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ANN modeling of kerf taper angle in CO_2 laser cutting and optimization of cutting parameters using Monte Carlo method

Miloš Madić[a*], Miroslav Radovanović[a] and Marin Gostimirović[b]

[a]*Faculty of Mechanical Engineering, University of Niš, A. Medvedeva 14, Niš, Serbia*
[b]*Faculty of Technical Science, University of Novi Sad, Trg Dositeja Obradovića 6, Serbia*

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A B S T R A C T

In this paper, an attempt has been made to develop a mathematical model in order to study the relationship between laser cutting parameters such as laser power, cutting speed, assist gas pressure and focus position, and kerf taper angle obtained in CO_2 laser cutting of AISI 304 stainless steel. To this aim, a single hidden layer artificial neural network (ANN) trained with gradient descent with momentum algorithm was used. To obtain an experimental database for the ANN training, laser cutting experiment was planned as per Taguchi's L_{27} orthogonal array with three levels for each of the cutting parameters. Statistically assessed as adequate, ANN model was then used to investigate the effect of the laser cutting parameters on the kerf taper angle by generating 2D and 3D plots. It was observed that the kerf taper angle was highly sensitive to the selected laser cutting parameters, as well as their interactions. In addition to modeling, by applying the Monte Carlo method on the developed kerf taper angle ANN model, the near optimal laser cutting parameter settings, which minimize kerf taper angle, were determined.

1. Introduction

Laser cutting is a thermal energy based advanced machining process which has many applications in industry where a variety of components in large numbers are required to be machined with high quality and close tolerance at low costs. The wide spectrum of industrial application of the laser cutting is due to its convenience of operation, high precision, small heat-affected zone (HAZ), minimum deformity, low cost, high product quality, high cutting speed, low level of noise, flexibility, ease of automation, etc. (Madić & Radovanović, 2013).

Due to many advantages that offer, laser cutting technology is area of continuous research and development. A number of analytic, numerical and experimental modeling studies have been carried out in order to analyze the laser cutting process, and some of the findings and possibilities of this cutting technology are summarized in a comprehensive review paper (Dubey & Yadava, 2008).

* Corresponding author. Tel: +381 18500687 Fax: +381 18 588244
E-mail: madic@masfak.ni.ac.rs (M. Madić)

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Of particular interest to companies using laser cutting are the maximization of the productivity and the subsequent quality of components made by the laser cutting process (Rajaram et al., 2003). There are different quality characteristics used for assessing the laser cut quality, wherein kerf quality characteristics, surface roughness, and size of the HAZ were mostly investigated. It has been reported in literature that the optimum parameter settings for one quality characteristic may deteriorate other quality characteristics. With a limited theoretical and practical background to assist in systematical selection, these parameters are usually set by previous experience in a time consuming trial and error procedure. However, this trial-and-error approach is extremely costly in terms of time and labor (Ciurana et al., 2009).

Hence, it is of great importance to exactly quantify the relationship between cut quality characteristics and laser cutting conditions through mathematical modeling and subsequently determine the near optimal laser cutting parameter settings via application of optimization algorithms. In the field of laser cutting, most of the time the optimal cutting conditions are determined using the Taguchi method (Prajapati et al., 2013) and by coupling response surface models (Sivarao et al., 2013) and ANNs models with different optimization and metaheuristic algorithms such as particle swarm optimization (Ciurana et al., 2009), genetic algorithm (GA) (Tsai et al., 2008), and simulated annealing (Chaki & Ghosal, 2011). The open literature reveals several research attempts based on ANNs such as for modeling and optimization of laser micromachining process (Ciurana et al., 2009; Biswas et al., 2010; Dhara et al., 2008; Dhupal et al., 2007), selection of optimal laser cutting parameters through integration of ANNs with GA (Tsai et al., 2008; Ghoreishi & Nakhjavani 2008), development of a prediction model through integration with the Taguchi method (Yang et al., 2012) and parametric modeling and optimization of lasox cutting (Chaki & Ghosal, 2011). The ANNs are the learning algorithms and mathematical models, which imitate the information processing capability of human brain and can be applied to non-linear and complex data, even if the data are imprecise and noisy (Raja et al., 2012). 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 (Karnik et al., 2008).

