2.603
14	**5000**	**1300**	**3**	**1.173**
15	5000	1500	4	1.380
16	6000	700	6	1.660
17	6000	900	7	1.710
18	6000	1100	3	0.963
19	**6000**	**1300**	**4**	**1.007**
20	6000	1500	4	1.143
21	7000	700	7	1.587
22	7000	900	3	0.832
23	7000	1100	4	0.903
24	**7000**	**1300**	**5**	**0.88**
25	7000	1500	6	1.073

* bolded rows denotes data for ANN testing

Two cuts each of 60 mm length were made in each experimental trial. Surface roughness on the cut edge was measured in terms of the average surface roughness (R_a) using Surftest SJ-301 (Mitutoyo) profilometer. Cut off length was 0.8 mm and evaluation length was 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.

3. ANN Based Modelling

The ability of the ANN to learn and generalize the behaviour of any complex and nonlinear process makes it a powerful modelling tool [17]. In the present study a feed-forward BP ANN was used to model the CO_2 laser cutting process. Three neurons in the input layer for representing the cutting speed, the laser power and the assist gas pressure, one neuron in the output layer for calculating (predicting) the surface roughness and only one hidden layer were used for the ANN model. This ANN was chosen, because it is widely reported that single hidden layer ANN can be trained to approximate most functions arbitrarily well.

It is common practice that about 75% of experimental data are selected for the training of ANN and the remaining for the ANN testing in ANN model development. Regarding the number of data for ANN training and testing, Zain et al. [18] showed that, although trained with 16 experimental data, ANNs are capable for achieving accurate results for predicting surface roughness. Similarly, Davim et al. [19] obtained accurate ANN predictions for surface roughness using 27 experimental data from Taguchi's L_{27} OA for ANN training and 3 testing data.

In this study, out of the 25 experimental data (Table 2), 20 data were considered for ANN model development (training) and the rest were used for ANN testing. The selection of data for training and testing was made by random method. The development, training and testing of the ANN models was performed in MATLAB software package.

3.1. ANN model development

In order to develop an ANN model with high prediction accuracy which generalizes well, one has to take into consideration a number of issues, particularly related to ANN architecture and ANN training parameters. The selection of ANN architecture can be reduced to finding the "optimal" number of hidden neurons. The issue of determining the optimal number of hidden neurons is of crucial importance since the number of neurons determines the "expressive power" of the ANN. The upper limit of number of hidden neurons was determined knowing that the number of weights doesn't exceed the number of data for training. Though the ANN can still be trained, the case is mathematically undetermined [20]. Therefore, in order to take full potential of the ANN modelling, the 3-5-1 ANN architecture was selected (Fig. 1).

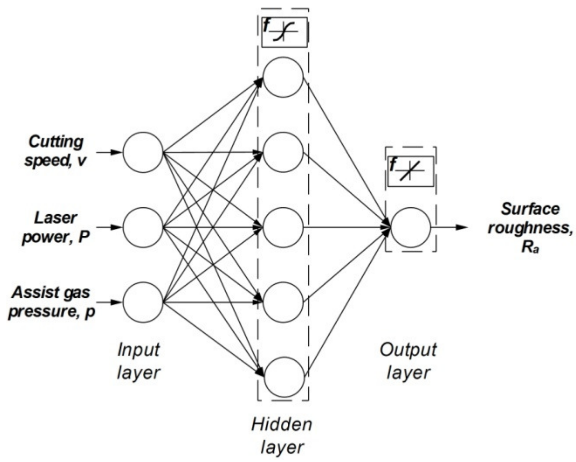


Fig. 1. ANN Architecture.

Linear transfer function and hyperbolic tangent sigmoid activation function were used in the output and hidden layer, respectively. The input and output data from Table 2 were normalized between -1 and 1 in order to stabilize and enhance ANN training. It was found that the selected ANN architecture provides the best data fitting capability when using gradient descent with momentum method as training algorithm while learning rate (η) and momentum (μ) were kept 0.01 and 0.9, respectively. The ANN training process performance was followed according to the mean squared error (MSE). The training was stopped after 3000 epochs since no further improvement in ANN performance was achieved and by considering the well known bias-variance trade-off in ANN model development [21]. Figure 2 shows the variation of MSE as function of the number of epochs. From Fig. 2 it can be seen that after 3000 epochs, MSE between ANN predictions and experimental data was gradually reduced to 0.01375. It has to be noted that prolonged training would cause ANN to memorize training data which results in poor generalization ability of the ANN model.

