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MULTI-OBJECTIVE OPTIMIZATION OF CUT QUALITY CHARACTERISTICS IN CO_2 LASER CUTTING OF STAINLESS STEEL

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Original scientific paper

In this paper, multi-objective optimization of the cut quality characteristics in CO_2 laser cutting of AISI 304 stainless steel was discussed. Three mathematical models for the prediction of cut quality characteristics such as surface roughness, kerf width and heat affected zone were developed using the artificial neural networks (ANNs). The laser cutting experiment was planned and conducted according to the Taguchi's L_{27} orthogonal array and the experimental data were used to train single hidden layer ANNs using the Levenberg-Marquardt algorithm. The ANN mathematical models were developed considering laser power, cutting speed, assist gas pressure, and focus position as the input parameters. Multi-objective optimization problem was formulated using the weighting sum method in which the weighting factors that are used to combine cut quality characteristics into the single objective function were determined using the analytic hierarchy process method.

Keywords: *analytic hierarchy process; artificial neural networks; CO_2 laser cutting; cut quality characteristics; genetic algorithm; multi-objective optimization*

Višekriterijska optimizacija karakteristika kvalitete reza kod CO_2 laserskog rezanja nehrđajućeg čelika

Izvorni znanstveni članak

U ovom je radu predstavljena metodologija višekriterijske optimizacije karakteristika kvalitete reza kod CO_2 laserskog rezanja AISI 304 nehrđajućeg čelika (korozijski postojanog čelika). Za predviđanje karakteristika kvalitete reza kao što su hrapavost površine reza, širina reza i zona utjecaja topline, kreirani su matematički modeli pomoću umjetnih neuronskih mreža. Eksperiment laserskog rezanja je planiran i izveden prema Taguchijevom L_{27} ortogonalnom nizu, a eksperimentalni podaci su korišteni za treniranje umjetnih neuronskih mreža pomoću Levenberg-Marquardtovog algoritma. Matematički modeli umjetnih neuronskih mreža su kreirani uzimajući u obzir snagu lasera, brzinu rezanja, tlak pomoćnog plina i položaj fokusa kao ulazne parametre. Problem višekriterijske optimizacije je formuliran koristeći metodu težinskih koeficijenata, pri čemu su težinski koeficijenti, na osnovu kojih je izvršena kombinacija karakteristika kvaliteta reza u jednu ciljnu funkciju, određeni metodom analitičkog hijerarhijskog procesa.

Ključne riječi: *CO_2 lasersko rezanje; karakteristike kvalitete reza; realno kodirani genetski algoritam; umjetne neuronske mreže; višekriterijska optimizacija*

1 Introduction

Laser cutting is one of the most extensively used non-conventional material removal processes applied for processing a wide variety of materials. In laser cutting, the material is melted or evaporated by focusing the laser beam on the workpiece surface and coaxial jet of an assist gas removes the evaporated and molten material from the affected zone. Laser cutting is a high energy-density process that works quickly on the complex shapes, and is applicable to almost any type of material, generates no mechanical stress on the workpiece, reduces waste, provides ecologically clean technology, and has the ability to do work in the micro range [1]. Compared with other conventional machining processes, laser cutting removes much less material, involves highly localized heat input to the workpiece, minimizes distortion, and offers no tool wear [2]. Numerous additional advantages such as convenience of operation, high precision, small heat-affected zone (HAZ), minimum deformity, low level of noise, flexibility, ease of automation etc., made laser cutting to become an area of intense research and development activity in the past decade constantly attracting the attention of many researchers and practitioners. Comprehensive review papers summarizing experimental and theoretical studies, developments and opportunities for future research in laser cutting are available in the reference books [3, 4, 5, 6].

Different types of lasers are available on the market such as solid lasers, liquid lasers and gaseous lasers, but Nd:YAG and CO_2 are the two most widely used industrial lasers [7, 8]. The technological improvements in laser cutting machines made laser cutting technology more prevalent in today's production systems. Laser cutting finds many applications in various manufacturing industries where a variety of components in large numbers are required to be machined with high quality and close tolerance at low costs. Of particular interest to manufacturers using the laser cutting technology are the maximization of productivity and quality and minimization of cost. As noted by Karpat and Ozel [9], in a globally competitive manufacturing environment, simultaneously increasing productivity, while improving and maintaining high quality surfaces, is required to gain a competitive advantage for manufacturers.

