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MATHEMATICAL MODELLING OF THE CO_2 LASER CUTTING PROCESS USING GENETIC PROGRAMMING

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Abstract. *The development of mathematical models by using experimental data is of great importance for modelling and optimization of the laser cutting process. Motivated by the lack of research regarding the use of genetic programming (GP) for deriving empirical mathematical models that describe the laser cutting process, the present study discusses the application of GP to the development of a kerf taper angle mathematical model. The aim was to quantify the relationship between three selected input parameters (cutting speed, laser power and assist gas pressure) and kerf taper angle using GP in the CO_2 laser cutting of aluminium alloy AlMg3. To obtain the experimental database for the GP model evolution process, a laser cutting experiment was planned as per standard full factorial design where all three selected parameters were varied at three levels. The fit between the experimental and the GP model prediction values of kerf taper angle was found to be appropriate. Finally, by using the derived GP mathematical model, the analysis of the effects of input parameters on the change in kerf taper angle values was performed by generating 3D surface plots.*

Key words: *Kerf taper angle, Genetic programming, Laser cutting*

1. INTRODUCTION

Laser cutting technology is one of the leading non-conventional technologies used in modern industry for contour cutting of different materials, with CO_2 and Nd:YAG lasers being the most used [1]. Numerous benefits and advantages of this technology have led to it becoming an area of great and continuous industrial and scientific research. A number of experimental, theoretical, modelling and optimization studies have been performed

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aiming at better understanding and optimization of the laser cutting process with respect to different criteria such as quality performance, cost, productivity, cutting time, etc. An essential element in these studies is the development of mathematical models for exact quantification of the relationships between the laser cutting parameters (inputs) and performances (outputs).

The identification of empirical mathematical models for the approximation of the laser cutting process performance is of great practical importance considering that the complexity of the laser cutting process limits the practical use of analytical models. Moreover, the development of analytical models usually requires certain assumptions and generalizations and the modelling process itself is time-expensive and requires considerable expert domain knowledge. On the other hand, for the purpose of empirical mathematical modelling of the laser cutting process only a set of input-output data is needed. Input data refer to process variables (factors) such as laser power, cutting speed, assist gas type/pressure, etc., and output data, which can be experimentally measured or calculated, refer to process performances such as material removal rate, surface roughness, kerf width, cost, etc. In order to develop a reliable and accurate empirical model, a number of experimental trials with associate measurements are to be taken, where the application of design of experiments (DOE) saves time and resources while ensuring systematic and comprehensive investigation.

Once the input-output data are available, the aim of empirical mathematical modelling is to develop the functional dependence between dependent variables (performance) and independent variables (factors), which is at the same time the best approximation of the actual laser cutting process. These dependencies can be modelled using polynomials as in the regression analysis (RA) approach, a combination of nonlinear functions and matrix calculus as in the artificial neural network (ANN) approach, fuzzy numbers and membership functions as in the fuzzy logic approach, or they can simply be modelled by power, exponential or other more specific mathematical models. In the field of the laser cutting process modelling, RA, ANN, fuzzy logic and adaptive neural fuzzy inference system (ANFIS) models are predominantly used for the development of empirical mathematical models.