This paper aims at understanding the relations between the laser cutting parameters (laser power, cutting speed, assist gas pressure and focus position) and kerf taper angle obtained in CO_2 laser cutting of stainless steel. Back propagation (BP) ANN trained with gradient descent with momentum algorithm was applied to construct a mathematical model for the kerf taper angle. To obtain data for ANN training, the laser cutting experiment was conducted according to Taguchi's L_{27} orthogonal array (OA) experimental layout plan. Statistically assessed as adequate, the ANN model was then used to investigate the effect of the laser cutting parameters on the kerf taper angle by generating 2D and 3D plots. In addition to modeling, the kerf taper angle mathematical model was optimized. Although the aforementioned metaheuristic algorithms can provide acceptable results, its effective application, requires a substantial amount of parameter tuning. On the other hand, the Monte Carlo method has been proven efficient in optimization, but its application in solving machining optimization problems has been given less attention (Madić et al., 2014). Furthermore, to the authors' knowledge, little work has been reported in the literature on optimization through integration of ANN models and the Monte Carlo method. Hence in this paper the near optimal laser cutting parameter settings that minimize kerf taper angle were identified by exploring the solution space of the developed ANN kerf taper model using the Monte Carlo method.

2. Experimental work

In this study, AISI 304 stainless steel was chosen as the work material because of its extensive use in the aerospace, automotive and food industry. The chemical composition is given in Table 1. The sheet dimensions were 500 x 500 mm with thickness of 3 mm.

Table 1
Nominal chemical composition of AISI 304 stainless steel

Cr	Ni	C	Mn	Si	S	Fe
18.9	9.22	0.07	1.64	0.5	0.006	Balance

The experiment was performed using a ByVention 3015 CO_2 laser cutting machine with a nominal 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}). In consideration of the numerous parameters that influence the cutting process, some of the process parameters were kept constant throughout the experimentation. During conducting experiment trials, laser beam was focused through a lens of focal length of 127 mm and the distance between workpiece and nozzle was controlled at 1 mm. The nitrogen gas with 99.95 % purity was used as assist gas and it was passed through a conical shape nozzle (HK20) with nozzle diameter of 2 mm.

On the other hand, the laser cutting parameters such as the laser power (P), cutting speed (v), assist gas pressure (p), and focus position (f) were taken as controllable input parameters. Since it was assumed that the effects of laser cutting parameters on the kerf taper angle were complex and non-linear, the experiment was set up with parameters with more levels. The numerical values of control parameters at different levels are shown in Table 2. The value range for each parameter was chosen such that full cut for each parameter combination was achieved and by considering manufacturer's recommendation for parameter settings.

Table 2
Cutting parameters and their levels

Cutting parameter	Unit	Level		
		1	2	3
Laser power, P	kW	1.6	1.8	2
Cutting speed, v	m/min	2	2.5	3
Assist gas pressure, p	bar	9	10.5	12
Focus position, f	mm	-2.5	-1.5	-0.5

The experiment trials were conducted according to Taguchi's L_{27} orthogonal array design matrix (Table 3). The L_{27} chosen consisted of 13 columns and 27 rows (experimental trials). Control parameters, laser power, cutting speed, assist gas pressure and focus position were assigned to columns 1, 2, 5 and 9, respectively.

In this study, kerf taper angle was selected as the laser cut quality characteristic for modeling and optimization. Kerf taper angle is one of the most important cut quality characteristics in laser cutting since it determines the geometrical accuracy of the finished parts. Due to converging-diverging shape of laser beam profile the kerf taper angle always exists during laser cutting. The kerf taper angle (K_t) was calculated using the following formula:

$$K_t(^\circ) = \left(\frac{K_w - K_b}{2 \cdot d}\right) \cdot \frac{180}{\pi} \tag{1}$$

where d is the workpiece thickness, and K_w and K_b represent the top and bottom kerf width, respectively. The kerf widths at top and bottom of each machined workpiece were measured at three equally distanced locations along the length of the cut by means of optical microscope (Leitz, Germany). The average kerf taper angle values corresponding to each experimental trial are listed in Table 3.

