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RESEARCH

Modeling and Simulated Annealing Optimization of Surface Roughness in CO_2 Laser Nitrogen Cutting of Stainless Steel

M. Madić[a], M. Radovanović[a], B. Nedić[b]

[a]*University of Niš, Faculty of Mechanical Engineering, Serbia.*
[b]*University of Kragujevac, Faculty of Engineering, Serbia.*

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Corresponding author:

M. Madić
University of Niš,
Faculty of Mechanical Engineering,
Serbia
E-mail: madic@masfak.ni.ac.rs

A B S T R A C T

This paper presents a systematic methodology for empirical modeling and optimization of surface roughness in CO_2 laser nitrogen cutting of stainless steel. The surface roughness prediction model was developed in terms of laser power, cutting speed, assist gas pressure and focus position by using the artificial neural network (ANN). To cover a wider range of laser cutting parameters and obtain an experimental database for the ANN model development, Taguchi's L_{27} orthogonal array was implemented in the experimental plan. The developed ANN model was expressed as an explicit nonlinear function, while the influence of laser cutting parameters and their interactions on surface roughness were analyzed by generating 2D and 3D plots. The final goal of the experimental study focuses on the determination of the optimal laser cutting parameters for the minimization of surface roughness. Since the solution space of the developed ANN model is complex, and the possibility of many local solutions is great, simulated annealing (SA) was selected as a method for the optimization of surface roughness.

1. INTRODUCTION

Laser cutting is one of the most used non-conventional machining processes for straight and contour cutting of sheet stock. By directing the focused laser beam onto the workpiece surface it comes to rapid heating which results, depending on the workpiece characteristics and beam intensity, in melting or evaporation of workpiece material. The molten material is then removed using a coaxial jet of an assist gas.

Laser cutting technology requires relatively high capital cost of equipment, however, low operational costs justifies its use for both large batch processing and processing of customized products. The other main advantages over the competing machining processes include better productivity, higher quality, applicability for both very soft and thin materials as well as difficult to cut materials.

Laser cutting is a complex, multifactor machining process. The principal factors that affect the cutting process include [1]: beam power and characteristics, cutting speed, type of assist gas and flow and focus position. The effects of these parameters on the laser cutting performances have been widely studied [2,3]. As reported in many experimental studies, depending on materials characteristics, workpiece thickness as well as varying interval of process factors, the main process factors differently affect the process performances. This makes prediction of process performance characteristics and identification of near optimal factors quite difficult [4].

In this paper mathematical model for surface roughness prediction in CO_2 laser nitrogen cutting of stainless steel was developed. Detailed reviewed about surface roughness in laser cutting is available in literature [5]. As seen from previous studies, the mechanism of surface roughness formation in laser cutting is complex, requiring modeling of multiple non-linearities which justifies the use of artificial neural networks (ANNs). The back propagation (BP) ANN trained with gradient descent with momentum algorithm was applied to construct a mathematical model wherein the surface roughness was expressed as an explicit nonlinear function of the four laser cutting parameters. For conducting the laser cutting experiment, Taguchi's L_{27} orthogonal array (OA) was used where the laser cutting parameters, namely the laser power, cutting speed, assist gas pressure, and focus position, were arranged. Statistically assessed as adequate, the ANN model was then used to study the effect of the laser cutting parameters on surface roughness. Furthermore, in order to determine the optimal laser cutting parameters for achieving minimum surface roughness, the ANN model was integrated with SA.

2. EXPERIMENTAL PROCEDURE

2.1. Experimental details

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 the continuous wave mode. The cuts were performed with a Gaussian distribution beam mode (TEM_{00}) on 3 mm thick AISI 304 stainless steel. In consideration of the numerous parameters that influence the cutting process and final cut quality, i.e. surface roughness, some of the process parameters were kept constant throughout the experimentation. On the other hand, the laser cutting parameters such as laser power (P), cutting speed (v), assist gas pressure (p) and focus position (f) were taken as controllable input parameters. The laser cutting conditions are summarized in Table 1.

Table 1. Laser-cutting conditions.