Nassar et al. [2] used an RA model for the prediction of surface roughness in order to optimize laser cutting parameters such as cutting speed, laser power and assist gas pressure in CO_2 laser cutting of stainless steel 307. The empirical mathematical model was developed based on the 3^3 full factorial experimental design. Singh and Gangwar [3] conducted an experimental analysis in CO_2 laser cutting of AISI 321 stainless steel by using Taguchi’s orthogonal array design. In order to develop the mathematical relationship between laser cutting parameters (cutting speed, frequency and assist gas pressure) and surface roughness, an RA approach was adopted. Subsequently, a genetic algorithm was used to provide a set of optimum values for input parameters for surface roughness minimization. Parametric modelling and optimization of Nd:YAG laser cutting of AISI 316L stainless steel was conducted by Gadallah and Abdu [4]. Taguchi’s L_{27} orthogonal array design was adopted as the experimental matrix where laser power, cutting speed, assist gas pressure and frequency were varied at three levels. Empirical mathematical models for the prediction of surface roughness, kerf taper and width of the heat affected zone (HAZ) in terms of considered parameters were developed using response surface methodology (RSM). Abhimanyu and Satyanarayana [5] conducted an optimization study of cut quality during pulsed CO_2 laser cutting of mild steel. To this aim they developed two RA models relating surface roughness and hardness with independent parameters such as laser power, cutting speed and material thickness. With the development of ANN models, Klancnik et al. [6] investigated the effects of laser power, cutting speed and assist gas type on kerf width and surface roughness in CO_2 laser cutting of the tungsten alloy. Among 42 experimental results, 34 data sets were chosen for training the ANN model, whilst the remaining results were used as test data. Experimental analysis of the effects of laser power, laser repetition rate, and laser scanning speed on surface roughness in laser micro-cutting of polymer plate was conducted by Bachy and Al-Dunainawi [7]. The mathematical model relating surface roughness and independent parameters was developed using ANN after performing a number of experimental tests. Good agreement was observed between theoretical results and ANN predictions. Multi-objective optimization of pulsed Nd:YAG laser cutting of an aluminium alloy through integration of ANN models and non-dominated sorting genetic algorithm (NSGA-II) was performed by Chaki et al. [8]. A full factorial experimental design was conducted where cutting speed, pulse energy and pulse width were considered as input parameters while kerf width, kerf deviation, surface roughness and material removal rate were considered as process outputs. For the purpose of ANN model development, a Bayesian regularization algorithm was used. Syn et al. [9] developed a fuzzy logic model to predict surface roughness and dross inclusion in CO_2 laser cutting of Incoloy alloy 800. A set of training and testing comprised 125 data. The model was developed in terms of three input parameters, i.e. laser power, assist gas pressure and cutting speed. For the prediction of dross formation in CO_2 laser oxygen cutting of mild steel, Madić et al. [10] proposed a fuzzy logic model. The model was developed based on data from Taguchi’s experimental design. The developed fuzzy logic model was based on the use of Mamdani-type inference system. With the use of fuzzy and RA models, Rajamani and Tamilarasan [11] predicted kerf deviation and metal removal rate in Nd:YAG laser cutting of a titanium super alloy. Pulse width, pulse energy, cutting speed and assist gas pressure were considered as independent variables. The experimental trials were performed according to the standard Box-Behnken experimental design. Zhang and Lei [12] developed ANFIS models for the prediction of kerf width and surface roughness in fiber laser cutting of AISI 201 stainless steel. The models were developed in terms of laser power, cutting speed and assist gas pressure. It was noted that ANFIS models had a superior performance in comparison to the ANN model considering error dimensions, training speed and convergence precision. A hybrid approach of ANN and fuzzy logic models was applied to develop a fuzzy expert system to predict kerf width and kerf deviation in pulsed Nd:YAG laser cutting of a titanium alloy [13]. The predicted results were compared with the experimental data and found appropriate.

From the above summary of studies it can be observed that empirical mathematical modelling was mainly performed with the application of linear, quazi-linear and non-linear regression models, while in the case of ANNs, multi-layer perceptron (MLP) type models were mostly used. The thing which is common for both approaches, as well as for fuzzy logic and ANFIS models, is that the mathematical model constants (coefficients) are determined based on experimentally collected data where the functional form of the mathematical model (approximation structure) is defined by the decision maker [14]. For example, in the case of ANN based mathematical modelling, the number of hidden layers and neurons as well as the selection of transfer functions, which largely determine the (non)linearity of the mathematical model, is determined by the decision maker.

Apart from the aforesaid approaches, genetic programming (GP) is an empirical mathematical modelling approach intended to identify the model structure as well as constants (model parameters) at the same time. In that sense it represents a more advantageous approach for mathematical modelling without requiring the specification of the mathematical model structure in advance. Regression methods and RSM may require the use of statistical tests for the assessment of significant model terms, whereas GP self-prunes the insignificant terms because of the inherent evolutionary traits [15]. In addition, as noted by Mitra et al. [16], GP can incorporate very diverse data sets that contain markedly different types of variables and can also handle missing values in the data, where missing data in regression methods and RSM may make impartial estimates of the parameters of interest difficult or impossible. To this aim the focus of the present paper is the application of GP to the development of empirical mathematical models for describing the CO_2 laser cutting process. To the best of the authors' knowledge, the GP empirical mathematical modelling approach has not been previously applied to CO_2 laser cutting process modelling. Recent studies promote the use of GP for modelling laser drilling [17], laser microdrilling [18] and laser cladding [19]. In that sense the novelty of the manuscript is reflected in fulfilling the research gap in the CO_2 laser cutting modelling domain, as well as in the analysis of the obtained results using the developed GP model through consideration of two-factorial interaction effects. In the present study GP was implemented using the data from an experimental investigation of CO_2 laser cutting of an aluminium alloy. The GP mathematical model for the prediction of kerf taper angle was developed in terms of three laser cutting parameters, namely, laser power, cutting speed and assist gas pressure.

