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APPLICATION OF CUCKOO SEARCH ALGORITHM FOR SURFACE ROUGHNESS OPTIMIZATION IN CO_2 LASER CUTTING

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ABSTRACT: In this paper, empirical modeling of surface roughness in CO_2 laser cutting of stainless steel using was presented. Mathematical modeling was based on using feed forward neural network by exploiting experimental measurements obtained from the Taguchi's L_{27} experimental design. The mathematical models of surface roughness was expressed as explicit nonlinear functions of the selected input parameters such as laser power, cutting speed, assist gas pressure and focus position. Training of the feed forward neural network was based on Levenberg-Marquardt algorithm and the average absolute percentage errors on training and testing data were 8.71 % and 9.66%, respectively. In addition to modeling, through ANN integration with cuckoo search algorithm optimal laser cutting conditions with minimal surface roughness were identified.
KEYWORDS: surface roughness, artificial neural networks, cuckoo search algorithm, CO_2 laser cutting

INTRODUCTION

Laser cutting is one of the most extensively used non-conventional material removal process for contour cutting of wide variety of materials. It is a high energy-density process that works quickly on complex shapes, and is applicable to any type of material, generates no mechanical stress on the workpiece, reduces waste, provides ecologically clean technology, and has the ability to do work in the micro range [1]. Laser cutting is the process of melting or vaporizing material in a very small, well-defined area. The processes of heating, melting, and evaporation are produced by the laser beam, affecting a workpiece's surface. Laser beam is a cutting tool able to cut almost all materials, focused into a very small spot of 0.1…0.2 mm in diameter concentrating thousands of watts. Considerable research studies were carried out to investigate laser cutting process. A number of researchers performed theoretical as well as experimental investigations in order to examine laser cutting process [8, 15]. The most of investigations were focused on the analysis of machined geometry (kerf width, kerf taper), surface quality characteristics such as surface roughness and metallurgical characteristics (heat affected zone, burr formation).

Experimental studies show that the process input parameters (laser power, cutting speed, type and pressure of assist gas, focus position, nozzle diameter, etc.) and their interactions variously affect cut quality characteristics. Also, the functional dependences are complex and nonlinear. Development of mathematical models for the main laser cutting process performances such as product quality, productivity, cost is essential for better understanding and optimization of the laser cutting process. As the laser cutting is complex process characterized by a multiplicity of interacting parameters, which in turn determine efficiency of the whole process, application of artificial neural networks (ANN) for modeling laser cutting is becoming proffered trend [1, 3-6, 13]. The ability of ANNs to capture any complex input-output relationships from limited data is very valuable in manufacturing processes where huge experimental data for the process modeling is difficult and expensive to obtain [10]. For finding optimal process parameters, ANNs are usually integrated with different metaheuristics algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing (SA), etc. In recent years, due to the complexity of optimization problems, there is a growing interest in applying hybrid and new approaches and comparing the results. Despite the numerous capabilities of recently developed cuckoo search algorithm (CSA) for solving engineering problems [2, 7, 11, 19], there is no its application for optimization of process parameters in laser cutting. In this paper, an attempt has been made to develop ANN surface roughness prediction model for CO_2 laser cutting of stainless steel. To this aim, the laser cutting experiment planned according to Taguchi's L_{27} orthogonal array considering four laser cutting parameters (laser power, cutting speed, assist gas pressure and focus position) was conducted. It has also been attempted to optimize the *cutting parameters so that a minimum surface roughness could be achieved by integrating the ANN model with the CSA algorithm. The CSA optimization procedure was done using Matlab on the basis of the developed ANN model.*

EXPERIMENTAL PROCEDURE

In the present work, the experiment was performed: (i) to provide an knowledge-base of input/output data pairs to model the laser CO_2 cutting process using an ANN aimed at predicting the surface roughness for any combination of input values, and (ii) applying a CSA to the developed ANN for obtaining optimal laser cutting parameter values.

