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AN ARTIFICIAL NEURAL NETWORK APPROACH FOR ANALYSIS AND MINIMIZATION OF HAZ IN CO_2 LASER CUTTING OF STAINLESS STEEL

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This paper present an approach for modeling and analysis of the effects of the laser cutting parameters on the width of HAZ obtained in CO_2 laser cutting of stainless steel by using artificial neural network (ANN). ANN model was developed in terms of the specific laser energy (laser power to cutting speed ratio), assist gas pressure and focus position. Using the experimental data the ANN was trained with gradient descent with momentum algorithm and the average absolute percentage errors on training and testing were 3.68 % and 3.52%, respectively. In addition to modeling and analysis, through ANN simulation optimal cutting conditions with minimal width of HAZ were identified.

Keywords: CO_2 laser cutting, artificial neural networks, heat affected zone, modeling, optimization, simulation.

1. Introduction

Laser cutting is a thermal, non-contact, and automated process well suited for various manufacturing industries where a variety of components in large numbers are required to be machined with high dimensional accuracy and surface finish. 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 all materials, focused into a very small spot of 0.1…0.2 mm in diameter concentrating thousands of watts. The power density for cutting steels is typically 10^5-10^6 MW/m^2 [1]. This high density of power allows welding, engraving and cutting of different materials [2]. The high power density of the focused laser beam in the spot melts or evaporates material in a fraction of a second, and coaxial jet of an assist gas removes the evaporated and molten material from the cutting zone.

Laser cutting is a complex machining process with numerous parameters which in consort have essential role on the process performance. Maximization of

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productivity and quality along with costs minimization are of particular interest to manufacturers. Each of these goals often requires "optimal" selection of the cutting parameter settings. However, the optimum parameter settings for one quality characteristic may deteriorate other quality characteristics. A number of researchers performed theoretical as well as experimental investigations in order to examine laser cutting process [3, 4]. When the cut quality is considered, in most reported studies, kerf width, surface roughness and width of the heat affected zone (HAZ), were commonly used as cut quality characteristics [5].

Through appropriate selection and optimization of the laser and operating parameters cutting performance characteristics can be improved considerably. Mathematical models of the laser cutting processing relates the laser cutting parameters and cutting performance and hence provides a means for determining optimal or near-optimal cutting conditions. Different methodologies such as: multiple regression analysis [6], response surface method [7], fuzzy expert system [8] were applied for the analysis of the laser cutting parameters on the cutting performance characteristics. 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 (ANNs) for modeling laser cutting is becoming preferred trend [9-12]. 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 [13]. They are especially suitable in situations where mathematical formulas and prior knowledge on the functional relationship between process parameters are unknown.

Although a good number of research studies have already been done in the area of laser cutting, very few have focused on the analysis of the HAZ in laser cutting. Rajaram et al. [6] investigated the combined effects of the laser power and cutting speed on the width of HAZ in CO_2 laser cutting of 4130 steel. It was found that an increase in the cutting speed and a decrease in the laser power resulted in a decrease in the width of HAZ for the power range from 700 to 1100 W. However, it was observed that when using laser power of 1300 W, HAZ width increases with an increase in the cutting speed up to 46.6 mm/s and then decreases with further increase in the cutting speed. Mathew et al. [14] conducted parametric studies on pulsed Nd:YAG laser cutting of carbon fiber reinforced plastic composites. The HAZ predictive model was developed using response surface methodology (RSM). Repetition rate, cutting speed, pulse duration and beam energy are the parameters that were found to have an influence on the HAZ. Paulo Davim et al. [15] conducted an experimental study for CO_2 laser cutting of polymeric materials. It was observed that the HAZ increases with the laser power and decreases with the cutting speed. Similar conclusions were drawn by Sheng and Joshi [16] as a result of a numerical study in CO_2 laser cutting of stainless steel.

This paper presents an approach for the analysis of the effects of the laser cutting parameters on the width of HAZ obtained in CO_2 laser nitrogen cutting of stainless steel using the ANN model. Backpropagation (BP) ANN trained with gradient descent with momentum algorithm was applied to construct a mathematical model for the width of HAZ. For conducting the laser cutting experiment, Taguchi's L_{27} orthogonal array (OA) was used where laser cutting parameters, namely laser power, cutting speed, assist gas pressure, and focus position were arranged. In addition to modelling and analysis, the laser cutting conditions for width of HAZ minimization were identified through the simulation of the ANN.