2. Experimental Details

The experimental investigation of the CO_2 laser cutting process was conducted on an aluminium alloy (AlMg3) sheet with the thickness of 5 mm. This is magnesium alloyed aluminium (AA5754) with a maximum of 3.0% Mg. It is a standard sheet metal alloy with good mechanical properties, good corrosion resistance, excellent weldability and anodizing, and as such has a wide application in construction industry.

Experimental trials were performed using the cutting head with a focusing lens with a focal length of 5 in (127 mm). The nitrogen gas was used as assist gas and it was passed through a conical shape nozzle with the nozzle diameter of 2 mm. The stand-off distance was set at 0.8 mm. The entire experimental investigation was performed using a Prima Industry 4 kW CO_2 laser cutting machine operating in the continuous wave mode. The focus position was always defined to be on the bottom surface of the sheet.

Based on the literature review, pre-analysis and pilot experimentation, three laser cutting parameters were selected for variation during experimentation, i.e. laser power (P), assist gas pressure (p) and cutting speed (v). For the purpose of experimentation, a full factorial experimental plan (3^3) L_{27} OA was adopted where the considered parameters were varied at three levels as given in Table 1. This design had 27 rows corresponding to the number of tests (26 degrees of freedom) with 13 columns at three levels [20, 21].

Laser power, assist gas pressure and cutting speed were assigned to columns 1, 2, and 5, respectively. It has to be noted that in trial 9 (laser power 3.2 kW, assist gas pressure 15 bar and cutting speed 2 m/min) no throughout cut was achieved, and this may be attributed to the laser power to cutting speed ratio and high reflectivity and thermal conductivity of the workpiece material. Therefore, only measurements from 26 trials were considered as the basis for mathematical modelling.

Kerf width and kerf taper are one of the most important cut quality parameters in the laser cutting process that determine the geometrical accuracy of the finished parts. Due to the converging–diverging shape of the laser beam profile kerf taper always exists in laser cutting (Fig. 1).

Table 1 Laser cutting parameters and ranges used in the experiment

Laser cutting parameter	Unit	Level		
		1	2	3
Laser power, *P*	kW	3.2	3.6	4
Assist gas pressure, *p*	bar	10	12.5	15
Cutting speed, *v*	m/min	1.6	1.8	2

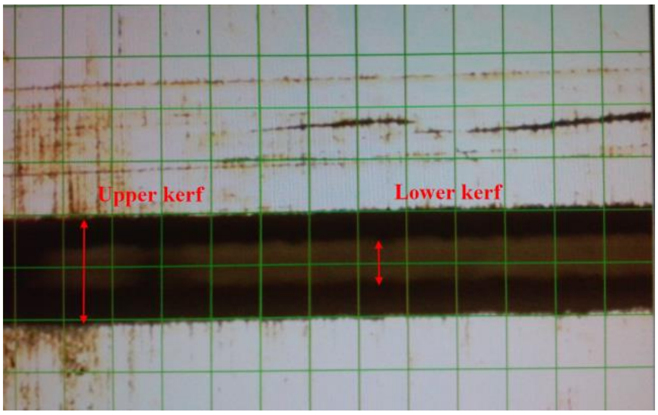

Fig. 1 Laser cut kerf geometry recorded using Q-spark image processing software

Let K_u and K_b designate the upper and lower kerf widths, respectively. For the workpiece thickness of d the resulting kerf taper angle (K_t) in the laser cutting operation can be calculated using the following equation:

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

The upper and lower kerf widths were measured using the optical coordinate measuring device Mitutoyo (type: QSL-200Z) with the resolution of the length measuring system of 0.5 µm. The kerf widths were measured at three equally distanced positions along the picture of the kerf, which covers the distance of 3.15 mm (9×0.35 mm), taken approximately in the middle of the cut. For the purpose of mathematical modelling, the average values of kerf taper angle were considered for each experimental trial.

3. GENETIC PROGRAMMING (GP)

3.1. GP overview

GP is an artificial intelligence (AI) method aimed at intelligent and adaptive evolution of empirical mathematical model structures. Each mathematical model corresponds to a given program structure (i.e. individual), which is determined by the unique combination of basic elements-genes. An individual program is a tree-like structure and as such there are two types of genes, primitive functions and terminals [22]. The set of primitive functions consists of arithmetic operators, mathematical functions, Boolean logical operators and special functions. The set of terminals, which also constitute the chromosome structure, are usually input parameters (independent variables) and different numerical constants [23].