Laser cutting is a complex process with numerous parameters which in consort play an essential role in the process performance. Complex nonlinear relationships among the multiple process parameters and process performance characteristics, which characterize the laser cutting process, limit the practical usage of mechanistic models, which involve many simplifications and approximations. Furthermore, the theoretical predictions of laser cut quality are very complicated, requiring very complex and sophisticated modelling approaches due to the great variety of parameters involved [10]. In the available reference books, there is evident trend on using design of experiment (DOE), Taguchi's optimization methodology, response surface methodology (RSM), artificial neural networks (ANNs) and other soft computing tools for the laser cutting optimization.

Laser cutting requires some trade-offs, since the optimum parameter settings for one performance may deteriorate other performance characteristics [2, 11]. With a limited theoretical and practical background to assist in systematical selection, the laser cutting parameters are usually set by the previous experience in a time consuming trial and error procedure. But, this trial-and-error approach is extremely costly in time and labour [2]. Satisfying multiple performance characteristics call for mathematical modelling of the laser cutting process, formulation of multi-objective optimization problem and subsequently determination of acceptable (near optimal) cutting conditions through the use of optimization methods. Thus, researchers worldwide are focusing on the process modelling and optimization of laser cutting to achieve the enhanced machining performance. In solving the multi-objective optimization problems in the laser cutting process, there are two general approaches.

The first one is based on the mathematical modelling of laser cutting process through the use of analytical, numerical and empirical approaches (regression analysis, RSM and ANNs) and subsequently determination of the optimal cutting conditions through the use of optimization algorithms, such as genetic algorithms, particle swarm optimization, simulated annealing, etc. [1, 2, 12, 13, 14, 15]. The multi-objective optimization is done by combining the multiple objectives into single objectives through the use of weights or utility function. Another approach is based on obtaining Pareto-optimal set of non-dominated decision variables settings using the non-dominated sorting genetic algorithm. Alternatively, for determining optimal settings one can apply stochastic search using the Monte Carlo methods.

The second approach is based on the integration of the Taguchi method (TM) with grey relational analysis, principal component analysis, weighted sum method and fuzzy logic [7, 8, 11, 16, 17, 18, 19, 20, 21]. The integration of the TM without formulation of any kind of model is an attractive alternative, relatively simple and efficient and became very popular. However, the major drawback of this approach is that it limits the optimization to the specific levels of parameter values. Hence, the optimization does not consider some intermediate combination of parameter values that may yield better results.

Analysis of the referenced works indicates that most of optimization approaches that integrate mathematical models and an optimization method dealt with parametric modelling and optimization in the field of laser micromachining. On the other hand, it has been observed that optimization based on TM considered in most cases laser cutting using the Nd:YAG lasers. The analysis of reference books revealed that there is a lack of research on the multi-objective optimization of CO_2 laser cutting, and furthermore, there is no investigation reported on the stainless steel.

In this context, in the present research paper an attempt has been made for the multi-objective optimization of CO_2 laser cutting of stainless steel. To this aim, three mathematical models for the prediction of cut quality characteristics such as the surface roughness, kerf width and HAZ were developed using the ANNs on the basis of experimental data obtained from Taguchi's L_{27} orthogonal array (OA). Three ANN models were developed to relate each of the cut quality characteristics with the different laser cutting parameters, such as laser power, cutting speed, assist gas pressure and focus position. The multi-objective optimization problem aimed at the simultaneous optimization of cut quality characteristics was formulated using the weighting sum method. To determine the weighting factors that are used to combine the cut quality characteristics into the single objective function named the cut quality index (CQI), the analytic hierarchy process (AHP) method was used. For solving the multi-objective optimization problem, MATLAB computer code was developed so as to integrate the ANN models with the real coded genetic algorithm (RCGA). Furthermore, the multi-objective optimization results with the corresponding optimal values of laser cutting parameters were presented for three different scenarios, that is better profitability, higher productivity, and better profitability and higher productivity at the same time.

2 Experimental procedure and details

Stainless steel is an important engineering material having wide application in the industry such as automotive, aircrafts, food, etc. In this study, AISI 304 stainless steel was used as the workpiece material. The sheet dimensions were 500 × 500 mm with thickness of 3 mm. 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 continuous wave mode. The cuts were performed with a Gaussian distribution beam mode (TEM_{00}) using a focusing lens of focal length of 127 mm. Nitrogen with purity of 99,95 % used as assist gas in all experimental trials was supplied coaxially using the conical shape nozzle HK20 (∅2 mm). The distance between the workpiece and the nozzle was controlled at 1 mm.