Constant parameters:			
Workpiece material	AISI 304 stainless steel		
Material thickness, mm	3		
Laser	CO_2		
Operating mode	continuous wave		
Max. power, kW	2.2		
Lens focal length, mm	127		
Nozzle	conical shape, ∅ = 2 mm		
Stand off distance, mm	1		
Type of assist gas	N_2		
Controllable parameters:			
	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 value range for each of the laser cutting parameter was chosen such that wider experimental range was covered, a full cut for each parameter combination was achieved, and by considering manufacturer's recommendation for parameter settings. Two straight cuts, each of 60 mm in length, were made in each experimental trial to ascertain surface finish. Surface roughness on the cut edge was measured in terms of the average surface roughness (R_a) using Surftest SJ-301 (Mitutoyo) profilometer. 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.

2.2. Experimental plan

Taguchi experimental design provides an efficient plan to study the entire experimental region of interest for the experimenter, with the minimum number of experiment trials, therefore it was chosen to perform the laser cutting experiment. To this aim, Taguchi's L_{27}

orthogonal array with 4 input parameters and 3 levels was used. Table 2 shows the 27 conducted trials with the combination of the laser cutting parameters and the experimental results.

3. SURFACE ROUGHNESS ANN MODEL

The objective of the surface roughness modeling is to quantify the relationships that exist between process parameters and surface roughness, so as to be able to identify the near optimal laser cutting conditions in which the required surface roughness will be obtained. MATLAB software was used for the development of the ANN model for the average surface roughness (R_a) in terms of four laser cutting parameters, that is, laser power (P), cutting speed (v), assist gas pressure (p), and focus position (f). All experimental data were used to generate an experimental database for the ANN model development, i.e. ANN training.

The ANN architecture consisted of four input neurons, each to represent P, v, p and f, and one output neuron for estimating R_a. The number of hidden neurons was selected by considering that the total number of weights and biases in the ANN does not exceed the number of data for training. Considering the total number of weights and biases in the ANN model, it is easy to calculate that for four inputs and one output, the upper limit of the number of hidden neurons is 4 for 27 available training data. Therefore, 4-4-1 ANN architecture was selected for surface roughness modeling.

Table 2. Experimental layout using an L_{27} orthogonal array and experimental results.

Exp. trial	Natural factor				Coded factor				Experimental results
	P (kW)	v (m/min)	p (bar)	f (mm)	A	B	C	D	R_a (μm)
1	1.6	2	9	−2.5	1	1	1	1	1.84
2	1.6	2	10.5	−1.5	1	1	2	2	1.98
3	1.6	2	12	−0.5	1	1	3	3	2.17
4	1.6	2.5	9	−1.5	1	2	1	2	2.34
5	1.6	2.5	10.5	−0.5	1	2	2	3	2.08
6	1.6	2.5	12	−2.5	1	2	3	1	1.67
7	1.6	3	9	−0.5	1	3	1	3	2.20
8	1.6	3	10.5	−2.5	1	3	2	1	1.83
9	1.6	3	12	−1.5	1	3	3	2	2.30
10	1.8	2	9	−1.5	2	1	1	2	1.71
11	1.8	2	10.5	−0.5	2	1	2	3	1.96
12	1.8	2	12	−2.5	2	1	3	1	2.20
13	1.8	2.5	9	−0.5	2	2	1	3	1.70
14	1.8	2.5	10.5	−2.5	2	2	2	1	1.77
15	1.8	2.5	12	−1.5	2	2	3	2	1.69
16	1.8	3	9	−2.5	2	3	1	1	2.09
17	1.8	3	10.5	−1.5	2	3	2	2	2.15
18	1.8	3	12	−0.5	2	3	3	3	1.91
19	2	2	9	−0.5	3	1	1	3	1.89
20	2	2	10.5	−2.5	3	1	2	1	3.02
21	2	2	12	−1.5	3	1	3	2	1.83
22	2	2.5	9	−2.5	3	2	1	1	2.294
23	2	2.5	10.5	−1.5	3	2	2	2	1.47
24	2	2.5	12	−0.5	3	2	3	3	2.16
25	2	3	9	−1.5	3	3	1	2	1.60
26	2	3	10.5	−0.5	3	3	2	3	2.21
27	2	3	12	−2.5	3	3	3	1	1.93