The CO_2 laser cutting experiment was carried out using on 3 mm thick AISI 304 stainless steel sheet on the CO_2 laser cutting machine ByVention 3015 (Bystronic). More details about laser cutting system used and workpiece material chemical composition are listed in Table 1.

Table 1. Laser cutting system and nominal chemical composition of the workpiece

Laser cutting system	CO_2 laser cutting machine delivering a maximum output power of 2.2 kW at a wavelength of 10.6 μm, operating in continuous wave (CW) mode; CO2 laser beam profile in the TEM_{00}; Lens focal length of 127 mm; Conical shape nozzle with diameter of 2 mm (HK20)						
Assist gas	Nitrogen (purity of 99.95 %)						
Workpiece chemical composition	Cr	Ni	C	Mn	Si	S	Fe
	%						
	18.9	9.22	0.07	1.64	0.5	0.006	Balance

Conducting an experiment using scientific design of experiment (DOE) techniques allows for systematic investigation and analysis of the effects of process parameters on process performance of a certain manufacturing process. While designing the experiment trials, the cutting parameter ranges that influence the surface roughness were selected based on the manufacturer's recommendation and past experimentation considering that the full cut is achieved. The cutting parameters and their levels are given in Table 2.

Table 2. Cutting parameters and levels

Coded	Laser cutting parameter	Level 1	Level 2	Level 3
A	laser power, P (kW)	1.6	1.8	2
B	cutting speed, v (m/min)	2	2.5	3
C	assist gas pressure, p (bar)	9	10.5	12
D	focus position, f (mm)	–2.5	–1.5	–0.5

The average surface roughness (R_a) of the machined surface was measured using Surfrest SJ-301 (Mitutoyo) profilometer. Each measurement was repeated twice to obtain averaged values. To carry out this work, a design matrix (Table 3) in accordance with the standard L_{27} (3^{13}) Taguchi orthogonal array (OA) consisting of a 27 trials was constructed. Cutting parameters P, v, p and f were assigned to columns 1, 2, 5 and 12, respectively.

Table 3. L_{27} Taguchi's orthogonal array and experimental results

Trial No	Coded cutting parameters				Actual cutting parameter values				Experimental results	ANN predicted
	A	B	C	D	P (kW)	v (m/min)	p (bar)	f (mm)	R_a (μm)	$\hat{R}_a$ (μm)
1	1	1	1	1	1.6	2	9	-2.5	1.840	1.842
2	1	1	2	2	1.6	2	10.5	-1.5	1.982	1.903
3	1	1	3	3	1.6	2	12	-0.5	2.168	2.090
4	1	2	1	2	1.6	2.5	9	-1.5	2.344	2.186
5	1	2	2	3	1.6	2.5	10.5	-0.5	2.084	2.171
6	1	2	3	1	1.6	2.5	12	-2.5	1.667	1.898
7	1	3	1	3	1.6	3	9	-0.5	2.204	2.188
8	1	3	2	1	1.6	3	10.5	-2.5	1.834	2.189
9	1	3	3	2	1.6	3	12	-1.5	2.303	2.187
10	2	1	1	2	1.8	2	9	-1.5	1.712	1.749
11	2	1	2	3	1.8	2	10.5	-0.5	1.958	1.892
12	2	1	3	1	1.8	2	12	-2.5	2.202	2.361
13	2	2	1	3	1.8	2.5	9	-0.5	1.704	1.795
14	2	2	2	1	1.8	2.5	10.5	-2.5	1.771	1.827
15	2	2	3	2	1.8	2.5	12	-1.5	1.698	1.779
16	2	3	1	1	1.8	3	9	-2.5	2.089	1.841
17	2	3	2	2	1.8	3	10.5	-1.5	2.149	1.843
18	2	3	3	3	1.8	3	12	-0.5	1.912	1.907
19	3	1	1	3	2	2	9	-0.5	1.889	1.911
20	3	1	2	1	2	2	10.5	-2.5	3.015	2.766
21	3	1	3	2	2	2	12	-1.5	1.833	1.891
22	3	2	1	1	2	2.5	9	-2.5	2.294	1.803
23	3	2	2	2	2	2.5	10.5	-1.5	1.467	1.738
24	3	2	3	3	2	2.5	12	-0.5	2.155	2.092
25	3	3	1	2	2	3	9	-1.5	1.604	1.825
26	3	3	2	3	2	3	10.5	-0.5	2.205	1.738
27	3	3	3	1	2	3	12	-2.5	1.926	1.814
Bolded rows represent data for testing the ANN model										