Table 3
L_{27} matrix for the experiment and kerf taper angle experimental results

Exp. trial	P (kW)	v (m/min)	p (bar)	f (mm)	K_t (°)
1	1.6	2	9	-2.5	1.18
2	1.6	2	10.5	-1.5	-0.6
3	1.6	2	12	-0.5	-6.02
4	1.6	2.5	9	-1.5	0.83
5	1.6	2.5	10.5	-0.5	-3.63
6	1.6	2.5	12	-2.5	1.46
7	1.6	3	9	-0.5	-4.07
8	1.6	3	10.5	-2.5	2.07
9	1.6	3	12	-1.5	0.51
10	1.8	2	9	-1.5	-4.46
11	1.8	2	10.5	-0.5	-4.93
12	1.8	2	12	-2.5	1.34
13	1.8	2.5	9	-0.5	-5.63
14	1.8	2.5	10.5	-2.5	1.27
15	1.8	2.5	12	-1.5	-3.12
16	1.8	3	9	-2.5	1.5
17	1.8	3	10.5	-1.5	-3.09
18	1.8	3	12	-0.5	-4.01
19	2	2	9	-0.5	-5.06
20	2	2	10.5	-2.5	1.15
21	2	2	12	-1.5	-5.57
22	2	2.5	9	-2.5	0.35
23	2	2.5	10.5	-1.5	-5.25
24	2	2.5	12	-0.5	-5.95
25	2	3	9	-1.5	-4.84
26	2	3	10.5	-0.5	-6.49
27	2	3	12	-2.5	1.12

3. Kert taper angle mathematical model

Modeling studies in laser cutting are the scientific ways to study the system behaviors and help us to get a better understanding of this complex process (Syn et al., 2011). A mathematical model of a system is the relationship between input and output parameters in terms of mathematical equations (Dubey & Yadava 2008). Although the regression models are very promising for practical applications, they are of limited applicatability and reliability in laser cutting modeling. Therefore, to establish a mathematical relationship between the kerf taper angle and the laser cutting parameters, a multilayer perceptron type ANN was selected.

3.1. ANN architecture and training

Four neurons at the input layer (for each of the cutting parameter), one neuron at the output layer for calculating kerf taper and only one hidden layer were used to define ANN architecture. The determine the number of hidden neurons the following equation was considered (Madić & Radovanović, 2013):

$$T = m(n + k + 1) + k \tag{2}$$

where n is the number of input neurons, m is the number of hidden neurons and k is the number output neurons and T is the total number of weights and biases. Regarding previous equation and the number of available experimental data, 4-4-1 ANN architecture was selected for kerf taper modeling. Nonlinear and linear activation (transfer) functions were used in hidden layer and output layer, respectively. These transfer functions were used since it was assumed that there existed a nonlinear relationship between input and output process parameters. In order to develop robust and accurate mathematical model, the ANN training process was repeated several times using different initial weights. 10000 iterations was set as termination criterion for ANN training while learning rate and momentum were set at 0.1 and 0.9, respectively. The mean squared error at the end of the training process was found to be 0.00509298.

3.2. ANN model function and validation

After ANN training, the set of weights and biases of the developed ANN model were saved (Table 4), upon which explicit mathematical model for the kerf taper angle was developed.

Table 4
The weights and biases of the developed ANN model for the kerf taper angle

	W_1			W_2	B_1	B_2
0.897	-1.197	-0.579	-0.356	0.131	-2.543	1.035
-0.649	-1.764	-1.406	3.705	-0.871	1.796	
-0.094	-1.460	1.494	1.446	0.112	-0.001	
-2.501	-0.831	-1.477	-0.430	0.897	-3.043	

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

The mathematical equation for the prediction of the kerf taper angle is as follows:

$$K_t = 4.28 \cdot \left(\left(\left[\frac{2}{1+e^{-2(X \cdot W_1 + B_1)}} - 1 \right] \cdot W_2 + B_2 \right) + 1 \right) - 6.49 \tag{3}$$

where X is the column vector which contains normalized values of P, v, p and f. To test the prediction capability of the developed model, the trained ANN was initially tested by presenting 27 input data patterns, which were employed for the training purpose. Furthermore, 4 new experiment trials were conducted with cutting parameter levels which did not belong to the training data set (Table 5).

