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AN ANN APPROACH ON THE OPTIMIZATION OF THE CUTTING PARAMETERS DURING CNC PLASMA-ARC CUTTING

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ABSTRACT

The objective of the present study is to develop an Artificial Neural Network (ANN) in order to predict the bevel angle (response variable) during CNC plasma-arc cutting of St37 mild steel plates. The four (4) input parameters (plate thickness, cutting speed, arc ampere, and torch standoff distance) of the ANN was selected following the results (relative importance) of the Analysis Of Variance (ANOVA) performed based on seven (7) factors (plate thickness, cutting speed, arc ampere, arc voltage, air pressure, pierce height, and torch standoff distance) in a previous study. A multi-parameter optimization was carried out using the robust design. An L_{18} (2^1x3^7) Taguchi orthogonal array experiment was conducted and the right bevel angle was measured, aiming at the investigation of the influence of plasma-arc cut process parameters on right side bevel angle of St37 mild steel cut surface. The selection of quality characteristics, material, plate thickness and other process parameter levels and experimental limits was based on the experience and current needs of the Greek machining industry. A feed-forward backpropagation (FFBP) neural network was fitted on the experimental data. The results show that accurate predictions of the bevel angle can be achieved inside the experimental region, through the trained FFBP-ANN. The developed ANN model could be further used for the optimization of the cutting parameters during CNC plasma-arc cutting.

INTRODUCTION

The use of plasma-arc cutting (PAC) for steel plates can offer substantial advantages in terms of cutting speed and cost when compared to oxy-fuel cutting (OFC) on plate thicknesses below 25mm [1]. Moreover, PAC is used when low volume pressed metal (carbon steel, stainless-steel, aluminium, cast iron and non-ferrous metals) panels and tubes are cut, trimmed and pierced rapidly [2]. Other thermal processes which are antagonistic with PAC are the laser beam machining process (LMP) and flame cutting. The choice of the most suitable of these processes for industrial applications depends on several factors such as type of material, layer thickness, cutting speed and quality indicators (Fig. 1) of each process as well as cost.

Experimental multi-parameter optimization of the PAC process according to quality indicators such as kerf characteristics, dimensional accuracy and quality of cut surface have been studied by several researchers in several materials and experimental regions [3-9].

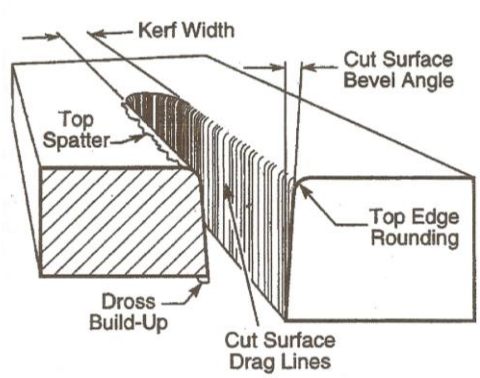

Figure 1. QUALITY INDICATORS OF PLASMA-ARC CUTTING.

Gariboldi and Previtali [3] investigated the quality of cuts performed on titanium sheets of 5mm thickness. They tried several feed rates and used oxygen or nitrogen as cutting gases. An investigation of the PAC parameters on the structure variation and hardness of the heat affected area of AISI and St52 steels was carried out by Gullu and Atici [4], while the influence of nozzle length, arc current, and mass flow rate on plasma cutting arc was studied by Zhou *et al.* [5]. In [6] a design of experiments approach was used to experimentally investigate the influence of cutting parameters on kerf characteristics. They found that on cutting of 15mm mild steel plates by high tolerance PAC process, the most influencing parameters on kerf characteristics are the cutting speed and the arc voltage. Narimanyan [7] performed finite element modeling of the cut front during plasma cutting using unilateral conditions. An industrial case study [8] investigated the influence of the cutting process parameters on roundness of holes made by an aging plasma-cutting machine using the design of experiments approach. Asiabanpour *et al.* [9] investigated the influence of the process parameters of a CNC PAC machine on cutting of mild steel, and regressions models were extracted for the prediction of several quality indicators. On the other hand, Artificial Neural Networks (ANNs) have been used in the past in a wide range of non-linear modeling applications, as well as in optimization problems [10-18]. All these studies concluded that ANN can be efficiently used to model complex relationships between multiple inputs and outputs and to accurately predict the behavior of the response variables (outputs) once the values of the input parameters are varied inside the ranges studied.