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

$$p_{norm} = 2 \cdot \frac{(p_i - p_{min})}{(p_{max} - p_{min})} - 1. \quad (1)$$

where p_{norm} and p_i represent the normalized and original (raw) data, and p_{min} and p_{max} are the minimum and maximum values of the original data. To train the ANN, the gradient descent with momentum algorithm was used. The ANN training process performance was followed according to the mean squared error (MSE) [6]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - d_i)^2 . \quad (2)$$

where N is the number of data; d_i is the experimental value (target); and y_i is the predicted value of ANN for the training sample i. It was found that the selected ANN architecture provided the best data fitting capability when learning rate (α) and momentum (μ) were kept at 0.1 and 0.9, respectively. The MSE achieved during the training was 0.0131. Regarding the architecture of the developed ANN, the used transfer functions in hidden and output layer, and by using the weights and biases from trained ANN, the mathematical model for surface roughness in terms of the laser cutting parameters can be expressed by the following equation:

$$R_{a|norm} = \left[\frac{2}{1 + e^{-2\left(X \cdot w_{ji} + b_j\right)}} - 1\right] \cdot w_{kj} + b_k . \quad (3)$$

where X is the column vector which contains normalized values of P, v, p, and f, and $R_{a|norm}$ is the normalized value of the R_a. In order to obtain the actual values for R_a, one needs to perform the denormalization by the following equation:

$$R_{a|actual} = \frac{1}{2} \cdot (R_{a|norm} + 1) \cdot (p_{max} - p_{min}) + p_{min} . \quad (4)$$

In order to check the reliability of the developed ANN model, the prediction accuracy of the ANN model was tested. Initially, the ANN model for surface roughness was tested by presenting 27 input data patterns, which were employed for the training purpose. Using Eqs. 3 and 4 the predicted and experimentally measured average surface roughness values are compared in Fig. 1.

In addition, the absolute percentage errors were found to be δ_{max} = 11.02 %, δ_{min} = 0.06 %, δ_{aver} = 3.37 %. In order to test the generalization ability (i.e. model robustness) of the developed ANN model, 3 new experiment trials were conducted, with the laser cutting parameter levels which did not belong to the training data set (Table 3).

Table 3. Experiment trials for testing the ANN prediction model.

P (kW)	v (m/min)	p (bar)	f (mm)	Exp. measured R_a (μm)	ANN predicted R_a (μm)
1.8	2.5	12	–2.5	2.068	1.847
2	2.5	10.5	–0.5	1.733	1.760
1.8	3	10.5	–0.5	1.879	2.093

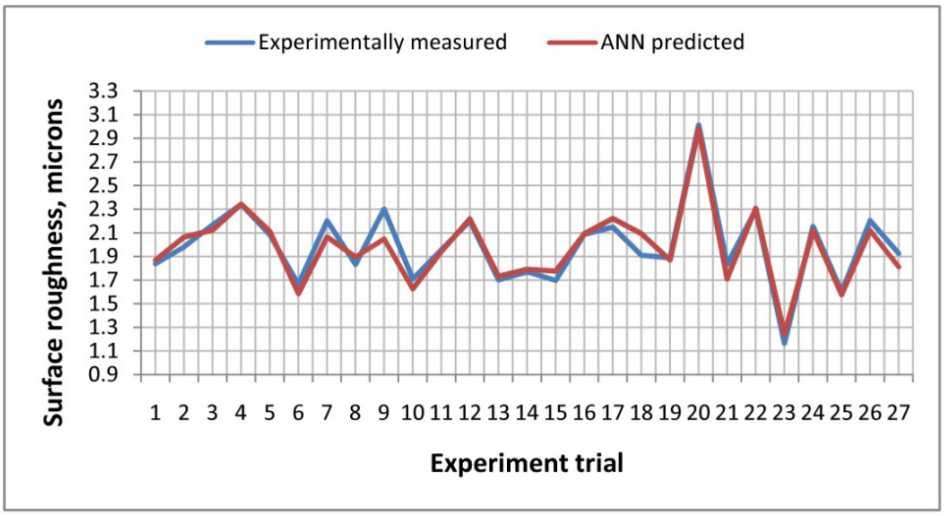


Fig. 1. Comparison of ANN predicted and experimentally measured average surface roughness.