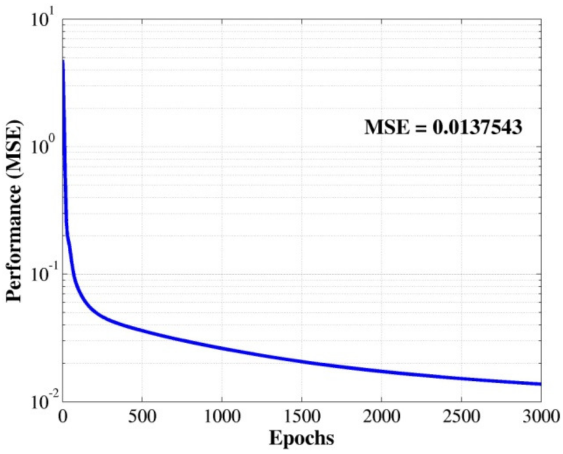


Fig. 2. ANN Training Error.

3.2. ANN model function

Once the ANN training process is finished, the weights and biases of the ANN are determined (Table 3) and can be used to develop the mathematical function for the surface roughness.

Table 3. The Weights and Biases of the ANN Model for Surface Roughness.

Weights				Biases	
W_1			W_2	B_1	B_2
1.9791	1.3284	-0.19092	-0.10194	-2.3487	0.26743
0.83205	-1.4783	1.9678	0.32045	-0.67774	
1.4983	-1.737	0.28778	-0.16644	-0.24118	
2.0107	1.4134	0.50625	-0.18866	0.95467	
-1.3884	0.24879	2.2228	0.6731	-2.1917	

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

Regarding the data normalization, activation functions used in hidden and output layer and by using the weights and biases from Table 3, the equation for calculating R_a becomes:

$$R_a = 1.277\left[\left\{\left(\frac{2}{1+e^{-2\left(X\cdot W_1+B_1\right)}}-1\right)W_2+B_2\right\}+1\right]+0.753 \qquad (1)$$

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

4. Results and Discussion

The statistical methods of correlation coefficient, R and mean absolute percentage error (MAPE) were used for statistical evaluation of the ANN model for surface roughness. These values are mathematically defined by the following equations [11, 22]:

$$R = \frac{\sum_{i=1}^{N}(t_i - \bar{t}) \cdot (o_i - \bar{o})}{\sqrt{\sum_{i=1}^{N}(t_i - \bar{t})^2} \cdot \sqrt{\sum_{i=1}^{N}(o_i - \bar{o})^2}} \tag{2}$$

$$MAPE(\%) = \left(\frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - o_i}{t_i}\right|\right) \times 100 \tag{3}$$

where N is the number of data, and t_i, o_i are target (experimental) value and ANN predicted value, respectively, of one data point i and bars indicate mean values. Table 4 shows the performance of the developed ANN model using both training and test data.

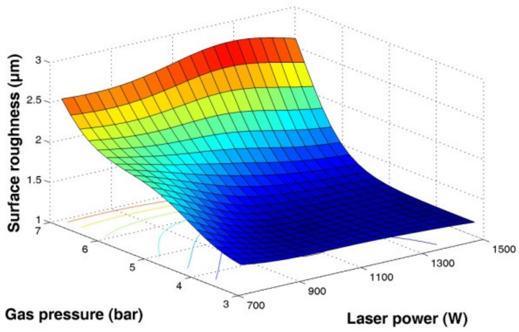
Table 4. ANN Model Prediction Accuracy.

