

COMPARISON OF FUZZY LOGIC, REGRESSION AND ANN LASER KERF WIDTH MODELS

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This paper focuses on development and comparison of empirical models for the prediction of kerf width obtained in CO₂ laser cutting of AISI 304 stainless steel using regression analysis, artificial neural network (ANN) and fuzzy logic. Laser cutting experiment, conducted according to Taguchi's experimental design using L₂₇ orthogonal array, and provided a set of data for model's development. All three models considered the laser power, cutting speed, assist gas pressure and focus position as input parameters. Statistical values of the coefficient of determination and absolute percentage error were employed to compare the three developed models by considering initial experimental as well as additional experimental (validation) data. Analysis and results indicate that all three modeling approaches can be equally effectively used for the prediction of kerf width in CO₂ laser cutting. However, fuzzy logic model showed the best overall prediction results, while developed ANN model best generalization capability.

Keywords: Regression, artificial neural networks, fuzzy logic, laser cutting, kerf width, modeling.

1. Introduction

Laser cutting is one of the most used nonconventional machining processes based on the use of lasers, i.e. highly concentrated light energy generated by stimulated radiation for material processing by heating, melting or evaporation. By focusing the laser beam on the material surface high power density per unit area is achieved (over 10⁸ W/cm²), leading to melting and evaporation of materials in a fraction of second. In order to eject melted material from the cutting zone as soon as possible, assist gas stream is used.

The laser cutting process is characterized by a number of process parameters and their interactions, which in turn determine the efficiency of the whole process in terms of productivity, quality, and costs [1]. In order to avoid time consuming trial and error procedure in parameter setting for a particular application of laser cutting it is of prime interest to accurately quantify relationships between process parameters and cutting performances through development of mathematical models.

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Numerous advantages and possibilities of laser cutting motivated a number of modeling studies with the ultimate aim to better understand and optimize the process. The modeling of laser cutting process has been investigated by a number of methodologies. Most of the current literature used classical regression modeling [2-7]. The application of artificial neural networks (ANNs) also marks the growing use for laser cutting process modeling. Chaki and Ghosal [8] developed an optimized simulated annealing-ANN model to predict and optimize cutting quality of LASOX cutting process of mild steel plates. Results indicate that the SA-ANN model can predict the optimized output with reasonably good accuracy (around 3%). Yang et al. [9] proposed a progressive Taguchi-ANN model, which combines the Taguchi method with the ANN to construct a prediction model for a CO₂ laser cutting experiment. The analysis and results confirmed that the construction of Taguchi-ANN model improves upon the traditional ANN, which has the inherent disadvantage of requiring a large number of training samples. Recently, Madić and Radovanović [1] presented an approach of using a real coded genetic algorithm for the development of ANN mathematical models for the kerf width and surface roughness obtained in CO₂ laser cutting of mild steel. It was observed that ANN model predictions and experimental results are in good agreement. Some researchers used fuzzy logic to predict the laser cutting performance characteristics. Syn et al. [10] developed an expert system using fuzzy logic model to predict surface roughness and dross inclusion in CO₂ laser cutting of Incoloy alloy 800. The relationships between experimental results, fuzzy logic model and statistical results for both training and testing performance exhibited a good correlation. Pandey and Dubey [11] proposed a hybrid approach of Taguchi robust parameter design and fuzzy logic for multi-objective optimization of laser cutting of duralumin sheet. Kerf width and kerf deviations at top and bottom sides were considered as performance characteristics. Recently, the same authors [12] applied a hybrid approach consisting of ANN and fuzzy logic to develop the fuzzy expert system to predict the kerf widths and kerf deviation in laser cutting of Ti alloy. The predicted results were compared with the experimental data and found appropriate.

The survey of literature indicates that the aforementioned modeling methodologies were successfully applied for laser cutting process modeling. These approaches integrate different experimental, mathematical, and soft computing methods, thus provide sufficient accuracy of predictions. A recent comprehensive review of the various methods used for modeling and simulation of the laser cutting process as well as key researches done in this field so far is given in [13]. However, a comprehensive study to compare the performances of regression analysis, ANNs and fuzzy logic for modelling different performance characteristics in laser cutting is still missing. Still, within the application of these methods the authors observed certain shortfalls including: (i) overestimating or

underestimation of the experimental data in the case of regression analysis [6], (ii) requirement of a large number of training samples [9] and determination of suitable ANN model architecture as well as determination of (near) optimal weights and biases [1], (iii) the selection of a right membership functions for each input and output variable, which determines performance of a fuzzy model [10].