The results from Fig. 1 and Table 3 suggest that the ANN predictions are in good agreement with experimental values for R_a within the scope of cutting conditions investigated in the study. Thus, the ANN model can be used to analyze the effects of the laser cutting parameters on surface roughness. Furthermore, the ANN model can be used in conjunction with the SA algorithm for the optimization purpose.

4. EFFECT OF THE LASER CUTTING PARAMETERS ON SURFACE ROUGHNESS

4.1. Main effects – 2D plots

Initially, the effect of the laser cutting parameters on surface roughness was analyzed by changing one parameter at a time, while keeping all of the other parameters constant at low, center and high level (Fig. 2). As shown in Fig. 2a, the effect of the laser power on surface roughness is variable and dependable on the values of other parameters. When all other parameters are kept at low level, an increase in the laser power increases surface roughness. However, an increase in the laser power decreases surface roughness when all other parameters are kept at high level. The figure shows no significant change in surface roughness with the laser power, when all other parameters are kept at center level. Fig. 2a suggest that the best surface finish can be obtained using the laser power of 2 kW, however, the effect of this parameter is to be considered through the interactions.

Fig. 2b shows that an increase in the cutting speed results in nonlinear increase in surface roughness and this functional dependence is constant, apart from the values of other parameters. The effect of the cutting speed can be explained by the fact that as the cutting speed increases, the interaction time between the laser beam and material decreases, i.e. the heat generation decreases, which leads to minimum side burning.

From Fig. 2c it can be seen that, in respect to other parameter values, the assist gas pressure between 9.75 bar and 11.25 bar negatively affects the surface finish. A decrease in the assist gas pressure shows a good decrease in surface roughness. The pressure that is too high expels the melt more efficiently, and has a positive effect on surface quality, particularly for impending burr formation, i.e. rather creates high gas consumption.