Starting from the random population of programs (chromosomes, models), having various tree-shapes and forms, and implementing the Darwinian concept of natural selection through application of selection (reproduction), crossover and mutation operators, the programs evolve until the final solution. During the evolution process each program in the population is monitored via the fitness function, which represents a certain measure of the program appropriateness. Actually, the fitness function is one of the key elements which to the great extent control the evolution process, i.e. the improvement of the solution correctly evaluating all the improvements which are being made during the evolution process. The evolution process lasts until the pre-specified number of iterations is achieved, the given evolution process time is expired or an appropriate solution is found.

During the evolution process the selection operator controls the selection process of programs which are to be transferred to the next population. Koza allowed 10% of the population to reproduce [24]. The essence of this genetic operator is the survival of chosen individuals and the expected consequence is an increase in the mean value of the fitness function of the entire population, i.e. transfer of better genetic material from generation to generation. The crossover operator is intended to combine the genetic material from two, randomly selected, individuals in the randomly chosen point of intersection. As a result of the crossover operation two offsprings are obtained having genetic material from both parents. Koza suggested a crossover of 90% of the population since it provides the source of new (and eventually better) individuals [23, 24]. The mutation operator represents a mean for introducing new genetic material into the population. The goal is to introduce certain random changes of individuals so as to maintain diversity in the population, prevent problems of local optimum convergence and/or enable an escape from the local optimum. The mutation is carried out by choosing an individual at random, followed by random selection of the node which is to be mutated, where function is being replaced by function and terminal by terminal.

3.2. GP control parameters

An efficient implementation of GP in empirical mathematical modelling depends on a careful selection of genes, i.e. sets of functions and terminals, as well as the specification of main controlling parameter values. The main control parameters are population size, maximum number of generations, probability of crossover and probability of reproduction [22]. Other parameters are summarized in [23] and discussed by Koza [24].

Population size and maximum number of generations depend on the complexity of the problem being solved. Generally, a population of 500 or more individuals gives better chances for finding the global optimum. For a small number of independent variables, a starting population of 100 may be sufficient [25]. Optimal selection of main GP parameter values is reflected both on the quality of the determined mathematical models as well as the performance of the evolution process. The correct use of GP parameters represents a difficult task, and is primarily affected by the end user knowledge and experience [26].

4. GP Mathematical Model for the Prediction of Kerf Taper Angle

Implementation of the GP approach in the development of mathematical models implies making a number of modelling decisions related to different parameters including: selection of functional set, definition of fitness function, selection of population size and mechanism for its initialization, definition of terminal set, i.e. specification of independent variables, adjustment of genetic operators, specification of selection mechanism, etc.

After comprehensive pilot experimentation with mathematical operators and other GP parameters, the GP parameters, as given in Table 2, were used so as to obtain an acceptable error for the mathematical model that is yet quite simple. For the assessment of the GP mathematical model quality, the fitness function in the form of the mean absolute error (MAE) was used:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \left| E(i) - M(i) \right|}{n}, \tag{2}$$

where n is the number of trials, $E(i)$ represents the experimentally obtained value and $M(i)$ is the GP modelled value for the i-th trial.

Table 2 GP parameters used in mathematical modelling

Number of data for modelling: 26	Fitness function: MAE
Terminal set: laser power (P), assist gas pressure (p), cutting speed (v)	Probability of crossover: 0.8
Functional set: +,-,*,/,power of 2, polynomial terms	Probability of mutation: 0.1
Population size: 500	Probability of reproduction: 0.1
Initialization: ramped half-and-half algorithm	Selection: roulette wheel

It has to be noted that some solutions with better fitness function values were rejected because of their excessive length. Namely, as noted by Alvarez et al. [27], when the complexity of the GP mathematical model is increased its ability to generalize can be affected by the risk of over-fitting the data. In many trials during the GP program evolution it turned out that the final solution did not include the cutting speed (v), indicating its possible small influence on the change of kerf taper angle. If one considers the change of this parameter in the covered experimental hyper-space (Table 1) this indication might be justified. After reaching 500 generations the following GP mathematical model for the prediction of kerf taper angle emerged:

$$K_t = (100 \cdot (p - 3.92))/(749 \cdot ((161 \cdot p)/20 + 7.49) \cdot (P + 8.05 \cdot p - 0.21)) \\ - 571/(50 \cdot (P \cdot (v - 3.13) - 19.29)) \tag{3}$$

The derived GP model showed the mean absolute error of 0.128 over the entire set of training data consisting of 26 pairs of input/output data. This is an indication that the developed GP model has a considerably good prediction accuracy and that it can be used for the analysis of the effects of laser cutting parameters on kerf taper angle.