There are different quality characteristics which describe the laser cut quality. The standard ISO 9013 describes the criteria for evaluating the quality of cutting surfaces, quality classification and the dimensional tolerance. Evaluation of the laser cut quality is based on: cut geometry, cut surface, burr formation and characteristics of material in the cut zone. The evaluation and consequences of the imperfections depend on the specific job requirements. In this study, the experimental results after laser cutting were evaluated in terms of the average surface roughness (R_a), kerf width (K_w) and width of heat affected zone (HAZ). The specimen shape was designed in order to allow the measurement of all the cut quality characteristics in an accurate and simple way. Surface roughness on the cut edge was measured using a Surftest SJ-301 (Mitutoyo) profilometer. Each measurement was taken along the cut at approximately the middle of thickness. Kerf width, which represents the top kerf width, was measured at three different places at equal distances along the length of cut using the optical microscope (Leitz, Germany). A 20 mm long segment of the cut edge taken at the middle of the cut was examined using the optical microscope for measurement of the width of HAZ. Surface roughness, kerf width and width of HAZ measurements were repeated to obtain the averaged values. The CO_2 laser cutting parameters considered were the laser power (P_L), cutting speed (v_f), assist gas pressure (p) and focus position (f). The parameters were varied in the following range: laser power 1,6÷2 kW, cutting speed 2÷3 m/min, assist gas pressure 0,9÷1,2 MPa and focus position −2,5÷−0,5 mm. The value range for each parameter was chosen such that a wider experimental range is covered, full cut for each parameter combination is achieved and by considering manufacturer's recommendation for parameter settings. Taguchi's experimental design provides an efficient plan to study the entire experimental region of interest for the experimenter, with the minimum number of experimental trials as compared with the classical DOE, therefore, it was chosen for performing the laser cutting experiment. Based on the selected four laser cutting parameters at three levels, a design matrix was based on Taguchi's L_{27} (3^{13}) OA (Tab. 1). Laser cutting parameters, laser power, cutting speed, assist gas pressure and focus position were assigned to columns 1, 2, 5 and 9, respectively.

Table 1 Taguchi's L_{27} OA and experimental results

Exp. trial	P / kW	v / m/min	p / MPa	f / mm	Experimental results		
					Ra / µm	K_w / mm	HAZ / µm
1	1,6	2	0,9	−2,5	1,840	0,517	21,00
2	1,6	2	1,05	−1,5	1,982	0,398	23,67
3	1,6	2	1,2	−0,5	2,168	0,353	23,33
4	1,6	2,5	0,9	−1,5	2,344	0,393	15,33
5	1,6	2,5	1,05	−0,5	2,084	0,387	20,67
6	1,6	2,5	1,2	−2,5	1,667	0,483	18,67
7	1,6	3	0,9	−0,5	2,204	0,307	19,67
8	1,6	3	1,05	−2,5	1,834	0,512	17,67
9	1,6	3	1,2	−1,5	2,303	0,366	20,00
10	1,8	2	0,9	−1,5	1,712	0,435	30,33
11	1,8	2	1,05	−0,5	1,958	0,372	25,67
12	1,8	2	1,2	−2,5	2,202	0,550	20,33
13	1,8	2,5	0,9	−0,5	1,704	0,323	26,00
14	1,8	2,5	1,05	−2,5	1,771	0,477	19,67
15	1,8	2,5	1,2	−1,5	1,698	0,423	20,33
16	1,8	3	0,9	−2,5	2,089	0,488	18,33
17	1,8	3	1,05	−1,5	2,149	0,344	17,00
18	1,8	3	1,2	−0,5	1,912	0,287	19,33
19	2	2	0,9	−0,5	1,889	0,376	28,33
20	2	2	1,05	−2,5	3,015	0,542	19,33
21	2	2	1,2	−1,5	1,833	0,450	20,33
22	2	2,5	0,9	−2,5	2,294	0,493	19,67
23	2	2,5	1,05	−1,5	1,467	0,461	22,67
24	2	2,5	1,2	−0,5	2,155	0,372	26,33
25	2	3	0,9	−1,5	1,604	0,389	18,33
26	2	3	1,05	−0,5	2,205	0,320	20,67
27	2	3	1,2	−2,5	1,926	0,443	15,00

3 Mathematical models for the cut quality characteristics

The first step in the laser cutting process optimization is the development of mathematical models for exact quantification of the relationships of different laser cutting parameters and the performance characteristics. The mathematical model represents a formal and analytical expression of physical, geometrical and other characteristics of a real process. The selection of the mathematical model, which is used to establish a connection between the factors (inputs) and the target function (output), depends on the goal of research, the complexity of the phenomenon being researched, and the selected experimental design [22]. Theory and practice have shown that in most cases the best choice for the description of technological processes are the mathematical models in the form of first and second degree polynomials.