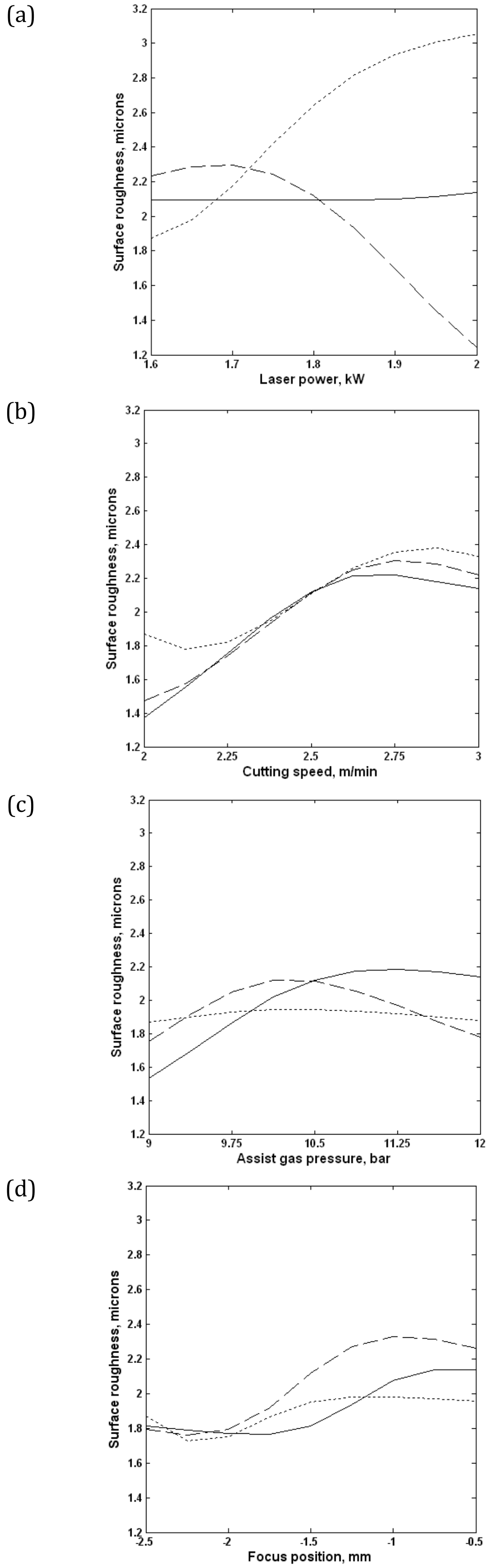


Fig. 2. Effect of the laser cutting parameters on surface roughness (······ other parameters at level 1; ——— other parameters at level 2; ---- other parameters at level 3).

In the case of the focus position, Fug. 2d suggests that focusing the laser beam deep into the bulk of the material is beneficial for achieving good surface finish. The functional dependence between the focus position and surface roughness is nonlinear and follows the same trend apart from the values of other parameters.

The results from Fig. 2 indicate that the mechanism behind surface roughness formation is complex and further complicated having in mind that the interactions between the laser cutting parameters have a huge impact on surface roughness. Thus, it is necessary to investigate the interaction effects of the laser cutting parameters on surface roughness.

4.2. Interaction effects – 3D plots

In order to determine the interaction effects of the laser cutting parameters on surface roughness, 3D surface plots were generated considering two parameters at a time, while the third and fourth parameter were kept constant at center level. Since there were six possible two-way interactions, six plots were generated (Fig. 3) using Eqs. 3 and 4.

Fig. 3a shows surface roughness as a function of the laser power and cutting speed. It can be seen that a parallel increase in the laser power and cutting speed linearly increases surface roughness. High cut quality can be obtained using high laser power and cutting speed in the 2.25-2.5 m/min range.

From Fig. 3b it can be seen that when using low assist gas pressure, increasing the laser power improves surface finish, and vice versa. Using the laser power of up to 1.8 kW with the combination of the assist gas pressure of up to 11 bar produces rough surface finish.

Fig. 3c shows that when the focus position is set to −2.5 mm, the effect of the laser power on surface roughness is negligible. When the focus position is shifted in positive direction (moves towards workpiece surface), an increase in the laser power has a positive effect on surface finish. Using the laser power of up to 1.9 kW, while focusing the laser beam at the half of the material thickness, results in high surface roughness.

In the case of interaction between the assist gas pressure and cutting speed, Fig. 3d suggests that using the assist gas pressure of up to 10.5 bar allows the cutting speed of up to 2.25 m/min for good surface finish.

From Fig. 3e it can be seen that the interaction effect of the focus position and cutting speed produces highly nonlinear change in surface roughness. Using the low cutting speed of up to 2.25 m/min while focusing the laser beam approximately at the half of the material thickness, is beneficial for obtaining low roughness values.

Finally, Fig. 3f shows that a low focus position in conjunction with low assist gas pressure is beneficial for surface finish. On the other hand, focusing the laser beam near the top surface, and increasing the assist gas pressure, results in surface roughness increase.

The results from Fig. 3 indicate that there are highly nonlinear interactions between the laser cutting parameters and surface roughness. Note that the plots in Fig. 3 were generated by keeping the two parameters constant. However, finding an optimal set of laser cutting parameter values to meet the desired surface roughness call for the parameter optimization in a four-dimensional laser cutting parameter hyperspace.