2. Experimental details

The experiment was performed by means of ByVention 3015 (Bystronic) CO_2 laser delivering a maximum output power of 2.2 kW at a wavelength of 10.6 μm, operating in continuous wave mode. The cuts were performed with a Gaussian distribution beam mode (TEM_{00}) on 3 mm thick AISI 304 stainless steel using the nitrogen as assist gas with purity of 99.95%. In consideration of the numerous parameters that influence cutting process and finally cut quality, some of the process parameters were kept constant through the experimentation. A focusing lens with a focal length of 5 in. (127 mm) was used to perform the cut. The conical shape nozzle (HK20) with nozzle diameter of 2 mm was used. The nozzle–work piece stand-off distance was controlled at 1 mm. The control laser cutting parameters considered in the study and the levels of each parameter are given in Table 1.

For the experimental design, the Taguchi method has been used, in which the experiment trials are performed as per standard orthogonal arrays (OA). Based on the selected parameters and parameter levels, a design matrix, constructed in accordance with the standard $L_{27}(3^{13})$ Taguchi OA, was used for performing the laser cutting experiment. Laser cutting parameters, laser power, cutting speed, assist gas pressure and focus position were assigned to columns 1, 2, 5 and 9, respectively. The experimental trials were performed with the combination of laser cutting parameter levels as given in Table 2.

Table 1

Laser cutting parameters and their levels

Laser cutting parameters	Unit	Levels		
		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

Table 2

Experimental design and results

Exp. trial	Input parameters				Experimental results
	P	*v*	*p*	*f*	HAZ
	(kW)	(m/min)	(bar)	(mm)	(μm)
1	1.6	2	9	-2.5	21.00
2	1.6	2	10.5	-1.5	23.67
3	1.6	2	12	-0.5	23.33
4	1.6	2.5	9	-1.5	15.33
5	1.6	2.5	10.5	-0.5	20.67
6	1.6	2.5	12	-2.5	18.67
7	1.6	3	9	-0.5	19.67
8	1.6	3	10.5	-2.5	17.67
9	1.6	3	12	-1.5	20.00
10	1.8	2	9	-1.5	30.33
11	1.8	2	10.5	-0.5	25.67
12	1.8	2	12	-2.5	20.33
13	1.8	2.5	9	-0.5	26.00
14	1.8	2.5	10.5	-2.5	19.67
15	1.8	2.5	12	-1.5	20.33
16	1.8	3	9	-2.5	18.33
17	1.8	3	10.5	-1.5	17.00
18	1.8	3	12	-0.5	19.33
19	2	2	9	-0.5	28.33
20	2	2	10.5	-2.5	19.33
21	2	2	12	-1.5	20.33
22	2	2.5	9	-2.5	19.67
23	2	2.5	10.5	-1.5	22.67
24	2	2.5	12	-0.5	26.33
25	2	3	9	-1.5	18.33
26	2	3	10.5	-0.5	20.67
27	2	3	12	-2.5	15.00

Straight cuts each of 60 mm in length were made in each experimental trial and the cut quality was evaluated in terms of the width of HAZ. An optical microscope (Leitz, Germany) was used to measure the width of HAZ along the 10 mm segment of the cut edge. The measurements were repeated three times to obtain averaged values (Table 2). All the experimental data given in Table 2 were used to form experimental data base for ANN training.

3. ANN modeling of CO_2 laser cutting process

Experimental data obtained from the laser cutting experiment, such as input-output data, can be used to form a mathematical model of the process. Through a mathematical model, any experimental result of the width of HAZ with any combination of the laser cutting parameters can be estimated. Recently, one of the most popular approaches for modeling the functional relationships between several measured inputs and one or more outputs is based on artificial neural networks (ANNs). Among the various types of ANNs, the feed-forward neural networks are one of the most popular because of their simplicity and powerful nonlinear modeling ability. The feed-forward ANN is a non-linear mapping system composed of many interconnected neurons which are grouped into input, hidden, and output layers.