FEED FORWARD NEURAL NETWORK

Artificial neural networks (ANNs) are one of the most powerful modelling techniques currently being used in many fields of engineering. When compared to multiple regression analysis (MRA), the competitive data mining technique, ANN offer better data fitting capability for complex processes with many non-linearities and interactions such as CO_2 laser cutting [13]. However, ANN based modeling is more complex since numerous decisions related to ANN architectural and training parameters had to be made. Actually, as noted by Pontes et al. [14], in order to take advantage of the full potential of ANNs for modeling, more effort should be spent on efficient ANN design.

Among the various types of ANNs, the feed-forward neural network (FFNN) is one of the most popular because of their simplicity and powerful nonlinear modeling ability. The FFNN is a non-linear mapping system composed of many neurons (as basic processing units) which are grouped into at least three layers input, hidden, and output layer. The input neurons are used to feed the ANN with the input data. Through neurons interconnections, each input data is processed with weights to be used in the hidden layer. As illustrated in Figure 1, j-th hidden neuron receives an activation signal which is the weighted sum from the neurons in input layer:

$$h_j = \sum_i w_{ji} \cdot x_i + b_j \qquad (1)$$

where x_i (i=1...4) represents input data for P, v, p, and f, w_{ji} is input to hidden units weights, and b_j biases (thresholds) of hidden neurons.

This sum is then passed through an transfer function (f) to produce the neurons output (H_j). With the transfer functions used in hidden and output layer, the non-linear data processing is enabled. When it is assumed that there exists nonlinear relationship between independent and depended variables, i.e. ANN inputs and output(s), sigmoid type transfer functions are used. For prediction, it is sufficient to use linear activation function (identity) in output layer. Transfer function in hidden layer is most commonly log-sigmoid, Eq. (2a), or hyperbolic tangent-sigmoid, Eq. (2b):

$$H_j = f(h_j) = \frac{1}{1+e^{-h_j}} \qquad (2a)$$

$$H_j = f(h_j) = \frac{e^{h_j} - e^{-h_j}}{e^{h_j} + e^{-h_j}} \qquad (2b)$$

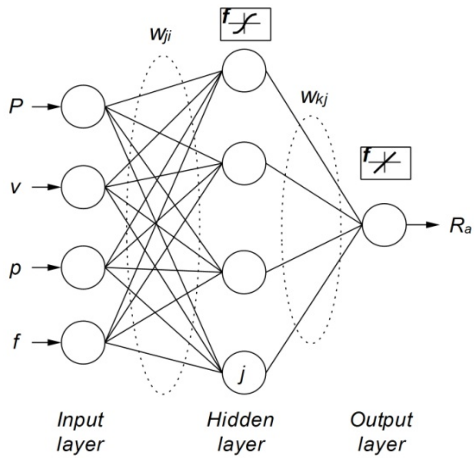

Figure 1. FFNN model for surface roughness prediction

Finally, the output neurons receive the following signals from the hidden neurons:

$$\hat{R}_a = \sum_j w_{kj} \cdot H_j + b_k \qquad (2b)$$

where w_{kj} is the weight of the connection between hidden and output neurons, and b_k bias of output neuron and $\hat{R}_a$ is the FFNN estimated (predicted) value for R_a.