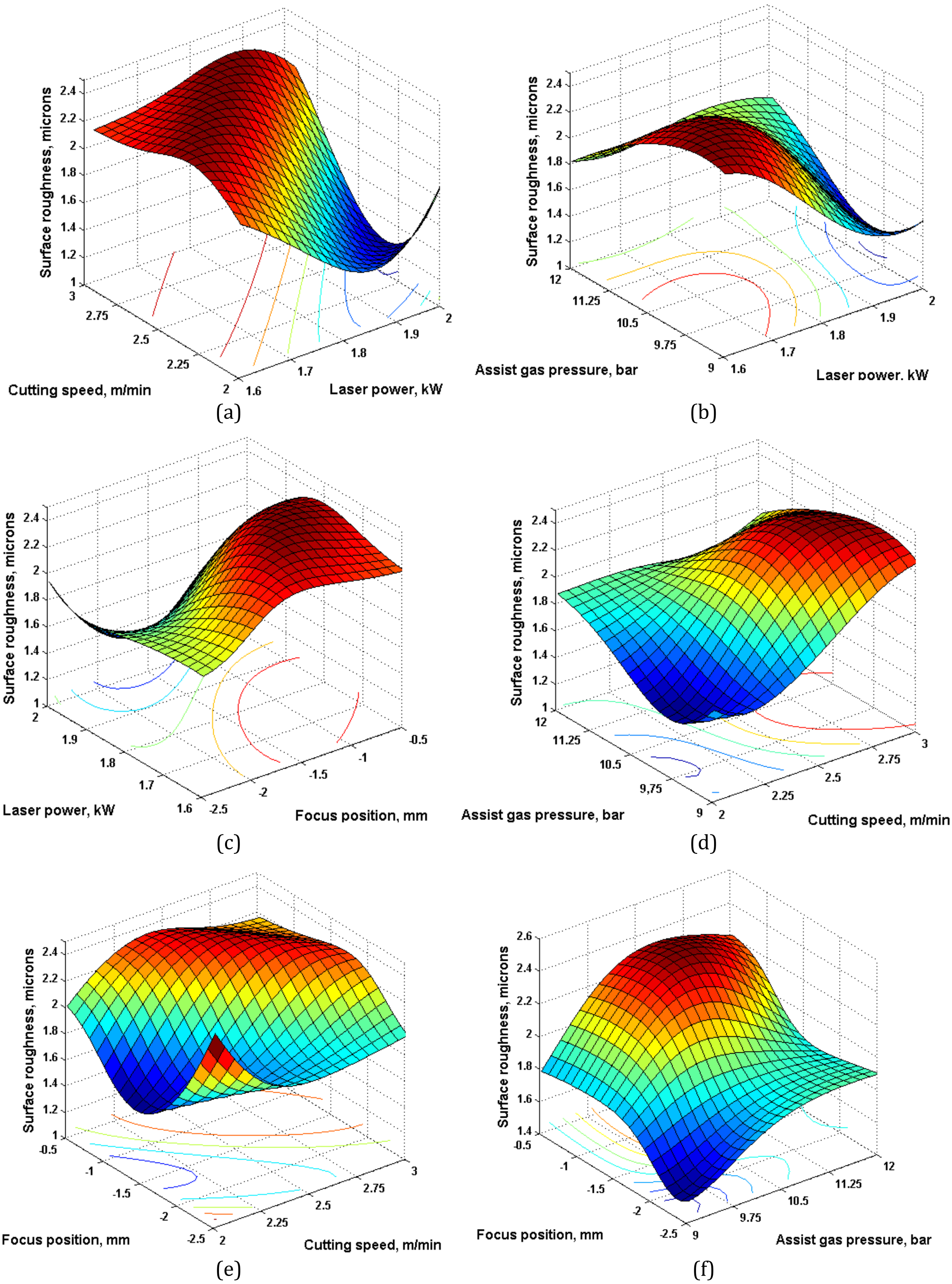


Fig. 3. Interaction effect of the laser cutting parameters on surface roughness.

5. OPTIMIZATION METHODOLOGY

Since the solution space of the developed ANN model is complex, and the possibility of many local solutions is great, SA was selected as the method for surface roughness optimization. The SA optimization procedure was done using the MATLAB Optimization Toolbox on the basis of the code of developed ANN model written in MATLAB. The details about the SA algorithm, optimization problem formulation and results are discussed bellow.

5.1. Simulated annealing (SA)

Initially presented by Kirkpatrick et al. [7], SA is a random search technique for global optimization problems able to escape local optima. The salient features of SA are its general applicability and ability to avoid local optima [8].