3.1. ANN model development

To establish a mathematical relationship between the HAZ and the laser cutting parameters a multilayer perceptron type ANN was selected. In the present paper, the laser power and cutting speed were combined into single parameter. Namely, the ratio of laser power to cutting speed is called specific laser energy, E_S, and defines the energy input per unit length of the material along the cut [17]:

$$E_S = \frac{P}{v} \tag{1}$$

Therefore, three neurons were used in the input layer, and one neuron in the output layer for calculating the width of HAZ. The number of hidden neurons was decided considering that the total number of connection weights and biases of the hidden and output neurons in the ANN architecture does not exceed the available number of data for training. As there are 27 experimental input/output data sets, three inputs and one output, the number of neurons in the hidden layer was set to 5. In order to increase prediction accuracy, stabilize and enhance ANN training, input and output data were normalized between -1 and 1. Linear transfer function and hyperbolic tangent sigmoid activation functions were used in the output and hidden layer, respectively. These transfer functions were used since it was assumed that there exists nonlinear relationship between the input and output process parameters.

3.2. ANN model training

The practical application of ANN comes with algorithms designed to determine the optimum weights and biases in the process called training. ANN training is considered as one of the most important step in ANN model development. The primary goal of ANN training is to achieve a good balance between the ANN ability to respond correctly to the input data used for the training and, more preferably, the ability to produce accurate predictions to input that is not used in training (generalization ability). The most common training algorithm for ANNs is the backpropagation algorithm and its variants because it is stable and easy to implement. In the present paper, the ANN training process was carried out using gradient descent with momentum procedure "*traingdm*" of MATLAB Neural Network Toolbox. Gradient descent with momentum algorithm has two parameters that control the speed and convergence of the ANN. These are learning rate (α) and momentum (μ), and usually take values between 0 and 1 [18]. The mean squared error (*MSE*) was selected as performance criterion for training process. The training process involves minimizing the mean square error (*MSE*) between desired (target), y, and ANN predicted outputs, for the same input pattern, using the available training data (N_{tr}):

$$MSE = \frac{1}{N_{tr}} \sum_{k=1}^{N_{tr}} \left(y_k - \hat{y}_k \right)^2 \tag{2}$$

Supervised learning was conducted with a zero as a target error value. In order to deal with converge to local minima problem and slow convergence, the ANN training process was repeated several times using different initial weights. It was found that the selected ANN architecture provides the best data fitting capability with MSE at the end of training process (10000 epochs) of 0.0135343 (Figure 1), when learning rate (α) and momentum (μ) were kept at 0.1 and 0.9, respectively.

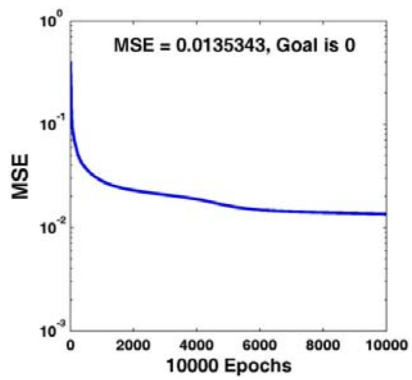


Fig. 1. ANN training process

3.3. ANN model testing

Once the ANN training process was finished and the near optimum weights and biases of the ANN were determined, the next step consists of comparing the ANN predicted values of the width of HAZ with experimental values. 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.

However, in order to test the generalization ability of the ANN model, 7 new experiment trials were conducted with the laser cutting parameter levels which do not belong to the training data set (Table 3).

Table 3

Experimental data set for ANN testing

Exp. trial	Input parameters				Experimental results
	P (kW)	*v* (m/min)	*p* (bar)	*f* (mm)	HAZ (μm)
1	2	2	10.5	-1.5	24
2	1.8	2.5	9	-2.5	20.33
3	2	2.5	10.5	-0.5	23.67
4	1.8	3	12	-1.5	17.33
5	1.6	2.5	12	-1.5	18.33
6	1.8	3	10.5	-2.5	18

Prediction capability of a best ANN is assessed by calculating absolute % error in prediction for every input/output data after corresponding de-normalization, as follows:

$$\text{Absolute \% prediction error} = \left| \frac{\text{Experimental result - ANN predicted output}}{\text{Experimental output}} \right| \times 100 \quad (3)$$

Fig. 2 shows the prediction errors for the ANN model using the training and testing data. As the maximum errors in prediction for the width of HAZ are 12.58% and 8.8% for training and testing data respectively, it can be said that the errors are within the tolerable limit. Furthermore, the average errors for training and testing data are 3.68% and 3.52%, respectively, which are very small indeed. Also it is evident that the developed ANN model has good generalization capability i.e. performs well on unseen data. The high performance of the ANN model is confirmed by very high correlation coefficient between experimental and predicted width of HAZ values as shown in Fig. 3.