Importance of comparison studies and their lack of consideration in the literature were the main motivation for development of different models for the prediction of laser cut quality obtained in CO₂ laser cutting of stainless steel. To the best readers' knowledge there is no comparative modeling research study using fuzzy logic, regression analysis and ANN regarding the process of CO₂ laser cutting of stainless steel using nitrogen as assist gas. In an initial attempt, regression model was employed for development of the kerf width model in terms of four laser cutting parameters, namely, the laser power, cutting speed, assist gas pressure and focus position. In addition, kerf width modeling was done by fuzzy logic and ANN. Comparative observation on using both experimental and validation trials indicated that the fuzzy logic model gives slightly smaller deviations in comparison to experimentally measured values than regression and ANN models at the same time providing possibility to include in the model some available expert knowledge about the process of laser cutting.

2. Experimental procedure

The experiment was performed in real industrial environment by using a ByVention 3015 CO₂ laser cutting machine with a maximal power of 2.2 kW. Conical shape nozzle with diameter of 2 mm was used in experiment and the distance between workpiece and nozzle was controlled at 1 mm. The laser beam was focused through a lens of focal length of 127 mm. The cuts were performed with a Gaussian distribution beam mode (TEM₀₀). As workpiece material AISI 304 sheet with dimensions of 500 x 500 mm and 3 mm thickness was used.

Laser power, cutting speed, assist gas pressure and focus position were selected as input (controllable) parameters. The numerical values of selected parameters at different levels are shown in Table 1. The values range for each parameter was chosen such that full cut is achieved at any combination of laser cutting parameter levels. The manufacturer's recommendation and literature data were also considered.

The appropriate selection of different input parameters and their levels have significant impact on the kerf width. Kerf width is the measure of the amount of the workpiece that is wasted during material processing. Obtaining high material removal rate in laser cutting of thin sheets of steels is not a difficult task but the most important thing is to get a narrow cut kerf [14].

Straight cuts of 60 mm long are made for each experimental trial and kerf widths were measured at three different places along the length of cut on the top side of the workpiece material. The measurement locations were decided at equal distances. The kerf widths were measured using the Leitz optical microscope (Fig. 1). The average values of kerf width corresponding to each experimental trial are given in Table 1.

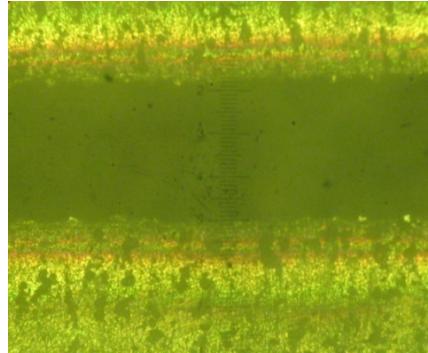


Fig. 1. Top view of the laser cut using shop microscopy

Table 1

L₂₇ matrix for the experiment and experimental results

Trial	Laser cutting parameters				Experimental results for kerf width, K_w (mm)
	P_L (kW)	v_f (m/min)	p (bar)	f (mm)	
1	1.6	2	9	-2.5	0.517
2	1.6	2	10.5	-1.5	0.398
3	1.6	2	12	-0.5	0.353
4	1.6	2.5	9	-1.5	0.393
5	1.6	2.5	10.5	-0.5	0.387
6	1.6	2.5	12	-2.5	0.483
7	1.6	3	9	-0.5	0.307
8	1.6	3	10.5	-2.5	0.512
9	1.6	3	12	-1.5	0.366
10	1.8	2	9	-1.5	0.435
11	1.8	2	10.5	-0.5	0.372
12	1.8	2	12	-2.5	0.550
13	1.8	2.5	9	-0.5	0.323
14	1.8	2.5	10.5	-2.5	0.477
15	1.8	2.5	12	-1.5	0.423
16	1.8	3	9	-2.5	0.488
17	1.8	3	10.5	-1.5	0.344
18	1.8	3	12	-0.5	0.287
19	2	2	9	-0.5	0.376
20	2	2	10.5	-2.5	0.542
21	2	2	12	-1.5	0.450
22	2	2.5	9	-2.5	0.493

23	2	2.5	10.5	-1.5	0.461
24	2	2.5	12	-0.5	0.372
25	2	3	9	-1.5	0.389
26	2	3	10.5	-0.5	0.320
27	2	3	12	-2.5	0.443

Table 1 represents standard L_{27} (3^{13}) Taguchi's orthogonal array which was used as experimental plan. Laser cutting parameters, laser power, cutting speed, assist gas pressure and focus position were assigned to columns 1, 2, 5 and 9, respectively.