Although the polynomial models developed using multiple regression analysis are very promising for the practical applications, they are of limited applicability and reliability in the laser cutting modelling. It was shown that ANNs, which are based on the matrix-vector multiplications combined with the non-linear (activation) functions, offer better data fitting capability than the regression models for complex processes with many nonlinearities and interactions such as CO_2 laser cutting [23].

Although applying ANNs for process modelling is not without some reported shortfalls, including their black box nature, larger computational time, proneness to under- and over-fitting, by the author's opinion, a systematic methodology of ANN design and training with a deeper understanding of neurocomputing principles ensures the development of accurate, robust and well generalized mathematical models. Therefore, in this study the mathematical relationships between the laser cutting parameters and the laser cut quality characteristics were developed using ANNs.

3.1 ANN design and training

To establish the mathematical relationships between the laser cutting parameters and the cut quality characteristics, multilayer feed forward type ANNs were selected. To develop the ANN models for the prediction of each cut quality characteristic, that is surface roughness, kerf width and width of HAZ, the available experimental data was divided into two data sets: 19 data for ANN model development (training) and 8 data for ANN model testing. Four neurons at the input layer (for each of the laser cutting parameter), one neuron at the output layer for calculating the cut quality characteristic and only one hidden layer were used to define the ANN architecture for all models. Therefore, three ANN models with the same architecture were developed: Model 1 which relates laser cutting parameters and surface roughness, Model 2 which relates laser cutting parameters and kerf width, and Model 3 which relates laser cutting parameters and width of HAZ. Single hidden layer ANN model was chosen, because it is widely reported that this architecture can be trained to approximate most functions arbitrarily well. Hyperbolic tangent sigmoid and linear activation functions were used in the hidden layer and output layer, respectively, for all ANN models. The number of hidden neurons was determined by considering the total number of connection weights and biases in the ANN architectures, as well as the available number of data for ANN training. For the single hidden layer ANN architecture with *n* input neurons, *m* hidden neurons and *k* output neurons, the total number of weights and biases can be expressed as [23]:

$$T = m \cdot (n + k + 1) + k . \quad (1)$$

It is easy to calculate that for four inputs and one output, the upper limit of the number of hidden neurons is 3 for 19 available training data. Therefore, 4-3-1 ANN architectures were selected for all three ANN models. The practical application of ANN comes with the algorithms designed to determine the near optimum weights and biases in the process called 'training'. 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 the input that is not used in the training (generalization ability). The ANN training was conducted using the Levenberg-Marquardt algorithm. This training algorithm was chosen due to its high accuracy and fast convergence. The mean squared error was selected as a performance criterion for the training process. The ANN training was stopped when no further improvement in the performance was achieved and by considering the well known bias-variance trade-off in the empirical model development [24]. In order to deal with the convergence to local minima problem and slow convergence, the ANN training process was repeated several times using different initial weights.

3.2 ANN models validation

Once the weights are adjusted, the performance of the trained ANN should be tested. Among the various statistical methods for assessing the prediction performance of mathematical models, the mean absolute percentage error (MAPE), as one of the most stringent criteria, was used. It is defined as:

$$MAPE = \frac{1}{n} \sum_{n} \left| \frac{\text{Experimental value} - \text{Predicted value}}{\text{Experimental value}} \right| \times 100, \% \quad (2)$$

where *n* is the number of data.

To test the prediction capability of the developed ANN models, the trained ANNs were initially tested by presenting 19 input data patterns, which were employed for the training purpose. Subsequently, the ANN models were tested for generalization ability using 8 testing data. The prediction performances of the developed ANNs are given in Tab. 2.