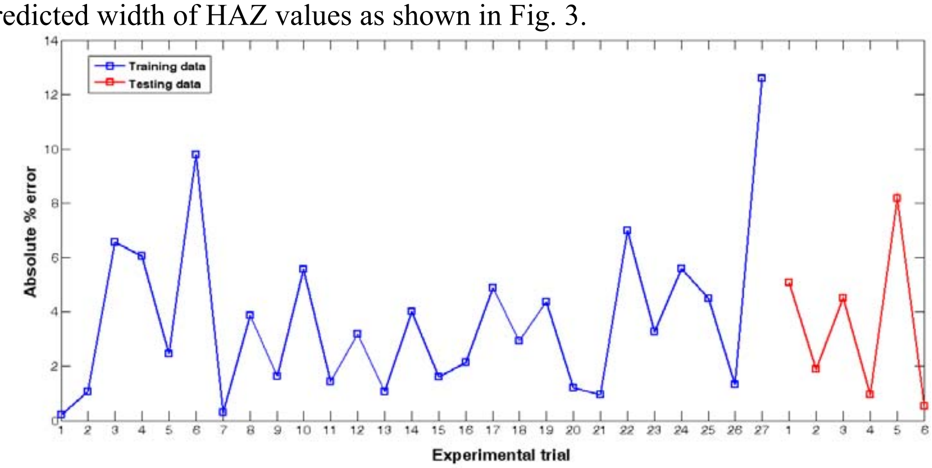
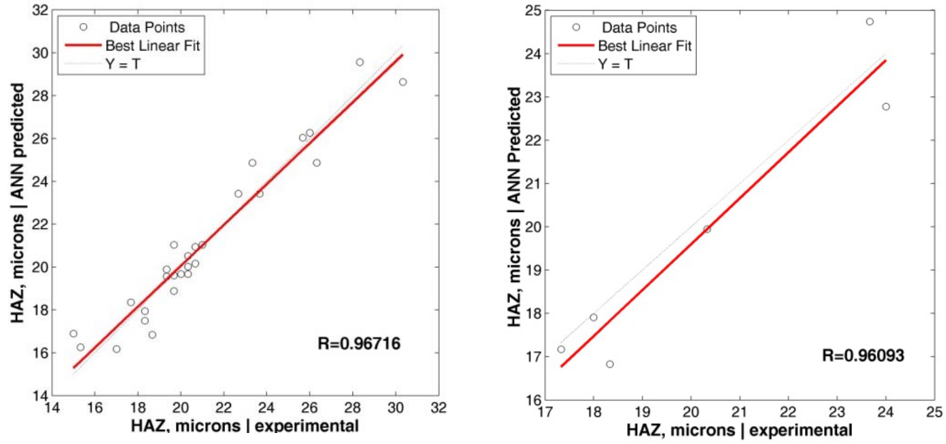


Fig. 2. Prediction performance of the developed ANN

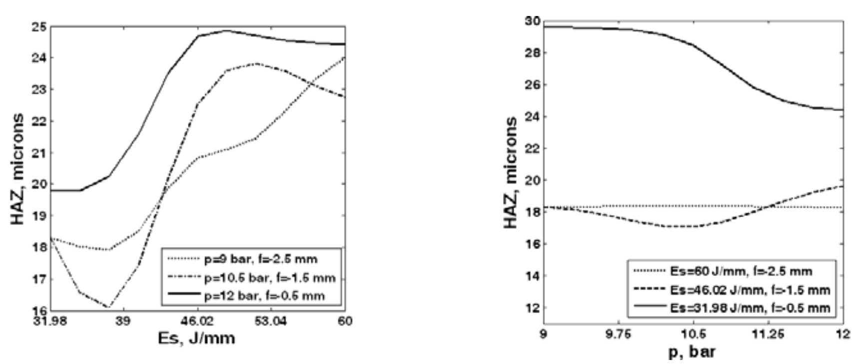


(a) (b)