3. Mathematical modeling

3.1. Regression modeling

Regression analysis is a conceptual simple empirical modeling technique for developing functional relationships between a set of input variables and output variable (response). The starting point is to select input variables that will figure in the final mathematical model. The best subset of input variables is usually selected based on some statistical criteria including: coefficient of multiple determination R^2 , adjusted R^2 , Mallows' Cp-statistic, Akaike's information criterion (AIC), percentage error, mean squared error, etc.

In regression analysis one needs to determine the right functional and order form of the polynomial and determine regression coefficients. A low degree polynomial will not have the needed flexibility and will make large errors on test sample because of a large bias. A high degree polynomial is too much sensitive to the sample and will make large errors on test sample because of a large variance. This is well-known bias-variance trade-off.

The mathematical model for the prediction of kerf width in terms of selected laser cutting parameters was obtained using the experimental data by applying the least square method. Out of many different mathematical models, the following full quadratic model with interactions was initially developed:

$$\begin{aligned}
 K_w = & -0.517 - 0.502 \cdot P_L + 0.509 \cdot v_f + 0.121 \cdot p - 0.124 \cdot f + 0.228 \cdot P_L^2 \\
 & - 0.039 \cdot v_f^2 - 0.004 \cdot p^2 + 0.016 \cdot f^2 - 0.0124 \cdot P_L \cdot v_f + 0.008 \cdot P_L \cdot p \\
 & + 0.037 \cdot P_L \cdot f - 0.015 \cdot v_f \cdot p - 0.004 \cdot v_f \cdot f + 0.004 \cdot p \cdot f
 \end{aligned} \quad (1)$$

The R^2 statistical value of 0.937 indicates that the proposed mathematical model explains 93.7 % of the variability in kerf width values. However, a large value of R^2 does not necessarily imply that the regression model is a good one [15]. On the other side, since the difference between the statistics R^2 and adjusted R^2 , having value of 0.864, is not negligible, there is a high probability that non-significant terms are included in the mathematical model. For that reason, the initial regression model of surface roughness was simplified (reduced) by

eliminating terms which had no significant effect at the 90% confidence level. After conducting a best subset routine, the following mathematical model was selected:

$$K_w = -0.513 + 0.505 \cdot v_f + 0.038 \cdot p - 0.0994 \cdot f + 0.108 \cdot P_L^2 - 0.0389 \cdot v_f^2 + 0.0158 \cdot f^2 - 0.118 \cdot P_L \cdot v_f + 0.0381 \cdot P_L \cdot f - 0.015 \cdot v_f \cdot p \quad (2)$$

Comparing the two developed mathematical models, one can see that by removing less significant terms from the initial model, the adjusted R^2 value improves from 0.864 to 0.892. Clearly, removing the less significant terms from the full regression model produces a final regression model that is likely to function more effectively as a predictor of new data.

The P value of 0 from analysis of variance (ANOVA) analysis (Table 2) confirms the validity of the developed mathematical model. Thus, Eq. 2 can be used to calculate kerf width values for arbitrarily chosen values of laser cutting parameters within the covered experimental hyperspace.

Table 2

ANOVA for the developed kerf width regression model

Source	DF	SS	MS	F	P
Regression	9	0.132667	0.014741	24.74	0
Residual error	17	0.010129	0.000596		
Total	26	0.142796			

P: probability density; DF: degree of freedom; SS: sum of squares; MS: mean square; F: value of Fisher's distribution

3.2. Fuzzy logic modeling

Two primary tasks of fuzzy modeling are structure identification and parameter adjustment. The former determines input-output space partition, rule antecedent and consequent variables, the number of fuzzy rules, and the number and initial positions of membership functions. The latter identifies a feasible set of parameters under the given structure [16]. Fuzzy logic is a way to map an input space to an output space upon which a basis for fuzzy inference and decision making is provided. A fuzzy system consists of four components (Fig. 2): the fuzzifier, the fuzzy inference engine, the defuzzifier, and the fuzzy rule base.