The concept of simulated annealing mimics the metals recrystallization in the process of annealing. Annealing is the slow cooling of metal that produces good low energy state crystallization, whereas fast cooling produces poor crystallization. At high temperatures, the movement of the atoms in molten metals is free. With temperature decreasing, the movement of the atoms becomes limited, the atoms tend to get ordered and, finally, form crystals having the minimum possible energy which depends on the cooling rate. Slow cooling produces good low energy state crystallization, whereas fast cooling produces poor crystallization (high energy polycrystalline state). If the temperature is reduced at a very fast rate, the system may achieve the high energy polycrystalline state instead of the low energy crystalline state.

SA uses a single point search method. It is a memoryless search algorithm in the sense that no information is saved from previous searches [9]. The SA algorithm starts with a random initial design vector (solution) X_i and a high temperature T. A second design point is created at random in the vicinity of the initial point and the difference in the function values ΔE at these two points is calculated as [10]:

$$\Delta E = \Delta f = f_{i+1} - f_i \equiv f(X_{i+1}) - f(X_i). \tag{5}$$

If the objective function value of the new solution is smaller, the new solution is automatically accepted and becomes the current solution from which the search continues. Otherwise, the point is accepted with a probability $e^{(-\Delta E/kT)}$ where k is the Boltzmann's constant. This completes one iteration of SA. Due to the probabilistic acceptance of a non improving solution, SA can escape from local optima. At a certain temperature T, a predetermined number of new points are tested. The algorithm is terminated when the current value of temperature is small enough or when changes in function values (Δf) are sufficiently small. Further details of SA can be found elsewhere [9,10].

5.2. Definition of the objective function and constraints

The goal of the optimization process in this study is to determine the optimal laser cutting parameter values that contribute to the minimum value of average surface roughness (R_a). To formulate the optimization problem, the ANN model which is proposed in Eq. 4 is taken to be the fitness function of the optimization solution and is formulated as follows:

$$\begin{aligned}
&\text{Find: } P_{opt}, v_{opt}, p_{opt}, f_{opt} \\
&\text{to minimize: } R_a = \text{function}(P, v, p, f) \\
&\text{subject to: } 1.6 \le P \le 2\ (\text{kW}) \\
&\qquad 2 \le v \le 3\ (\text{m/min}) \\
&\qquad 9 \le p \le 12\ (\text{bar}) \\
&\qquad -2.5 \le f \le -0.5\ (\text{mm})
\end{aligned} \quad . \tag{6}$$

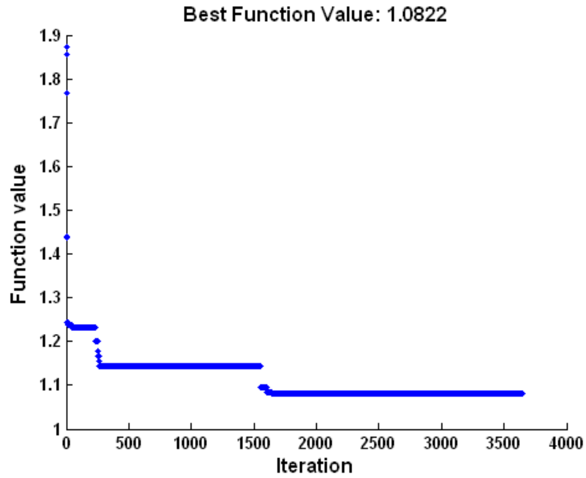
5.3. Optimization results

For solving the optimization problem formulated in Eq. 6, the computer code was written in MATLAB to integrate the ANN based process models and SA. The SA algorithm was implemented with the following parameters (Table 4):

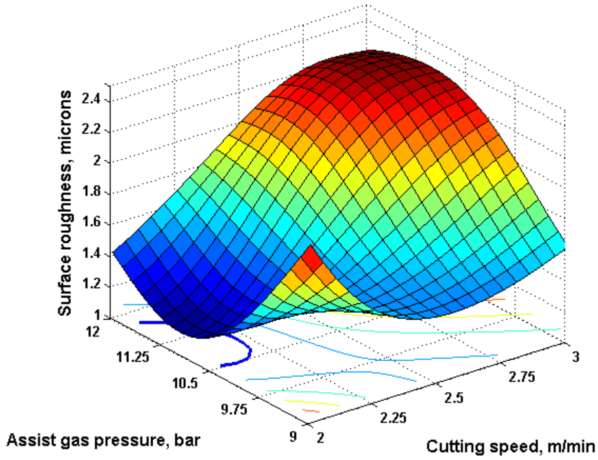
- Annealing function is selected as the Boltzmann annealing which takes random steps, with size proportional to square root of temperature.
- Reannealing interval is the number of points to accept before reannealing. Default value of 100 was used.
- Exponential temperature update which decreases as $0.95^{\text{iteration}}$ was used.
- Initial temperature of 100 °C was set at the beginning of the optimization.