Table 2 Prediction performance of the developed ANN models

MAPE / %	Model 1	Model 2	Model 3
Training data	8,71	5,51	1,26
Testing data	9,66	6,50	7,30

The results from Tab. 2 suggest that the ANN predictions are in good agreement with the experimental values of cut quality characteristics within the scope of laser cutting conditions investigated in the study. Thus, the ANN models can be used for the analysis of the laser cutting process, i.e. can be used as fitness functions for the optimization purpose. To this aim, the ANN mathematical models are to be explicitly expressed as the nonlinear function of the laser cutting parameters considering the used transfer functions in the hidden and output layer, and the weights and biases obtained after the training process. The methodology for developing the mathematical equations based on ANNs is discussed in detail in the reference books [25].

3.3 Formulation of multi-objective optimization problem

In this paper, a weighting method is adopted for the multi-objective optimization problem formulation, and the optimization results were obtained using the RCGA. The response functions are the cut quality characteristics such as surface roughness (R_a), kerf width (K_w) and width of the heat affected zone (HAZ) which are the functions of independent parameters, i.e. laser cutting parameters such as laser power, cutting speed, assist gas pressure and focus position. Three functions were generated in relation between the various dependent and independent parameters of the following form, i.e.:

$$R_a = f_{ANN_1}(P, v, p, f), \quad (3a)$$

$$K_w = f_{ANN_2}(P, v, p, f), \quad (3b)$$

$$HAZ = f_{ANN_3}(P, v, p, f), \quad (3c)$$

where f_{ANNi} (i = 1, 2, 3) represents the mathematical function based on the ANN generated using the set of weights and biases of each of the ANN models. The better cut quality considers minimization of the surface roughness, kerf width and width of the HAZ. Thus, the resultant weighted objective function to be minimized is:

$$CQI = w_1 \cdot R_a + w_2 \cdot K_w + w_3 \cdot \mathrm{HAZ}\ , \tag{4}$$

where w_1, w_2 and w_3 are the weighting factors of surface roughness, kerf width and width of the HAZ and CQI is the cut quality index.

To determine the weighting factors w_1, w_2 and w_3 that are used to combine the cut quality characteristics functions into a single-objective function, i.e. CQI, the analytic hierarchy process (AHP) was used.

3.4 Determining the weighting factors using the AHP method

AHP is an effective, relatively simple and widely used method for the decision analysis and calculation of weighting factors based on the multiple criteria. AHP decomposes a decision-making problem into a system of hierarchies of objectives, attributes (or criteria), and alternatives [18]. The AHP method is based on the pairwise comparisons to derive both weighting factors and comparative scores. In deriving criterion-weighting factors, each criterion is compared with every other, and the results are entered into computations that derive the relative factors. The weighting factors are calculated using eigenvectors and matrix algebra. Thus, the method has a mathematical basis to it, although the pairwise comparisons are usually subjective, adding uncertainty to the process. The result is the weighting factor distribution among the criteria, summing to one [26]. AHP can efficiently deal with tangible (i.e. objective), as well as non-tangible (i.e. subjective) attributes, especially where the subjective judgments of different individuals constitute an important part of the decision process [18]. The main procedure of AHP method and some examples are given in the referential literature [18].

In the present paper, the considered cut quality characteristics (surface roughness, kerf width and width of the HAZ) are non-beneficial attributes in nature, i.e. its lower values are more desirable. The relative importance of these attributes is given in the following pairwise comparison matrix (Tab. 3). The judgments are entered using the fundamental scale of the analytic hierarchy process.

Table 3 Decision matrix for cut quality characteristics

	A1	A2	A3
A1	1,00	7,00	3,00
A2	0,14	1,00	0,50
A3	0,33	2,00	1,00
A1 – surface roughness; A2 – kerf width A3 – width of HAZ			
λ_{max} = 3,0026	CI = 0,00132		CR = 0,002539 < 0,1

Using the AHP method, the criteria weights were determined as: w_1 = 0,68, w_2 = 0,1 and w_3 = 0,22. As the calculated value of consistency ratio (CR) is less than the allowed CR value of 0,1, there is good consistency in the judgments made. Also, there is no contradiction in the judgments.