Table 5
Experiment trials for testing the ANN

Test no.	P (kW)	v (m/min)	p (bar)	f (mm)	Experimentally measured	ANN predicted
1	2	2.5	10.5	-2.5	1.18	1.15
2	1.8	2	12	-1.5	-5.25	-5.31
3	2	2.5	12	-1.5	-0.8	-0.81
4	1.8	3	10.5	-2.5	1.43	1.08

The effectiveness of training of the ANN model and its ability to predict correct values for unseen data can be given in a form of regression analysis where correlation coefficient R determines the correspondence between the ANN outputs and targets (Bajić et al., 2008). The R-values of 0.987 and 0.999 were obtained for the training and testing of the ANN model, respectively. These values indicate that the ANN model has high prediction accuracy and that it also has good generalization ability. Thus, the ANN model can be used to analyze the effects of the laser cutting parameters on the kerf taper, as well as to serve as a fitness function for the optimization of laser cutting parameters.

4. Effect of laser cutting parameters on the kerf taper angle

4.1. Main effect plots

Initially, the effect of the laser cutting parameters on the kerf taper angle was analyzed by changing one parameter at a time, while keeping all other parameters constant at low, center and high level. The effect of the laser cutting parameters on the kerf taper angle is given in Fig. 1.

From Fig. 1a it can be seen that when all other parameters are kept at high level, an increase in the laser power results in a small linear decrease in the kerf taper angle. On the other hand, the effect of the laser power causes a non-linear change in the kerf taper angle. When all parameters are on low level, laser power in the (1.6 – 1.8 kW) range results in about ± 2º change in the kerf taper angle with the minimal value when using laser power of about 1.75 kW.

From Figs. 1b and 1c it is seen that an increase in the cutting speed and assist gas pressure results in nonlinear increase in the kerf taper angle and small linear increase when all other parameters are kept at high level. Further, as it could be seen, when all other parameters are at low level, increase in the cutting speed or assist gas pressure results in positive kerf taper angle. On the other hand, kerf taper angle has negative values.

In the case of the focus position (Fig. 1d), when all other parameters are kept at low level, the effect of the focus position has negligible influence on kerf taper angle change. On the other hand, the focus position has strong influence on kerf taper angle which can be related by nonlinear functional dependence. When all other parameters are kept at middle level, focusing the laser beam deep into the bulk of material is beneficial for obtaining small kerf taper angle. However, when using laser power of 2 kW, cutting speed of 3 m/min and assist gas pressure of 12 bar, focusing the laser beam up to the -1 mm results in small kerf taper angle.