5. Results and Discussion

The change of kerf taper angle values was analyzed by changing two parameters at a time, while keeping the third parameter constant at the centre level. The change of kerf taper angle values is given as a function of 3 interaction effects as given in Fig. 2.

From Fig. 2 it can be seen that kerf taper angle has no negative values, indicating that the upper kerf is always wider than the lower kerf. As noted by Genna et al. [28], since aluminium and its alloys are highly reflective metals, laser cutting of AlMg3 needs more energy input to initiate the cut, which results in widening the upper kerf. The results of Tahir and Rahim [29], in the case of CO_2 laser cutting of ultra high strength steel, also reported this observation. In CO_2 laser cutting of Al6061/SiCp/Al_2O_3 composite material with the thickness of 4 mm, a higher degree of melting was found at the top surface of the work material than at the bottom surface [30]. When comparing CO_2 and fiber laser cutting of AISI 304 stainless steel sheets in the thickness range between 1 and 10 mm, Stelzer et al. [31] observed that the kerf width was continuously decreased from top to bottom. However, it was noticed that, in the case of fiber laser cutting, the narrowest kerf width was typically found in the middle of the sheet. In the present experimental investigation the highest ratio of the upper and lower kerf of 2.72 was obtained when using the laser power of 3.2 kW, assist gas pressure of 10 bar and cutting speed of 1.6 m/min. In these conditions the upper and lower kerf widths of 0.734 and 0.27 mm were obtained. The lowest ratio of the upper and lower kerf of 1.72 was obtained under the same conditions except that the laser power of 3.6 kW was used. Considering this observation one may argue that laser power predominantly affects kerf taper angle.

From Figs. 2a and 2b it can be observed that the interactions of laser power and assist gas pressure and laser power and cutting speed are negligible and produce a kerf taper angle of about 2.2º in all parameter combination values. In CO_2 laser cutting of austenitic stainless steel, Ozaki et al. [32] reported that the cross-sectional shapes of kerf were almost the same though the laser power or the cutting speed were varied. Slight increases in kerf taper angle with an increase of cutting speed or decrease in laser power may be explained considering that with a decrease in the linear energy density, the angle at which a layer of melt is produced through the thickness of workpiece (inclination angle) is increased. In the present study, in the case of using low laser power level (3.2 kW) there is a sudden rise in kerf taper values. Namely, the heat input during the cutting operation is primarily determined with laser power. Thus, when the low laser power level was used, there was no sufficient heat to melt the material along the entire workpiece thickness and this resulted in increased kerf taper angle values, i.e. formation of a wide upper kerf and a narrow lower kerf. As noted by Tahir and Rahim [29], by increasing the laser power the