3.5 Multi-objective optimization results and discussion

The objective function (Eq. 4) to be minimized now becomes:

$$CQI = 0{,}68 \cdot Ra + 0{,}1 \cdot K_w + 0{,}22 \cdot \mathrm{HAZ} \tag{5a}$$

Independent variables laser power, cutting speed, assist gas pressure and focus position are constrained within the ranges of the experimental hyperspace covered:

$$\begin{aligned} &1{,}6 \le \text{laser power} \le 2\ \text{kW}, \\ &2 \le \text{cutting speed} \le 3\ \text{m/min}, \\ &0{,}9 \le \text{assist gas pressure} \le 1{,}2\ \text{MPa}, \\ &-2{,}5 \le \text{focus position} \le -0{,}5\ \text{mm}. \end{aligned} \tag{5b}$$

The RCGA was used to obtain the optimal laser cutting parameter values for solving the multi-objective optimization problem formulated in Eq. (5). The RCGA itself is not discussed and the details are available elsewhere along with numerous examples of applications. Basically, obtaining the best optimal results depends on some features related to the RCGA parameters. Although some general guidelines about such selections exist in the relevant literature, it was reported that the optimal setting is strongly related to the design problem under consideration. To optimize the multi-objective function, the RCGA parameters used in this study are summarized in Tab. 4.

Table 4 RCGA parameter value

Population size	20
Selection	Stochastic uniform
Reproduction	Elite count: 2 Crossover fraction: 0,9
Crossover function	Scattered
Mutation function	Gaussian

The results obtained after solving the multi-objective optimization problem formulated in Eq. 5 using the RCGA are shown in Tab. 5. The optimal laser cutting parameter values are: P_L = 2 kW, v_f = 3 m/min, p = 1,2 MPa and f = −0,5, and the corresponding surface roughness, kerf width and width of HAZ values are obtained as 1,646 μm, 0,349 mm and 16,86 μm, respectively. This means that the optimal point is actually the boundary point in the hyperspace of the laser cutting parameters. From the optimization results, it can be seen that all laser cutting parameters converge to the upper limits in the experimental hyperspace covered. This indicates that the RCGA optimized multi-objective solution is directly proportional to the laser cutting parameters.

The optimal laser cutting conditions are obtained for the parameter levels that do not occur in the experimental design matrix (Tab. 1), proving that the optimal laser cutting parameter settings cannot be estimated through the experiment trials using the Taguchi's L_{27} experimental design. However, they could be identified in a systematic approach including the application of full factorial design, but this approach is time and cost consuming.

The optimization of laser cutting process may consider the additional criteria such as processing costs and productivity. The productivity in laser cutting is mainly affected by cutting speed, with maximal cutting speed always preferred. The processing cost in CO_2 laser inert cutting is a function of the assist gas flow rate, which is dependent on the nozzle diameter and assist gas pressure. Since only one nozzle was used in the experiment, the processing cost comes in a direct relation with the assist gas pressure.

Table 5 Multi-objective optimization results for CO_2 laser cutting process

Parameters and objective function	Value
Laser power, P_L (kW)	2
Cutting speed, v_f (m/min)	3
Assist gas pressure, p (MPa)	1,2
Focus position, f (mm)	−0,5
Surface roughness, R_a (µm)	1,646
Kerf width, K_w (mm)	0,349
Width of heat affected zone, HAZ (µm)	16,86
CQI	−0,5536

Hence, the multi-objective optimization problem formulated in Eq. 5 was solved so that: (a) minimum assist gas pressure is used (p = 0,9 MPa) for better profitability, (b) maximum cutting speed is used (v_f = 3 m/min) for higher productivity, and (c) maximum cutting speed and minimum assist gas pressure are used (p = 0,9 MPa, v_f = 3 m/min) for better profitability and higher productivity at the same time. The RCGA optimization results are summarized in Tab. 6.

The optimization results from Tab. 6 suggest that for the better profitability, it is preferable to use an intermediate level of laser power, intermediate to high cutting speed and focus the laser beam to about one half of the material thickness. In the case when the goal is to achieve higher productivity, focusing the laser beam nearer to the sheet top surface while using high laser power and high assist gas pressure is beneficial. As can be seen, in this case the optimal combination of laser cutting parameter setting is the same as obtained in Tab. 5.

For obtaining better profitability and higher productivity at the same time (when using low assist gas pressure and high cutting speed), the laser beam is to be focused to the half of material thickness while using high laser power. An analysis of the obtained laser cutting parameter levels reveals that this combination occurs in the experimental design matrix (Tab. 1) and corresponds to the experimental trial 25. When comparing the obtained optimization results for the surface roughness, kerf width and HAZ width with the experimental values, good agreement could be observed.