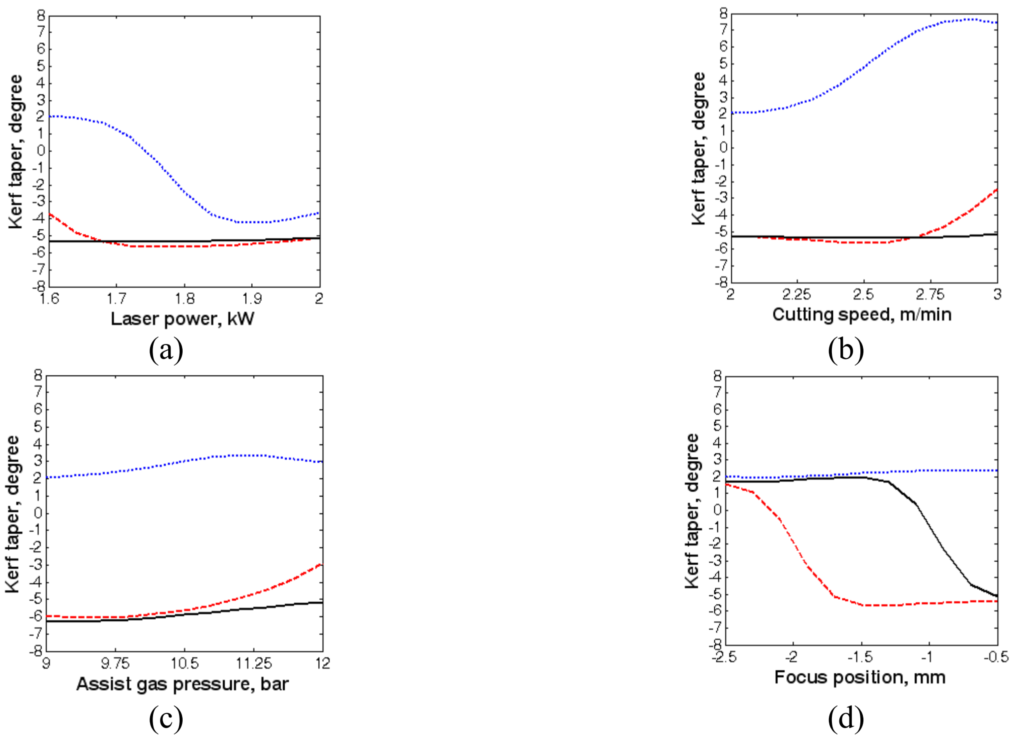


Fig. 1. Effect of laser cutting parameters on kerf taper

4.2. Interaction effect plots

The results from Fig. 1 indicate that there are certain interactions between the laser cutting parameters and the kerf taper angle. In order to determine the interaction effects of the cutting parameters on the kerf taper angle, 3D surface plots were generated considering two parameters at a time, while the third and fourth parameter were kept constant at level 2 (Fig. 2).

From Fig. 2a, it can be seen that the minimal kerf taper angle would be obtained either by using high laser power (P= 2 kW) in combination with high cutting speed (v= 3 m/min) or by using low laser power (P= 1.6 kW) in combination with low cutting speed (v= 2 m/min). A similar effect of the laser power can be observed in interaction with the assist gas pressure as shown in Fig. 2b. From Fig. 2c it can be seen that the minimal kerf taper angle is obtained by focusing the laser beam deep into the bulk of material (about f = -2 mm) independently from the laser power level. In the case of cutting speed and assist gas pressure interaction (Fig. 2d), it can be seen that higher cutting speed in conjunction with higher assist gas pressure is beneficial for minimizing the kerf taper angle. As shown in Fig. 2e, the interaction between the focus position and cutting speed results in a linear change in the kerf taper angle, and this is valid when focusing the laser beam beneath the half of the material thickness for all cutting speed values. A similar conclusion can be drawn from Fig. 2f in the case of focus position and assist gas pressure interaction.

Note that the plots in Fig. 1 were generated by keeping the three parameters constant at low, center and high level. Similarly the 3D surface plots in Fig. 2 were generated considering two laser cutting parameters at a time, while the third and fourth parameter were kept constant at center level. However, finding an optimal set of the laser cutting parameter values to meet the desired kerf taper angle, calls for the parameter optimization in four-dimensional laser cutting parameter hyperspace.