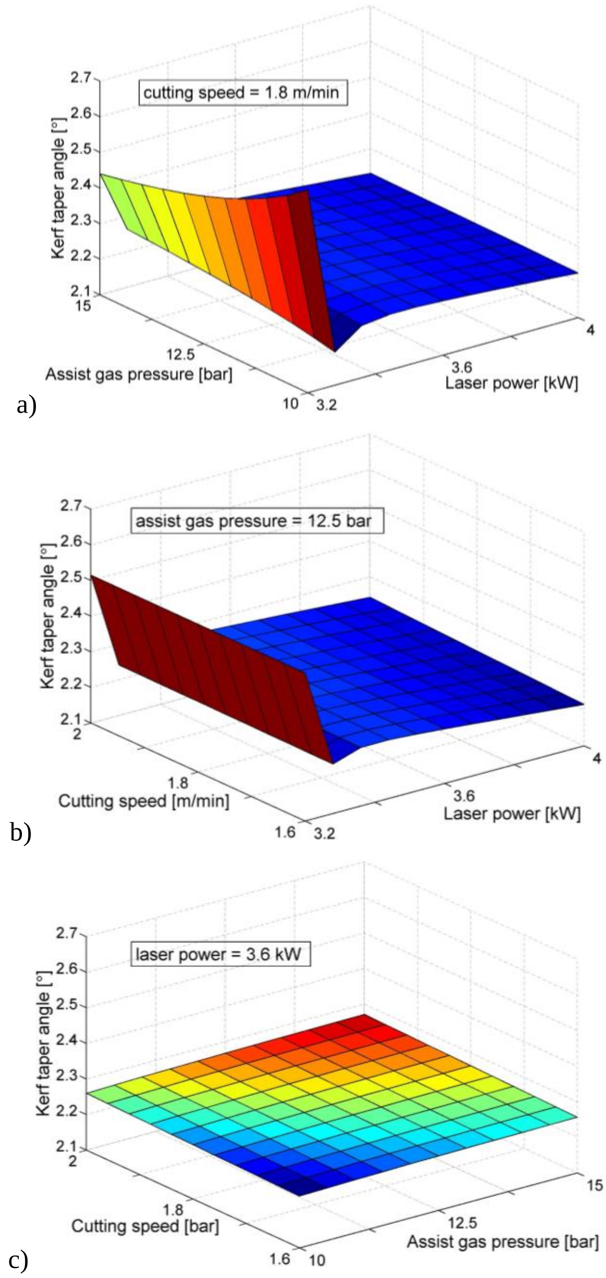

Fig. 2 Change of kerf taper angle with respect to: a) interaction effect of laser power and assist gas pressure, b) interaction effect of laser power and cutting speed, c) interaction effect of cutting speed and assist gas pressure

greater material removal rate was obtained which results in reducing the taper formation. The widening of the lower kerf width at high power levels, and a consequent decrease in taper angle, was observed by Yilbas et al. [33] in CO_2 laser cutting of 7050 Al alloy reinforced with Al_2O_3 and B_4C composites. Finally, for the constant laser power of 3.6 kW (Figure 2c), an increase in assist gas pressure as well as cutting speed results in a negligible increase of kerf taper angle values. This is in accordance with the results reported by Madić et al. [34]. In that research, it has been reported that for certain levels of laser power the effects of assist gas pressure and cutting speed on the change in kerf taper angle may be negligible.

Apart from kerf taper angle, another relevant information for industrial practitioners regarding perpendicularity of the cut is angularity or perpendicularity tolerance, which is defined in the ISO 9013 (2002) standard [35]. This standard, based on the given workpiece thickness, classifies laser cuts into five classes according to angularity tolerance (u). Based on obtained experimental values of upper and lower kerf widths, it was observed that different combinations of laser cutting parameters in the conducted experiment produced angularity tolerance values in the range u=0.145÷0.205mm, which covers classes 2 and 3 according to ISO 9013.

Finally, it is necessary to point out that the perceived observations and obtained results are valid for the covered experimental domain and used cutting conditions. For different ranges of cutting parameters and cutting conditions one may expect different effects of the laser cutting parameters on kerf taper angle, both quantitatively and qualitatively.

6. Conclusion

This paper reviewed some of the main approaches to mathematical modelling of the laser cutting process with the emphasis on the application of GP. In the present study a GP mathematical model was developed to predict kerf taper angle as a function of laser cutting parameters such as cutting speed, laser power and assist gas pressure in CO_2 laser cutting of an aluminium alloy using nitrogen as assist gas. From the analysis of the GP model development process and its analysis within the covered experimental hyper-space it was observed that the laser power has the most dominant effect on kerf taper angle and this is particularly pronounced in the case when there was no sufficient heat to melt the material along the entire workpiece thickness. The influences of cutting speed and assist gas pressure on kerf width are much smaller. It was also observed that in all experimental trials kerf profiles exhibited the typical slight v-profile.

Modelling results using GP indicated that the mathematical model evolution process is highly affected by the selection of main GP parameters, where there is no universal rule for setting these parameters. During the mathematical model development it was observed that there is no repeatability of the final solution even though the same initial conditions and GP parameter settings were used. As an advantage/disadvantage of GP one needs to point out that in some model evolution processes certain independent variables might be excluded from the final model.

In conclusion, GP mathematical models proved to be able to adequately represent mathematical relationships between laser cutting parameters and kerf taper angle. Increasing the number of training input/output sets, using a bigger initial population and fine tuning of other GP parameters would provide a means for the development of more accurate mathematical models. The development of GP mathematical models can improve the laser cutting process via an appropriate selection of process parameters through optimization. Finally, the ability of GP to work with incomplete data obtained from experimental design is particularly beneficial for the laser cutting process modelling considering that some combinations of laser cutting parameters in the experimental matrix might not be able to produce complete cuts.

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