Fuzzification represents the process of converting all input variables into fuzzy (linguistic) variables using membership functions. Basically, a membership function is a curve that defines how each point in an input space is mapped to a membership value (or degree of membership) between 0 and 1 [17]. The inference engine refers to using the fuzzy rule base, containing the described fuzzy IF-THEN rules, and the membership functions to obtain the fuzzy (linguistic) output values for the corresponding inputs [18]. Finally, the defuzzifier converts the aggregate fuzzy output value into a single number.

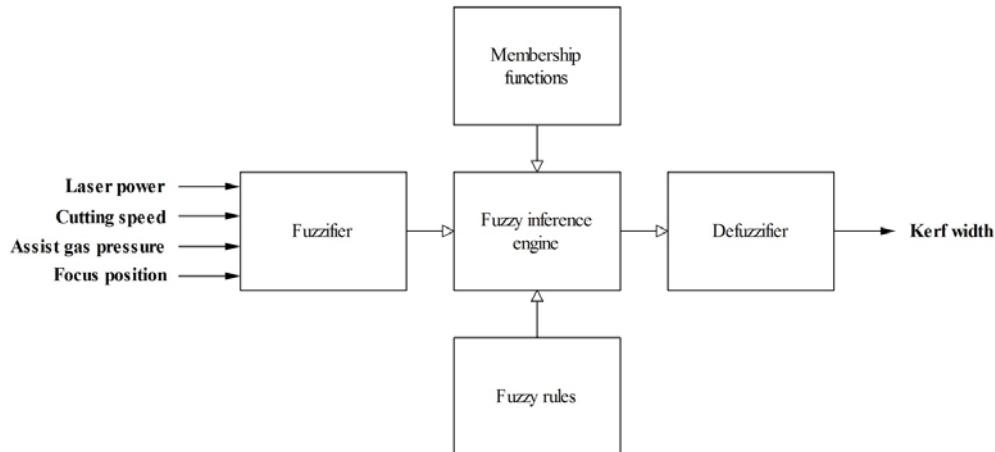


Fig. 2. Structure of fuzzy logic system with four inputs and one output

In this paper, laser cutting parameters, i.e. laser power, cutting speed, assist gas pressure and focus position were considered as inputs, while kerf width was considered as output. The minimum and maximum values of inputs and outputs, corresponding to experimental hyperspace covered, are given in Table 3. In this table fuzzy linguistic variables for inputs and output are also shown.

Table 3

Range of laser cutting parameters and fuzzy linguistic variables

INPUTS			
Laser cutting parameters	Range	Linguistic labels	
Laser power, P_L [kW]	1.6 ÷ 2	Low, Medium, High	
Cutting speed, v_f [m/min]	2 ÷ 3		
Assist gas pressure, p [bar]	9 ÷ 12		
Focus position, f [mm]	-2.5 ÷ -0.5		
OUTPUTS			
Kerf width [mm]	0.28 ÷ 0.55	Very Narrow, Narrow, Good, Wide, Very wide	

For each laser cutting parameter, three membership functions were used: Low, Medium and High. On the other hand for the kerf width, four membership functions were used: Very Narrow, Narrow, Good, Wide, Very wide.

Gaussian membership functions were employed to describe the fuzzy sets for inputs and output. Gaussian membership functions were chosen in order to provide smooth fuzzy model output surface, i.e. smooth change of output variable for moderate change of inputs. Membership functions and their ranges for inputs are shown in Fig. 3.