The present research work investigates the influence of plasma-arc cut process parameters on right side bevel angle of St37 mild steel cut surface (Fig. 1). A multi-parameter optimization was carried out using Artificial Neural Networks. An optimal design method for Artificial Neural Networks is applied using the Design of Experiments (DOE). This approach has recently been used by researchers in other application fields [19]. DOE efficiently acquires information on a target from experiments. The Taguchi method used in quality engineering is a well-known example. In full factorial experiments, all combinations of design parameter levels are tried, so the number of combinations increases exponentially as the number of design parameters increases. DOE features efficient experiments with orthogonal arrays and quantitative evaluation of factorial effects by Analysis of Variance (ANOVA). DOE is based on fractional factorial experiments and uses orthogonal arrays efficiently. Thus, the present work is based on the results of a previous study [20] where a multi-parameter optimization was presented using the robust design, using an L_{18} Taguchi orthogonal array. Robust design performs an Analysis of Variables (ANOVA) of the experimental results in order to evaluate the relative importance of the process parameters and error variances.

EXPERIMENTAL SETUP

In the experimental procedure, St37 carbon steel (mild steel), which is widely used in industrial applications, has been utilized. The CNC plasma-arc cutting machine uses a Thermal Dynamics® torch; PCH/M-120 type, and air gas.

Two plates of 6.5mm and 10mm thickness (Fig. 2) were used for the array experiment.

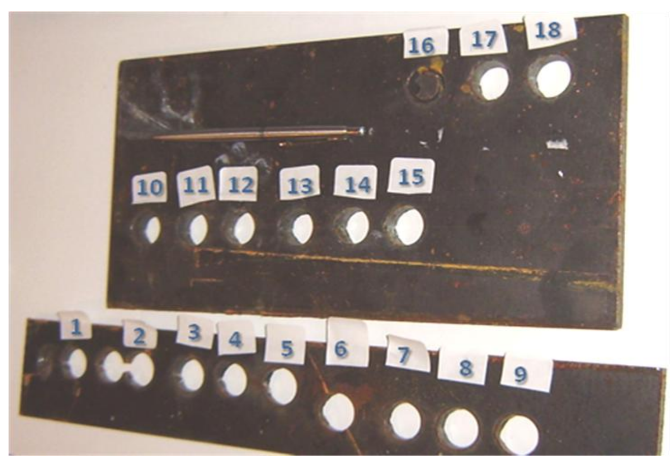

Figure 2. EXPERIMENTAL PLATES OF ST37.

The selection of quality characteristics, material, plate thickness and other process parameter levels and experimental limits was decided after real practice and market research of what the Greek Industry of metal cutting requires. Based on this selection, a seven parameter design of experiments was performed as shown in Tab. 1. The standard L_{18} (2^1x3^7) orthogonal array experiment was used (Tab. 2), since it can handle one parameter at two levels (2^1) and seven parameters at three levels and (3^7), defining 18 individual experiments. If all combinations of parameters and levels were used, this would involve $2^1 \times 3^7$=4.374 experiments; so it can be seen that there is a significant reduction in the number of experiments performed and, thereby, a significant reduction in cost and time.

Table 1. PARAMETER DESIGN.

No.	Process Parameters	Units	Level 1	Level 2	Level 3
1	Plate thickness	*mm*	6.5	10	-
2	Cutting speed	*m/min*	1	2.5	4
3	Arc ampere	*amp*	30	70	110
4	Arc voltage	*volt*	100	130	160
5	Air pressure	*bar*	4.5	4.65	4.8
6	Pierce height	*mm*	3.3	4.8	6.4
7	Torch standoff distance	*mm*	3.3	6.4	9.5

Table 2. ORTHOGONAL ARRAY L18 EXPERIMENTAL DATA AND RESULTS.

	Process Parameters								Performance Measures		
No. of Exp.	Plate thick-ness (*mm*)	Cutting speed (*m/min*)	Arc ampere (*amp*)	Arc voltage (*volt*)	Air pres-sure (*bar*)	Pierce height (*mm*)	Torch standoff distance (*mm*)	–	D_{up} (*mm*)	D_{down} (*mm*)	Bevel angle (^{o})
1	6.5	1	30	100	4.5	3.3	3.3	1	20.05	18.17	8.23
2	6.5	1	70	130	4.65	4.8	6.4	2	20.73	19.37	5.97
3	6.5	1	110	160	4.8	6.4	9.5	3	21.61	20.82	3.48
4	6.5	2.5	30	100	4.65	4.8	9.5	3	20.71	18.63	9.09
5	6.5	2.5	70	130	4.8	6.4	3.3	1	19.85	19.12	3.21
6	6.5	2.5	110	160	4.5	3.3	6.4	2	21.16	20.98	0.79
7	6.5	4	30	130	4.5	6.4	6.4	3	20.83	19.55	5.62
8	6.5	4	70	160	4.65	3.3	9.5	1	21.36	20.44	4.05
9	6.5	4	110	100	4.8	4.8	3.3	2	20.53	20.51	0.09
10	10	1	30	160	4.8	4.8	6.4	1	20.39	17.33	8.70
11	10	1	70	100	4.5	6.4	9.5	2	21.07	18.74	6.65
12	10	1	110	130	4.65	3.3	3.3	3	20.76	20.52	0.69
13	10	2.5	30	130	4.8	3.3	9.5	2	21.40	17.29	11.61
14	10	2.5	70	160	4.5	4.8	3.3	3	20.39	18.69	4.86
15	10	2.5	110	100	4.65	6.4	6.4	1	21.64	20.51	3.23
16	10	4	30	160	4.65	6.4	3.3	2	19.18	16.64	7.24
17	10	4	70	100	4.8	3.3	6.4	3	20.78	18.68	5.99
18	10	4	110	130	4.5	4.8	9.5	1	21.96	20.34	4.63
										Mean value:	**5.23**