The weights and biases are initially assigned to small random values and are determined during the so called training process. The ANN training represents a process of adjusting weights and biases on the basis of comparing the output values with the desired (target) ones for the same input ones. Training is a continuous process, which is repeated until the ANN is stabilized or overall error is reduced below a previously defined threshold [12]. The most common training algorithm for ANNs is the backpropagation (BP) algorithm and its variants. Generally BP is a procedure which minimizes a squared error by back propagating the error from the output layer, through hidden layer(s) to the input layer. In order to improve the converge speed of the BP, the input and output data should usually be normalized (scaled). The normalization usually considers transfer functions that are used in hidden layer.

CUCKOO SEARCH ALGORITHM

Cuckoo search algorithm (CSA) is a novel population based stochastic global search metaheuristic algorithm developed by Yang and Deb [18]. CSA is inspired by natural mechanisms and mimics, the breeding behavior of some cuckoo species that lay their eggs in the nests of host birds. Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The goal is to use new and potentially improved solutions (cuckoos) to replace worse solutions in the nests. For simplicity in describing the CS, the following three idealized rules are utilized [17]:

- Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest.
- The best nests with high quality of eggs (solutions) will carry over to the next generations.

- *The number of available host nests is fixed, and a host can discover an alien egg with a probability pa ∈ [0, 1]. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.*

With these three rules, the basic steps of the CSA are summarized in the pseudo code given in [16]. The salient feature of the CSA is its ability to find all the optima simultaneously if the number of nests is much higher than the number of local optima. The main control parameters of the CSA include the number of host nests (or the population size n) and the probability p_a. From the analysis of the CSA performance, Yang and Deb [18] observed that n = 15 to 25 and p_a = 0.15 to 0.30 are sufficient for most optimization problems.

OPTIMIZATION PROCEDURE AND RESULTS

The optimization procedure used for selection of optimal laser cutting parameters is illustrated in Figure 2. Details of each step are as follows:

- ***Step 1**. Objective: The objective of this paper is to identify optimal laser cutting parameter settings to minimize average surface roughness (R_a) in CO_2 laser cutting of stainless steel.*
- ***Step 2**. Experimental procedure: Laser cutting experiment trials were conducted according to Taguchi's experimental plan in which four laser cutting parameters (P, v, p and f) were arranged in L_{27} OA.*
- ***Step 3**. R_a measurement: The R_a of machined surface was measured using Surfrest SJ-301 (Mitutoyo) profilometer.*
- ***Step 4**. FFNN modeling: The experimental data was used for development of predictive model for R_a. A FFNN was trained using the Levenberg-Marquardt algorithm.*
- ***Step 5**. Optimization: The optimization problem was formulated and solved using CSA with the help of Matlab.*

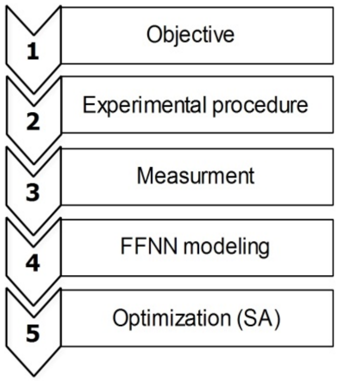

Figure 2. The flow chart of optimization procedure

Development of the FFNN prediction model

Matlab software was used for development of FFNN model for average surface roughness (R_a) in terms of laser cutting parameters (P, v, p and f). The FFNN model architecture is given in Figure 1. To develop FFNN, experimental data was used (Table 3), of which, 19 data sets were selected randomly and used for training, while the remaining 8 data sets (bolded rows in Table 3) were presented to the trained FFNN for testing the predictive accuracy of the developed model.

It was widely reported that FFNN with single hidden layer are able to approximate any arbitrary function to a given accuracy. Therefore, the selection of architecture can be reduced to finding the "optimal" number of hidden neurons. The number of hidden neurons is data dependent. The number of weights is equal to the sum of the product between the numbers of neurons in each layer. Therefore, the upper limit of number of hidden neurons is restricted by the number of available data for training.