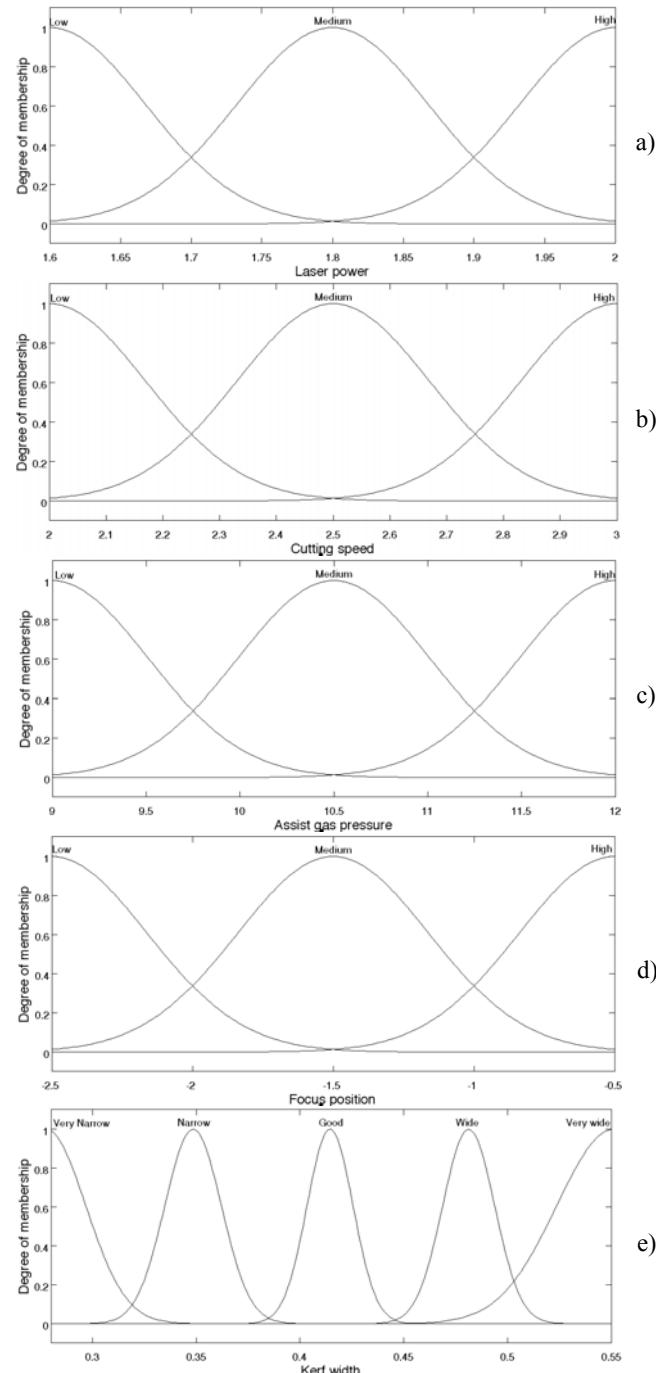


Fig. 3. Membership functions for: a) laser power, b) cutting speed, c) assist gas pressure, d) focus position and e) kerf width

After selection of membership functions, fuzzy rules were described to obtain fuzzy values. Based on conducted experimental trials, and using available expert knowledge on the laser cutting process, a set of 27 fuzzy IF-THEN rules was constructed. Each of these rules plays an important role in generating the fuzzy logic model and the accuracy of the numerical output [19]. Some of the rules fed into the fuzzy inference system are:

1. **If** (P_L is Low) **and** (v_f is Low) **and** (p is Low) **and** (f is Low) **Then** (Kerf width is Very wide)
2. **If** (P_L is Low) **and** (v_f is Low) **and** (p is Medium) **and** (f is Medium) **Then** (Kerf width is Good)
3. **If** (P_L is Low) **and** (v_f is Low) **and** (p is High) **and** (f is High) **Then** (Kerf width is Narrow)
- ...
- ...
- ...
27. **If** (P_L is High) **and** (v_f is High) **and** (p is High) **and** (f is Low) **Then** (Kerf width is Good)

Finally, a defuzzification method is used to transform the fuzzy output into a non-fuzzy value. The selection of defuzzification method is important as it greatly influences the speed and accuracy of the model [20]. In this study, defuzzification is carried out using centroid defuzzification method. It is one of the most commonly used methods capable of producing accurate results compared to other methods. In this method, the defuzzified output z^* is obtained as [18]:

$$z^* = \frac{\int \mu_A(z)z dz}{\mu_A(z)dz} \quad (3)$$

where z^* is the the defuzzified output i.e. the output for a given input vector, $\mu_A(z)$ is the aggregated membership function and z is the output variable (the centre value of the regions).

The non-fuzzy value z^* gives the predicted value of kerf width in numerical form. For example, the value of kerf width at a laser cutting condition, laser power of 2 kW, cutting speed of 3 m/min, assist gas pressure 12 bar and focus position of -2.5 mm is obtained as 0.414 mm. The Mamdani max-min approach was used as the fuzzy inference engine. This approach uses max operation for the aggregation of the rules and min operation is used for intersection of two fuzzy sets [21].