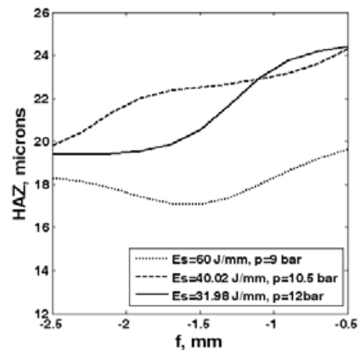
Fig. 3. The performance of ANN model (a) for training data set, (b) for testing data set

4. Analysis and discussion

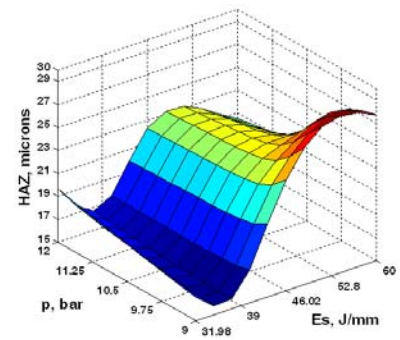
The developed ANN to predict the width of HAZ based on the cutting parameters showed high degree of accuracy within the scope of cutting conditions investigated in the study. Thus, the effect of the specific cutting energy, assist gas pressure and focus position on the width of HAZ can be studied using the ANN model. By changing one parameter at a time, while keeping the all other parameters constant at low, center and high level, the main effect plot were generated as shown in Fig. 4(a,b,c). In order to examine the interaction effects, 3D surface plots were generated considering two parameters at a time, while the third parameter was kept constant at center level (Fig. 4(d,e,f)).



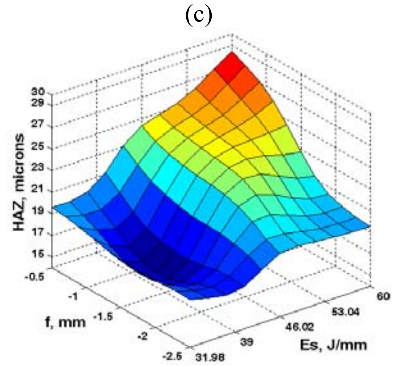
(a) (b)



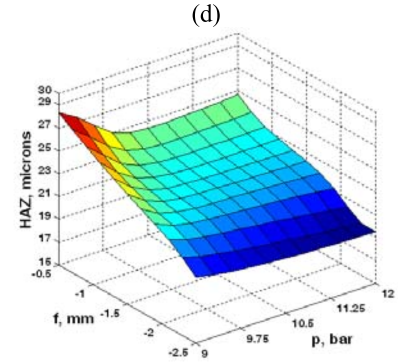
(c)



(d)



(e)



(f)

Fig. 4. Main and interaction effects of the specific cutting energy, assist gas pressure and focus position on the width of HAZ

It can be seen from Figure 4a that an increase in E_s produces a non-linear increase in width of HAZ, and this functional dependence is constant apart from the values of the other parameters. In the case of assist gas pressure (Figure 4b), it is seen that the effect of the assist gas pressure on the width of HAZ is variable. It can be observed that at intermediate E_s when focusing the laser beam at half of the material thickness, high assist gas pressure increases the width of HAZ. This effect may be attributed to the role the assist gas plays in heat transport through the thickness of the workpiece and to the rise in flow turbulence and less effective cooling at high pressure [17]. Figure 4c suggests that focusing the laser beam deep into the bulk of material is beneficial for decreasing the width of HAZ. From the interaction effect plot between E_s and p (Figure 4d) it is seen that the effect of the assist gas pressure is more pronounced for higher specific laser energy. From Figure 4e it is seen that the interaction effect of focus position and specific laser energy produces highly nonlinear change in the width of HAZ. It can be observed that when focusing the laser beam at half of the material thickness there exists a range of specific laser energy, i.e. laser power to cutting speed ratio, where the width of HAZ is minimum. Similar findings were reported by Mathew et al. [14].