The hyperbolic tangent sigmoid transfer function was used for the hidden layers, and linear transfer function was used for the output layer. Prior to FFNN training, the initial values of weights were set according to Nguyen-Widrow method. In order to stabilize and enhance ANN training the input and output data was normalized in [–1, 1] range.

To train the FFNN, Levenberg-Marquardt algorithm was used. This algorithm was selected because in practice, Levenberg-Marquardt algorithm is faster and finds better optima for a variety of problems than do the other usual methods. The ANN training process performance was followed according to the mean squared error (MSE).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(d_i - y_i\right)^2 \qquad (5)$$

where N is the number of data; d_i is experimental values; and y_i is predicted value of FFNN for training sample i.

The 4-4-1 FFNN architecture trained for 21 iterations turned out to be the best solution, after considering the well-known bias variance trade-off in empirical model building. FFNN surface roughness predicted values are given in Table 3. The prediction accuracy of the FFNN was checked by the mean absolute percentage error (MAPE). This statistic is defined by:

$$MAPE(\%) = \left(\frac{1}{N}\sum_{i=1}^{N}\left|\frac{d_i - y_i}{d_i}\right|\right)\times 100 \qquad (6)$$

Table 4 shows the comparison between FFNN model and experimental results. Good agreement between FFNN predictions and experimental results for R_a can be observed from Table 4. Therefore, the developed FFNN can be used to acquire the function that

Table 4. MAPE errors for FFNN predictions

	average MAPE(%)
Training data	8.71
Testing data	9.66

relates input laser cutting parameters (P, v, p and f) to the R_a using the weights and biases from the trained FFNN. This function was used as the objective function in CSA based optimization.

CSA optimization solution

The objective of this study is to identify the optimal cutting parameter settings minimizing the R_a. Optimization problem can be formulated as follows:

$$\begin{aligned} &Find:\ \ P, v, p, f \\ &\text{to minimize}:\ \ R_a = f(P, v, p, f) \end{aligned} \qquad (7a)$$

within cutting parameter ranges (constraints):

$$\begin{aligned} &1.6 \le P \le\ 2\ (\mathrm{kW}) \\ &2 \le v \le\ 3\ (\mathrm{m/min}) \\ &9 \le p \le 12\ (bar) \\ &\text{-}2.5 \le f \le \text{-}0.5\ (mm) \end{aligned} \qquad (7b)$$

For calculating average surface roughness (R_a), the mathematical function based on developed FFNN was used. CSA was implemented with the following parameters the n=25 and p_a=0.25. The number of objective function evaluation used by the CSA for optimization search process was 1000. Optimal laser cutting parameter values obtained are: 2 kW for laser power, 2 m/min for cutting speed, 12 bar for assist gas pressure, and –0.5 mm for focus position. In coded terms the optimal combination is A3B1C3D3. The combination of this cutting parameter settings lead to minimum R_a value of 1.2625 μm. This means that the optimal point is actually boundary point in the hyperspace of the laser cutting parameters.

From the optimization results it is seen that cutting speed converges to the lower limits, while laser power, assist gas pressure and focus positions converge to the upper limit in the experimental hyperspace covered. This indicates that CSA optimized average surface roughness is directly proportional with cutting speed, but inversely proportional with laser power, assist gas pressure and focus positions. These results are in accordance with the findings reported in the literature in the case of CO_2 laser cutting of stainless steel [9].

CONCLUSIONS

In this paper surface roughness prediction model for CO_2 laser cutting of AISI 304 stainless steel by considering laser power, cutting speed, assist gas pressure, and focus position as input model parameters was developed. A feed forward neural network was developed to model surface roughness by exploiting experimental measurements obtained from the Taguchi's experimental design. It is found that neural network can be used effectively to model the process parameters relationships and hence make accurate predictions of surface roughness obtained in laser cutting. Through the integration of the neural network model with cuckoo search algorithm, optimal laser cutting parameter settings were identified. The optimization results were validated by comparing with the findings in the relevant literature. Integrating neural networks and cuckoo search algorithm offers a simple and effective method for searching of the optimal process parameter settings in laser cutting.

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