3.3. Artificial neural network modeling

Artificial neural networks (ANNs) are one of the most powerful modeling techniques currently being widely used in many fields of engineering. When compared to regression analysis, ANNs offer better data fitting capability for complex processes with many non-linearities and interactions, however they require a substantial number of data for their training i.e. development. Furthermore, modeling with ANNs is much more complex since numerous decisions related to the selection of ANN architecture, training parameters, transfer functions, parameters of the training algorithm, etc. had to be made. Above all, there is limited theoretical and practical background to assist in systematical selection of these parameters.

To develop ANN mathematical model for the prediction of kerf width, 19 randomly selected experimental data were used for training, while the remaining 8 data were used for validation purpose. For modeling the relationship between kerf width and laser cutting parameters, single hidden layer perceptron type ANN was selected having the hyperbolic tangent sigmoid transfer function in the hidden and linear transfer function in the output layer. In order to stabilize and enhance ANN training the input and output data was normalized in $[-1, 1]$ range.

Levenberg–Marquardt algorithm [22] was used for training purpose and the training process was monitored by calculating the mean squared error. According to the available number of training data, the 4-4-1 ANN architecture trained for 21 iterations turned out to be the best solution.

Once the ANN has been trained, the knowledge acquired by the ANN can be represented in the form of mathematical equation [1]:

$$\hat{y}(X) = g \left(\sum_j w_{kj} \cdot f \left(\sum_i w_{ji} \cdot x_i + b_j \right) + b_k \right) \quad (4)$$

where $\hat{y}(X)$ is the computed ANN output (prediction) for the input vector X , b_j and b_k are biases of the hidden and output neurons, respectively, w_{kj} and w_{ji} are the hidden to output and input to hidden neuron weights, respectively, and f and g are the transfer functions used in the hidden and output layers, respectively.

4. Results and discussion

The comparison of the experimental and predicted values using different models, i.e. fuzzy logic, ANN and regression model are given in Figure 4.

As could be seen from Figure 4, the fuzzy logic model yielded the highest coefficient of determination, followed by regression and ANN model, respectively. In sum, all models gave reasonable predictions. Furthermore, the prediction accuracy of the developed models was assessed by calculating the mean absolute percentage error.

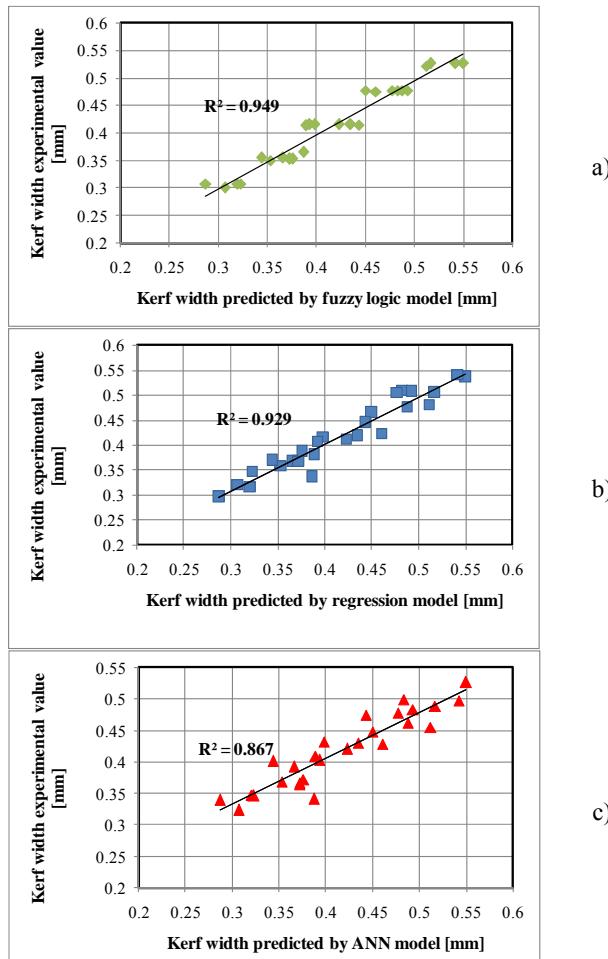


Fig. 4. Comparison of selected model predictions with corresponding experimental values

The mean absolute percentage errors for fuzzy logic, regression and ANN model were found to be 3.83%, 3.74% and 5.79%, respectively. Regarding all experimental trials maximal and minimal absolute percentage errors for fuzzy logic, regression and ANN model were found to be 6.97% and 0.21%, 13.01 and 0.36%, and 18.02% and 0.02%, respectively. It is clear that minimal error dispersion is obtained by fuzzy logic model followed by regression and ANN models. From these statistical results one can conclude that fuzzy logic modeling can be successfully used for predicting kerf width obtained in CO₂ laser cutting of AISI 304 stainless steel. Also, the accuracy of regression and fuzzy logic model are better in comparison to ANN model. Absolute percentage errors of all three mathematical models for conducted experimental trials are given in Figure 5.