Model	Data for model development		Data for model test	
	R	**MAPE**	***R***	**MAPE**
ANN	0.974	7.842	0.988	5.880

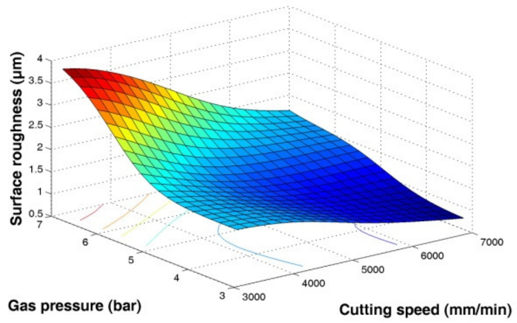
The results from Table 4 demonstrate that the proposed ANN model has good accuracy for predicting the surface roughness. It is important to note that the ANN model showed better results on test data which confirms the high generalization ability (i.e., model robustness) as one of the main criteria in model development process. Therefore, the developed ANN model can be used to examine the effect of input process parameters (v, P, p) on the surface roughness (R_a). To this aim, Eq. (1) was plotted to generate 3D response surfaces of the R_a for different combination of laser cutting parameters (Fig. 3).

From Fig. 3(a) it can be seen that the interaction effect of laser power and assist gas pressure on surface roughness is more significant at low levels of laser power. This is because laser cutting is less stable at low power levels [1]. The results show that for assist gas pressure below 5 bar, the roughness decreases as the laser power increase. The surface roughness decreases while the cutting speed increases as seen from Figs. 3(b) and (c). From Fig. 3(c) it can be seen that increasing the cutting speed with equivalent increase in laser power lead to better surface finish.

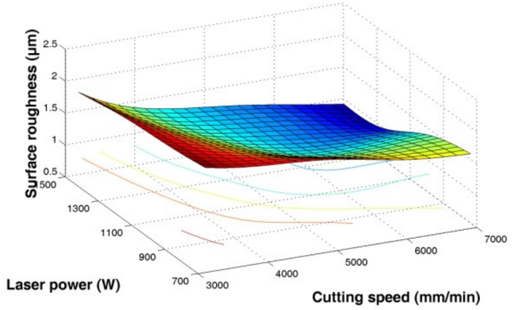
However, the effect of cutting speed must be considered through interaction with assist gas pressure. Using high assist gas pressures cause the thermal energy flow in the kerf surface, resulting in self-burning of the cut surface and high roughness of the cut, Figs. 3(a) and (b). On the other hand, decrease in assist gas pressure resulted in dross attachment due to low kinetic energy of the gas to blow the molten material out of the kerf surface. This effect was observed when using highest level of cutting speed and lower levels of laser power (experiment trials 23 and 24, Table 2). When the order of magnitude is considered, the effects of cutting speed and assist gas pressure are more pronounced than the effect of laser power on surface finish.



a) v = 3000 mm/min



b) P = 1100 W



c) p = 5 bar

Fig. 3. Interaction Effects of Cutting Parameters on the Cut Quality.

5. Conclusions

This paper proposes an ANN approach for modelling the relationship between laser cutting parameters, such as cutting speed, laser power and assist gas pressure and characteristic of surface quality in CO_2 laser cutting of mild steel. The ANN model with 3-5-1 architecture, trained with gradient descent with momentum algorithm, was proved effective to map the underlying input/output nonlinear relationships. The ANN mathematical model of surface roughness was expressed as explicit nonlinear function of the three laser input parameters. Statistical measures of R and MAPE indicate that the results of the developed ANN model compared to the experimental results were quite satisfactory.

The results of the performed analysis show that both effect of cutting speed and assist gas pressure were more pronounced than the effect of laser power on surface finish. The influence of laser power must be considered through interaction with cutting speed and assist gas pressure.

It can be concluded that the proposed ANN approach can be efficiently used for mathematical modelling and analysis of CO_2 laser cutting process. In order to take full potential of ANNs for modelling, Taguchi method and GA could be applied in ANN model design and training. Furthermore, in order to improve the quality of machined parts, ANN models can be coupled with optimization techniques in order to determine optimal laser cutting parameter settings.