Table 6 Multi-objective optimization solutions for CO_2 laser cutting process with constraints

Objective	(a) better profitability	(b) higher productivity	(c) better profitability and higher productivity
Parameters and objective function	Value		
Laser power, P_L (kW)	1,746	2	2
Cutting speed, v_f (m/min)	2,61	3	3
Assist gas pressure, p (MPa)	0,9	1,2	0,9
Focus position, f (mm)	−1,67	−0,5	−1,5
Surface roughness, R_a (µm)	1,843	1,646	1,826
Kerf width, K_w (mm)	0,419	0,349	0,409
Width of heat affected zone, HAZ (µm)	14,61	16,86	18,29
CQI	−0,4206	−0,5536	−0,33546

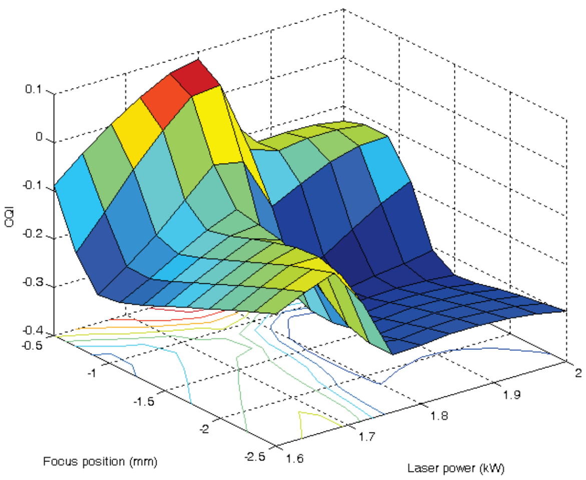

Figure 1 CQI as a function of laser power and focus position

An attempt has also been made to investigate whether there exist some other laser cutting parameter combinations which can be used for achieving better profitability and higher productivity. To this aim, CQI objective function was plotted as a function of the laser power and focus position (Fig. 1), while the cutting speed and assist gas pressure were set at high and low level, respectively.

As clearly seen from Fig. 1, there exists a significant interaction effect between the laser power and focus position on the CQI value. The CQI value varies non-linearly with the laser power and focus position. In the case of laser power, in the first stage the CQI increases with the increase of laser power, but after a certain limit, the increase of laser power decreases the CQI. On the other hand, the increase in focus position in the first stage decreases CQI, and after a certain limit, further increase in focus position increases CQI. Generally, using the laser power in the range 1,8 to 2 kW and focusing the laser beam in the bulk of material, approximately to the half of material thickness, is beneficial for the minimization of CQI value.

4 Conclusion

The identification of optimal cutting conditions in CO_2 laser cutting, due to their significant interest for the manufacturers, has been a subject of constant research. Moreover, in laser cutting there is always a need to determine the optimal laser cutting parameters settings so as to improve the multiple performance characteristics. In this paper, the optimal selection of laser cutting parameters for obtaining the high cut quality in terms of surface roughness, kerf width and width of the heat affected zone minimization was presented. ANNs have been used to develop the mathematical models for prediction of the cut quality characteristics using the experimental results obtained from the Taguchi's experimental plan. The multi-objective optimization problem was formulated using the weighting sum method, in which the weighting factors were determined using the analytic hierarchy process method. On the basis of the multi-optimization results obtained by using RCGA, the following points can be concluded within the experimental hyperspace covered:

- Statistical results indicate that quite basic ANN models, trained with the Levenberg-Marquardt algorithm using the limited training data set obtained from the Taguchi's experimental design, are able to provide reasonable accuracy for the prediction of cut quality characteristics.
- The AHP method can be used effectively, yet relatively easy for determining the weighting factors for the multi-objective optimization problems in CO_2 laser cutting.
- The optimal laser cutting settings for better profitability are laser power of 1,746 kW, cutting speed of 2,61 m/min, assist gas pressure of 0,9 MPa, and focus position of −1,67 mm.
- The optimal laser cutting settings for higher productivity are laser power of 2 kW, cutting speed of 3 m/min, assist gas pressure of 1,2 MPa, and focus position of −0,5 mm.
- The optimal laser cutting settings for both better profitability and higher productivity are laser power of 2 kW, cutting speed of 3 m/min, assist gas pressure of 0,9 MPa, and focus position of −1,5 mm.

The applied approach integrating the ANN based mathematical modelling, the AHP method for determining the weighting factors and optimization using RCGA can be efficiently used for the multi-objective optimization in CO_2 laser cutting process.

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