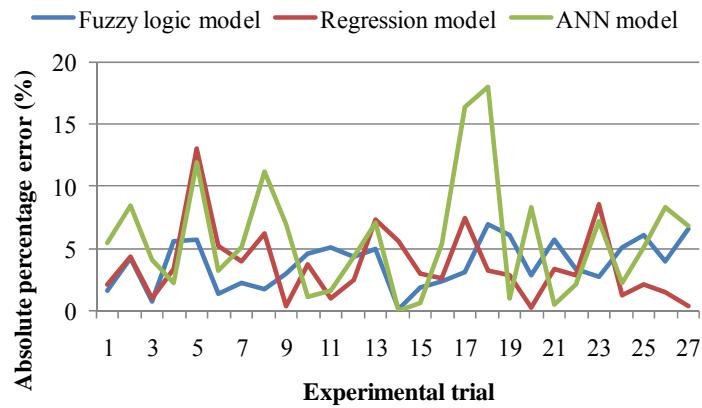


Fig. 5. Comparison of absolute percentage errors of all model predictions

In order to verify the initial conclusions and check the generalization abilities of the developed models, new experimental trials were conducted. Three validation experimental trials were conducted using the following combination of laser cutting parameter values:

Exp. trial 1: $P_L = 2$ kW; $v_f = 2$ m/min; $p = 10.5$ bar; $f = -1.5$ mm

Exp. trial 2: $P_L = 1.8$ kW; $v_f = 2.5$ m/min; $p = 10.5$ bar; $f = -1.5$ mm

Exp. trial 3: $P_L = 1.8$ kW; $v_f = 2$ m/min; $p = 10.5$ bar; $f = -2.5$ mm

The comparison of kerf width experimental values from these validation trials with the model's predictions is given in Fig. 6.

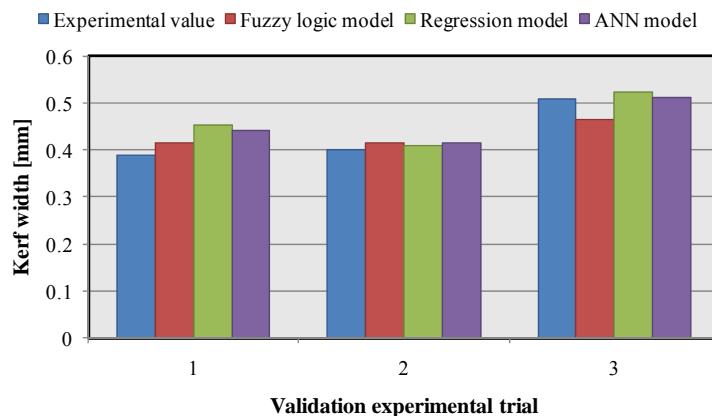


Fig. 6. Comparison of results obtained in validation experimental trials

The results from Figure 6 suggest that model's predictions are fairly close to the experimental results. Considering experimental validation trials, the mean absolute percentage errors for fuzzy logic, regression and ANN model were found

to be 6.32%, 7.18% and 5.93%, respectively. From these results it is clear that all three models exhibit good prediction performance, however it has to be noted that the accuracy of the ANN model was much better when new data was used. In other words, the ANN model showed very good generalization capability. In the case of other two models, fuzzy logic model maintained good generalization capability, while regression model showed somewhat larger errors on validation data.

Once developed and validated, a certain mathematical model can be used for process analysis. In this case, by using the fuzzy logic model, for the main effects of the laser cutting parameters on the kerf width the following was observed: an increase in laser power increases the kerf width, an increase in cutting speed decreases the kerf width, an increase in assist gas pressure has negligible effect on the kerf width and an increase in focus position (closer to the top sheet surface) increases the kerf width. It has to be noted that this analysis was obtained while changing one factor at a time while the other were fixed at their central level.