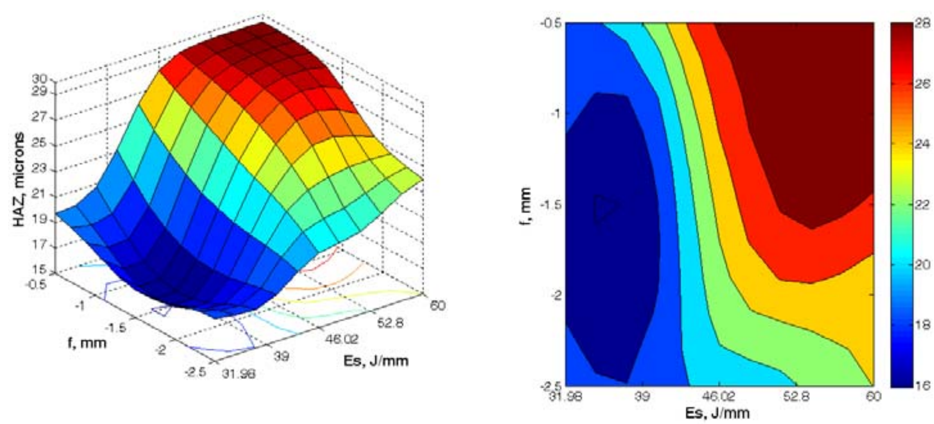
They observed that for laser power to cutting speed ratio of between 2 and 4, the HAZ is the minimum. From Fig. 4f it is seen that low focus position in conjunction with high assist gas pressure is beneficial for minimizing the width of HAZ. On the other hand, focusing the laser beam near the top surface and by using low assist gas pressure, results in increased width of HAZ.

5. Optimization of the width of HAZ through the ANN model

The optimal selection of cutting parameters should increase the product quality to some extent by minimizing the width of HAZ. In the present paper an attempt has been made to identify optimal laser cutting conditions for minimization of the width of HAZ by considering the laser cutting economics which imply that the assist gas pressure is kept at minimum. Therefore, the optimization problem can be formulated as follows:

$$\begin{aligned} &\text{Find:} && E_s, f \\ &\text{to minimize:} && HAZ = \mathrm{f}(E_s, p, f) \\ &\text{subject to:} && p = p_{\min} = 9 \text{ bar} \\ & && -2.5 \text{ mm} \le f \le -0.5 \text{ mm} \end{aligned} \tag{4}$$

To find the optimum laser cutting parameter settings formulated in Eq. 4 one may apply a large number of methods such as classical mathematical methods, Monte Carlo method, genetic algorithms, simulated annealing, particle swarm optimization, etc. However, as the optimization problem is reduced in finding optimal values of two bounded continuous decision variables (E_s and f), through the simulation of the developed ANN, one can identify the optimal region. Fig. 5 shows ANN simulations in the E_s and f plane when assist gas pressure of 9 bar is used.



(a) (b)

Fig. 5. Prediction of width of HAZ by the ANN model when p=9 bar: (a) 3D surface plot, (b) contour plot with optimal cutting region

From all of these predictions (Figure 5) it was observed when E_s is in the range between 32 J/mm and 39 J/mm (which corresponds to laser power to cutting speed ratio between 0.533 to 0.65), focusing the laser beam at the half of the material thickness produces region of minimal width of HAZ.

6. Conclusions

This paper presented artificial neural network approach for the modeling, analysis and optimization of the width of HAZ in CO_2 laser nitrogen cutting of stainless steel. On the basis of derived analysis within the range of laser cutting conditions investigated, the following conclusions can be drawn:

- the functional dependence between the width of HAZ and, assist gas pressure and focus position is nonlinear,
- specific laser energy has a major effect on the width of HAZ. An increase in specific laser energy generally led to increasing width of HAZ and this effect is dependent on the interaction with assist gas pressure and focus position,
- interaction of the specific laser energy and focus position produces highly nonlinear change in the width of HAZ,
- focusing the laser beam at the half of the material thickness with the combination of laser power to cutting speed ratio between 0.533 to 0.65 at nitrogen pressure of 9 bar produces minimal width of HAZ.

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