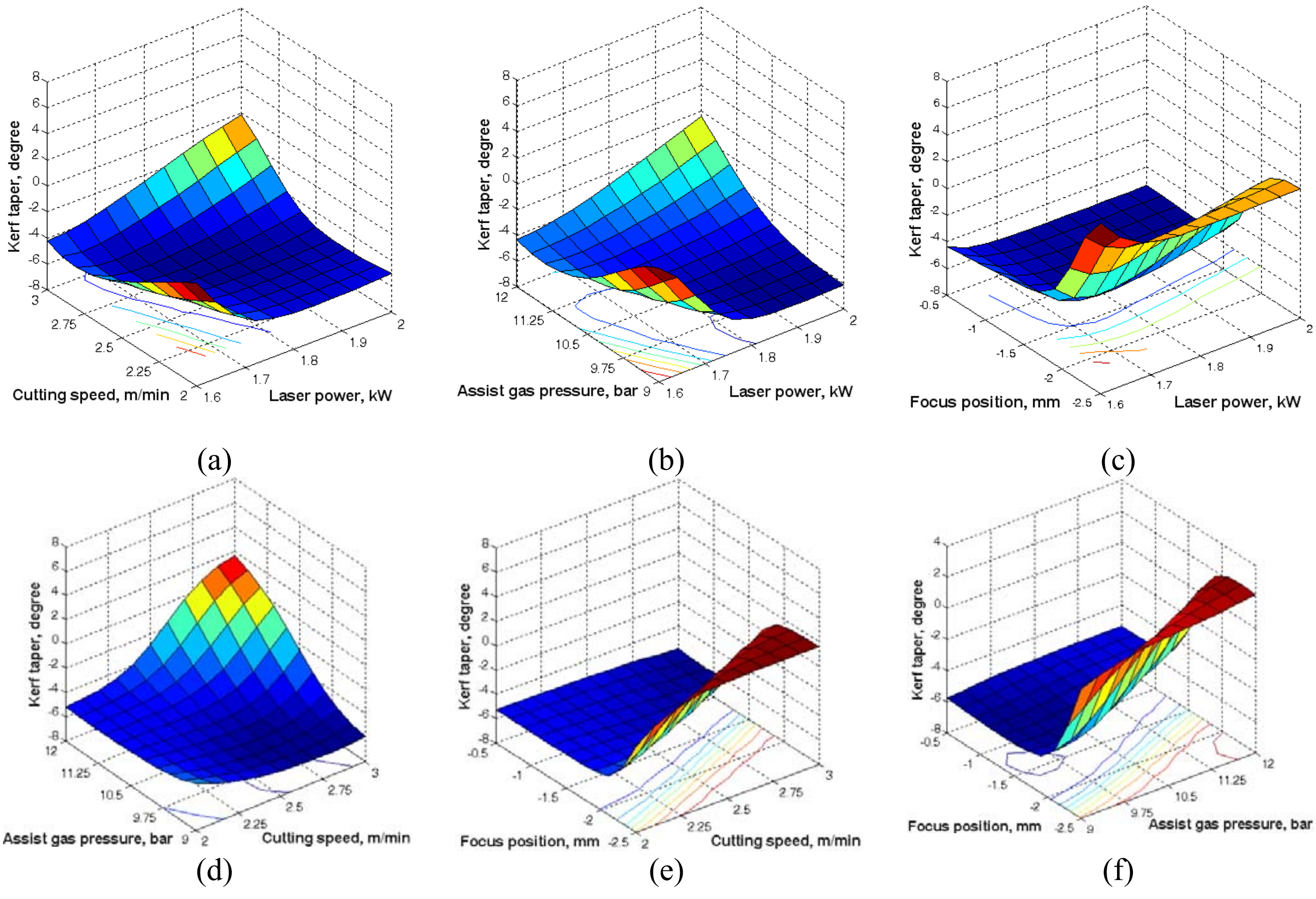


Fig. 2. Effect of laser cutting parameter interactions on kerf taper

5. Optimization methodology

For effective utilization of the laser cutting processes, it is very important to find out the optimal combinations of their process parameters to achieve enhanced machining performance with high dimensional accuracy (Samanta & Chakraborty, 2011). There are numerous methods and algorithms which provide acceptable results in laser cutting optimization. However, each of these techniques has its own advantages and disadvantages and often requires fine tuning of one or more parameters which can be difficult to use for engineers who are not experts in optimization theory and artificial intelligence.

The Monte Carlo method is an attractive and relatively simple technique which utilizes random numbers in simulation algorithm. The Monte Carlo method can be considered as a very general mathematical tool for solving a great variety of problems. The salient feature is that it offers a parameter free optimization procedure at low computation time and high effectiveness. The Monte Carlo optimization procedure was implemented in MS Excel which confirms the easiness of implementation. The details about the Monte Carlo, optimization problem formulation and results are discussed bellow.

5.1. Optimization problem formulation

The goal of the optimization process in this study is to determine the optimal laser cutting parameter values at which the minimum kerf taper angle (K_t) is obtained. An appropriate selection of cutting conditions should increase the product quality through minimizing kerf taper angle, increase the laser productivity and decrease the operation costs. Laser productivity and operation costs are in direct relation with the cutting speed and assist gas pressure, respectively. Therefore, the optimization problem can be formulated as:

$$\begin{aligned}
&\text{Find: } P_{opt}, v_{opt}, p_{opt}, f_{opt}\\
&\text{to minimize: } K_t = \mathrm{f}(P, v, p, f)\\
&\text{subject to: } 1.6\ \text{kW} \le P \le 2\ \text{kW}\\
&\qquad -2.5\text{mm} \le f \le -0.5\ \text{mm}\\
&\qquad v = v_{\max} = 3\ \text{m/min}\\
&\qquad p = p_{\min} = 9\ \text{bar}
\end{aligned} \tag{4}$$

For calculating kerf taper angle the ANN function given in Eq. 3 was employed.