Figure 7 represents example of the 3D surface plots obtained during fuzzy logic modeling of kerf width obtained in CO₂ laser cutting of AISI 304 stainless steel. Out of six possible combinations of interaction effects, this plot was selected as it is observed that simultaneous change of laser power and cutting speed, in the covered experimental hyperspace, produces the most significant change in the kerf width. This plot was obtained while keeping the other two laser cutting parameters constant at medium level, i.e. $p = 10.5$ bar and $f = -1.5$ mm.

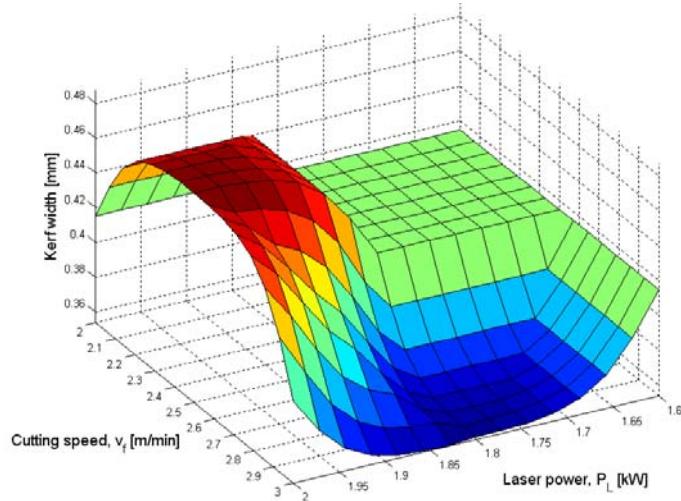


Fig. 7. Interaction effect of the cutting speed and laser power on the kerf width

5. Conclusions

In this paper, an attempt was made to develop and compare mathematical models for kerf width prediction in CO₂ laser cutting of AISI 304 stainless steel using regression analysis, ANN and fuzzy logic. Contribution of this paper is about development and comparison of three competitive models. The conclusions drawn can be summarized by the following points:

- All three modeling approaches provide fairly accurate models for the kerf width prediction. Regression model development follows straightforward procedure and requires less time and effort than the ANN model development in which one has to take a number of architectural and training parameters in consideration. On the other hand, the development of fuzzy logic model is quite complex and requires considerable knowledge and experience, but it provides the opportunity to encompass some of our available expert knowledge and previous experience on the laser cutting process.
- Considering the statistical performance criteria used for assessing the models' prediction accuracy, fuzzy logic model showed the best overall results. It turned out that the selected types of membership functions, Mamdani max-min reasoning approach and centroid defuzzification method are well suited for modeling laser cutting relationships.
- Somewhat worse results of ANN model considering initial experimental data with average and maximal absolute percentage errors of 5.79% and 18.02%, respectively, can be explained by the fact that this model was developed using less data. However, on the other hand, ANN model showed the best generalization capability when presented with new validation data. It should be noted that the prediction performance may be enhanced by exploiting the full potential of the ANNs through fine tuning of its training and architectural parameters as well using more experimental data.
- All three methods can be used efficiently for detailed analysis of the effect of process parameters and their interactions on the kerf width within the covered experimental hyper-space. Fuzzy logic model's results indicate that there exists an optimum region of the laser power to cutting speed ratio where the kerf width is minimal. This region corresponds to the combination of laser powers from 1.7 kW to 1.85 kW and cutting speed from 2.8 m/min to 3 m/min.
- All three modeling techniques are equally suitable and practical for kerf width modeling. By the authors opinion the first choice should be regression analysis, because of its simplicity and ease of application, and

in the case when one cannot obtain acceptable results, ANN and fuzzy modeling are to attempted.

- The developed models can aid the prediction, optimization, and improvement of the CO₂ laser cutting process via appropriate selection selection of process parameters. Their high prediction accuracy indicates that they can be practically applied in industry.
- Irrespective of applied approach, complexity of the laser cutting process requires taking into account different performance characteristics at the same time and their optimization. In this sense, modeling, single and multi-objective optimization and process control with the use of computationally intelligent methods may be advantageous, particularly when cutting complex contour on costly materials in large batch processing.
- Finally, one need to note that hybrid model, comprising of fuzzy logic and regression model showed best results, mean absolute percentage errors on experimental trials and validation trials are found to be 2.86% and 5.82%, respectively. This hybrid approach, however, may be practical in cases when single models do not make sufficiently acceptable predictions.

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