Table 4. SA parameters used.

Start point	[1 1 1 1]
Initial temperature, T	100
Annealing function	Boltzmann annealing
Temperature update function	Exponential temperature
Reannealing interval	100



(a)



(b)

Fig. 4. Optimization results.

Note that since the ANN function was developed using the normalized values of the laser cutting parameters in the [–1, 1] range, the initial points for the SA solution in Table 4 are also given as normalized values.

The optimization solution results of the MATLAB optimization toolbox are given in Fig. 4a. It is indicated that the near optimal solution was found at the 3646-th iteration. The combination of the laser cutting parameter settings lead to minimum R_a value of 1.082 μm with the following values: laser power P = 2 kW, cutting speed v = 2 m/min, assist gas pressure p = 11.06 bar and focus position f = –0.739 mm. Optimization of the laser cutting parameters was tested by using the Monte-Carlo method, and identical results were obtained. The optimization results can be confirmed from Fig. 4b.

Apart from the obtained optimization results, the near optimal laser cutting parameter values for obtaining minimal R_a were determined considering the following constraints: (a) maximal cutting speed was used, and (b) minimal assist gas pressure was used. The above optimization formulations are of practical importance since they assure maximal productivity and minimal costs, respectively.

The solution of the optimization problem formulated in Eq. 6, with the constraint v = 3 m/min, is obtained as: minimal R_a = 1.232 μm for P = 2 kW, p = 9 bar and f = –2.5 mm. It has to be noticed that the obtained solution is in the same time the optimal one for the optimization problem when the constraint is p = 9 bar. In other words, the obtained solution, which is actually a boundary point in the hyperspace of the laser cutting parameters, simultaneously satisfies both goals, i.e. maximal productivity and minimal costs.

6. CONCLUSION

In this paper, empirical modeling and optimization of surface roughness in CO_2 laser nitrogen cutting of stainless steel was presented. The applied methodology integrates surface roughness modeling using the artificial neural network (ANN), and single-objective optimization of laser cutting parameters using the simulated annealing (SA) algorithm. To obtain an experimental database for the ANN model development, Taguchi's L_{27} orthogonal array was implemented in the experimental plan in which four laser cutting parameters (laser power, cutting speed, assist gas pressure and focus position) were arranged at three levels. The mathematical model of the surface roughness developed by using the ANN was expressed as an explicit nonlinear function of the selected input parameters. The statistical results indicated good agreement between the predicted and experimental values so that the ANN model was used for analyzing the effect of the laser cutting parameters and their interactions on surface roughness. From the analysis of the effect of the laser cutting parameters on surface roughness the following conclusions can be drawn:

- Surface roughness is highly sensitive to the selected laser cutting parameters,
- The functional dependence between surface roughness and the laser cutting parameters is highly nonlinear,
- The effect of a given parameter on surface roughness must be considered through the interaction with other parameters.

In addition to modeling, optimization of surface roughness based on the integrated ANN-SA approach was conducted. Based on the optimization results, high laser power (2 kW), low cutting speed (2 m/min), medium assist gas pressure (11.06 bar) and focus position (–0.739 mm) yielded the minimum surface roughness (1.082 μm). However, using high laser power (2 kW), high cutting speed (3 m/min), low assist gas pressure (9 bar) and focus position (–2.5 mm) a minimal surface roughness of 1.232 μm was obtained and this turned out to be beneficial for both productivity and costs.

Findings in this paper indicate that the ANN-SA approach can be efficiently used for mathematical modeling and optimization of the CO_2 laser cutting process.

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