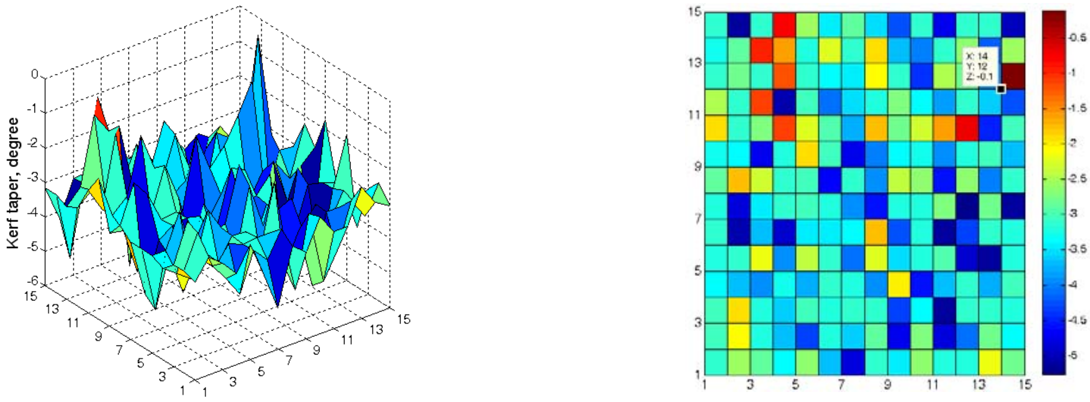
5.2. Optimization solution with Monte Carlo

The optimization problem in Eq. 4 was solved with the Monte Carlo simulation using the following procedure. The first step in the optimization procedure is the generation of random numbers $r_{i,j}$ uniformly distributed in the range [0,1] using the function *rand*. To satisfy the limitations of the laser cutting parameters values, random numbers $r_{i,j}$ were used to generate random numbers $q_{i,j}$ uniformly distributed into the range of interest for each of the laser cutting parameter [q_i^{min}, q_i^{max}]. This was accomplished using the following equation (Madić et al., 2014):

$$q_{i,j} = q_i^{min} + r_{i,j} \cdot \left(q_i^{max} - q_i^{min}\right) \tag{5}$$

Therefore, for each laser cutting parameter, the randomized values which were uniformly distributed in the interval of interest were generated and subsequently the kerf taper angle was calculated using the ANN mathematical model. In the optimization procedure only 225 Monte Carlo simulations were performed since the acceptable near optimal solution was identified. The results of Monte Carlo simulation runs are plotted in Fig. 3. Each point in the graph corresponds to a particular input laser cutting parameter settings.

As shown in Fig. 3b, in the 168th Monte Carlo simulation run, the minimal value of kerf taper angle $K_{t\,(min)} = 0.1^{\circ}$ was observed. This solution corresponds to the following combination of the laser cutting parameters: P=1.6 kW, v=3 m/min, p=9 bar and f= -1.966 mm. This was considered as an acceptable solution. Otherwise, the number of simulation runs would be increased.



(a) (b)

Fig. 3. Monte Carlo simulation runs (a) 3D view, (b) top view with identified near optimal solution

6. Conclusion

In this paper, ANN based mathematical model is developed in order to relate the laser cutting parameters i.e. laser power, cutting speed, assist gas pressure and focus position, and kerf taper angle in CO_2 laser cutting of stainless steel. Experiment trials were performed according to Taguchi's L_{27} experimental design and the obtained data was used for ANN training. Statistical results indicate that the ANN model can predict the kerf taper with good accuracy. By applying the Monte Carlo method, the optimal laser cutting parameter settings, which minimize kerf taper angle were determined. It was found that focusing the laser beam in about 2/3 of material thickness under the low assist gas pressure (9 bar) at combination of low laser power (1.6 kW) and high cutting speed (3 m/min), produced an acceptable kerf taper angle. The conclusions drawn can be summarized by the following points:

- kerf taper angle is highly sensitive to the selected laser cutting parameters, as well as their interactions,
- change in a given laser cutting parameter value can result in negative or positive kerf taper angle, depending of the values of other parameters,
- the influence of a given laser cutting parameter must be considered through interactions with other laser cutting parameters,
- the combined ANN-Monte Carlo approach is found to be very simple, easy to implement and efficient for the optimization of CO_2 laser cutting process.