References

1. Rajaram, N.; Sheikh-Ahmad, J.; and Cheraghi, S.H. (2003). CO_2 laser cut quality of 4130 steel. *International Journal of Machine Tools and Manufacture*, 43(4), 351-358.
2. Çaydaş, U.; and Hasçalik, A. (2008). Use of grey relational analysis to determine optimum laser cutting parameters with multi-performance characteristics. *Optics & Laser Technology*, 40(7), 987-994.
3. Dubey, A.K.; and Yadava, V. (2008). Laser beam machining - A review. *International Journal of Machine Tools and Manufacture*, 48(6), 609-628.
4. Meijer, J. (2004). Laser beam machining (LBM), state of the art and new opportunities. *Journal of Materials Processing Technology*, 149(1-3), 2-17.
5. Majumdar, D.J.; and Manna, I. (2003). Laser processing of materials. *Sadhana*, 28(3 & 4), 495-562.
6. Radovanović, M.; and Madić, M. (2011). Experimental investigations of CO_2 laser cut quality: a review. *Nonconventional Technologies Review*, XV(4), 35-42.
7. Chen, S.-L. (1998). The effects of gas composition on the CO_2 laser cutting of mild steel. *Journal of Materials Processing Technology*, 73(1-3), 147-159.
8. Chen, S.-L. (1999). The effects of high-pressure assistant-gas flow on high-power CO_2 laser cutting. *Journal of Materials Processing Technology*, 88(1-3), 57-66.
9. Rao, T.B.; and Nath, A.K. (2002). Melt flow characteristics in gas-assisted laser cutting. *Sadhana*, 27(5), 569-575.
10. Tsai, M.-J.; Li, C.-H.; and Chen, C.-C. (2008). Optimal laser-cutting parameters for QFN packages by utilizing artificial neural networks and genetic algorithm. *Journal of Materials Processing Technology*, 208(1-3), 270-283.

11. Syn, C.Z.; Mokhtar, M.; Feng, C.J.; and Manurung, Y.H.P. (2011). Approach to prediction of laser cutting quality by employing fuzzy expert system. *Expert Systems with Applications*, 38(6), 7558-7568.
12. Yousef, B.F.; Knopf, G.K.; Bordatchev, E.V.; and Nikumb, S.K. (2003). Neural network modeling and analysis of the material removal process during laser machining. *The International Journal of Advanced Manufacturing Technology*, 22(1-2), 41-53.
13. Ghoreishi, M.; and Nakhjavani, O.B. (2008). Optimization of effective factors in geometrical specifications of laser percussion drilled holes. *Journal of Materials Processing Technology*, 196(1-3), 303-310.
14. Ilzarbe, L.; Álvarez, M.J.; Viles, E.; and Tanco, M. (2008). Practical applications of design of experiments in the field of engineering: a bibliographical review. *Quality and Reliability Engineering International*, 24(4), 417-428.
15. Montgomery, D.C. (2001). *Design and analysis of experiments*. (5^{th} Ed.) John Wiley and Sons Inc, New York.
16. Marinković, V.; and Madić, M. (2011). Optimization of surface roughness in turning alloy steel by using Taguchi method. *Scientific Research and Essays*, 6(16), 3474-3484.
17. Krishnamoorthy, A.; Boopathy, S.R.; and Palanikumar, K. (2011). Delamination prediction in drilling of CFRP composites using artificial neural network. *Journal of Engineering Science and Technology* (*JESTEC*), 6(2), 191-203.
18. Zain, A.M.; Haron, H.; and Sharif, S. (2010). Prediction of surface roughness in the end milling machining using artificial neural network. *Expert Systems with Applications*, 37(2), 1755-1768.
19. Davim, P.J.; Gaitonde, V.N.; and Karnik, S.R. (2008). Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models. *Journal of Materials Processing Technology*, 205(1-3), 16-23.
20. Sha, W.; and Edwards, K.L. (2007). The use of artificial neural networks in materials science based research. *Materials & Design*, 28(6), 1747-1752.
21. Feng, C.-X.J.; Yu, Z.-G.; and Kusiak, A. (2006). Selection and validation of predictive regression and neural network models based on designed experiments. *IIE Transactions*, 38(1), 13-23.
22. Erbas, B.C.; and Stefanou, S.E. (2009). An application of neural networks in microeconomics: Input-output mapping in a power generation subsector of the US electricity industry. *Expert Systems with Applications*, 36(5), 2317-2326.