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References

Bajić, D., Lela, B., & Živković, D. (2008). Modeling of machined surface roughness and optimization of cutting parameters in face milling. *Metalurgija*, *47*(4), 331-334.

Biswas, R., Kuar, A. S., Biswas, S. K., & Mitra, S. (2010). Artificial neural network modelling of Nd: YAG laser microdrilling on titanium nitride—alumina composite. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *224*(3), 473-482.

Chaki, S., & Ghosal, S. (2011). Application of an optimized SA-ANN hybrid model for parametric modeling and optimization of LASOX cutting of mild steel. *Production Engineering*, *5*(3), 251-262.

Ciurana, J., Arias, G., & Ozel, T. (2009). Neural network modeling and particle swarm optimization (PSO) of process parameters in pulsed laser micromachining of hardened AISI H13 steel. *Materials and Manufacturing Processes*, *24*(3), 358-368.

Dhara, S. K., Kuar, A. S., & Mitra, S. (2008). An artificial neural network approach on parametric optimization of laser micro-machining of die-steel. *The International Journal of Advanced Manufacturing Technology*, *39*(1-2), 39-46.

Dhupal, D., Doloi, B., & Bhattacharyya, B. (2007). Optimization of process parameters of Nd: YAG laser microgrooving of Al2TiO5 ceramic material by response surface methodology and artificial neural network algorithm. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *221*(8), 1341-1350.

Dubey, A. K., & Yadava, V. (2008). Laser beam machining—a review. *International Journal of Machine Tools and Manufacture*, *48*(6), 609-628.

Ghoreishi, M., & Nakhjavani, O. B. (2008). Optimisation of effective factors in geometrical specifications of laser percussion drilled holes. *Journal of materials processing Technology*, *196*(1), 303-310.

Karnik, S. R., Gaitonde, V. N., Rubio, J. C., Correia, A. E., Abrão, A. M., & Davim, J. P. (2008). Delamination analysis in high speed drilling of carbon fiber reinforced plastics (CFRP) using artificial neural network model. *Materials & Design*, *29*(9), 1768-1776.

Madić, M., & Radovanović, M. (2013). Application of RCGA-ANN approach for modeling kerf width and surface roughness in CO2 laser cutting of mild steel. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *35*(2), 103-110.

Madić, M., Kovačević, M., & Radovanović, M. (2014). Application of multi-stage Monte Carlo method for solving machining optimization problems. *International Journal of Industrial Engineering Computations*, *5*(4), 647-659.

Prajapati, B. D., Patel, R. J., & Khatri, B. C. (2013). Parametric investigation of CO_2 laser cutting of mild steel and hardox-400 material. *IJETAE*, *3*(4), 204-208.

Raja, T. V., Ruhil, A. P., & Gandhi, R. S. (2012). Comparison of connectionist and multiple regression approaches for prediction of body weight of goats. *Neural Computing and Applications*, *21*(1), 119-124.

Rajaram, N., Sheikh-Ahmad, J., & Cheraghi, S. H. (2003). CO_2 laser cut quality of 4130 steel. *International Journal of Machine Tools and Manufacture*, *43*(4), 351-358.

Samanta, S., & Chakraborty, S. (2011). Parametric optimization of some non-traditional machining processes using artificial bee colony algorithm. *Engineering Applications of Artificial Intelligence*, *24*(6), 946-957.

Sha, W., & Edwards, K. L. (2007). The use of artificial neural networks in materials science based research. *Materials & design*, *28*(6), 1747-1752.

Sivarao, S., Robert, M., & Samsudin, A. R. (2013). RSM Modelling and Optimization of CO2 Laser Machining of Industrial PVC Foam. *International Review on Modelling and Simulations*, *6*(4), 1339-1343.

Syn, C. Z., Mokhtar, M., Feng, C. J., & Manurung, Y. H. (2011). Approach to prediction of laser cutting quality by employing fuzzy expert system. *Expert Systems with applications*, *38*(6), 7558-7568.

Tsai, M. J., Li, C. H., & 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), 270-283.

Yang, C. B., Deng, C. S., & Chiang, H. L. (2012). Combining the Taguchi method with artificial neural network to construct a prediction model of a CO2 laser cutting experiment. *The International Journal of Advanced Manufacturing Technology*, *59*(9-12), 1103-1111.