A 20mm diameter hole was cut in each of the 18 combinations as indicated in the orthogonal array experiment. The direction of the cut was counter clock wise (CCW) in order to measure the right side cut angle (right bevel angle).

The right bevel angle was calculated as follows:

$$bevel\ angle = \arctan \frac{(D_{up} - D_{down})}{(2 \times plate\ thickness)} \qquad (1)$$

Where D_{up} is the measured hole diameter at the top and D_{down} is the measured hole diameter at the bottom of the plate.

MODELING FRAMEWORK

The objective of this modeling work was to develop an Artificial Neural Network (ANN) in order to predict the bevel angle (response variable) during CNC plasma-arc cutting of St37 mild steel plates. The four (4) input parameters (plate thickness, cutting speed, arc ampere, and torch standoff distance) of the ANN was selected out of seven (7) studied factors (plate thickness, cutting speed, arc ampere, arc voltage, air pressure, pierce height, and torch standoff distance), performed in a previous study [20].

Since it was not reasonable to use all the process parameters for the ANN modeling, due to the limited amount of experimental data, it was decided to use the ones that affect the most the response variable (bevel angle). Thus, the selection made according to the results acquired during the analysis of variables (ANOVA), which quantified the relative importance of the seven (7) process parameters to the performance measure (bevel angle). The results of the ANOVA analysis that performed in a previous study [20] can be seen in Fig. 3.

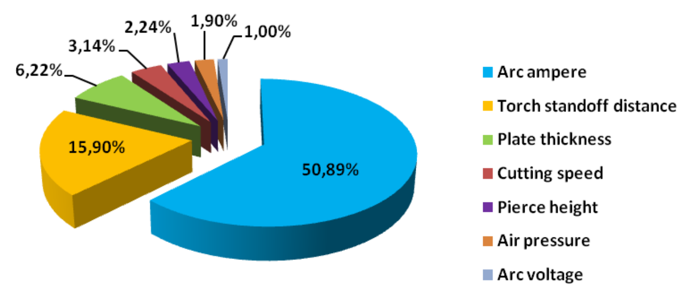

Figure 3. RELATIVE IMPORTANCE OF THE SEVEN PROCESS PARAMETERS TO THE BEVEL ANGLE (PIE CHART BASED ON ANOVA ANALYSIS RESULTS).

The four (4) most important process parameters were selected to be studied in the frame of this work. The experimental data related both to the four (4) selected input parameters and the output one (bevel angle), which were used for the modeling procedure, are presented in Tab. 3.

In the frame of the ANN modelling procedure, the 18 experimental data samples (Tab. 3), were separated into three groups, namely the training (green highlighted rows), the validation (blue highlighted rows) and the testing samples (yellow highlighted rows). Training samples are presented to the network during training, and the network is adjusted according to its error. Validation samples are used to measure network generalization, and to halt training when generalization stops improving. Testing samples have no effect on training and so provide an independent measure of network performance during and after training (confirmation runs).

Table 3. EXPERIMENTAL DATA USED FOR ANN MODELING PROCEDURE (GREEN HIGHLIGHTED: TRAINING SAMPLES, BLUE HIGHLIGHTED: VALIDATION SAMPLES AND YELLOW HIGHLIGHTED: TESTING SAMPLES).

	Process Parameters				Performance Measure
No. of Exp.	Plate thickness (*mm*)	Cutting speed (*m/min*)	Arc ampere (*amp*)	Torch standoff distance (*mm*)	Bevel angle (°)
1	6.5	1	30	3.3	8.23
2	6.5	1	70	6.4	5.97
3	6.5	1	110	9.5	3.48
4	6.5	2.5	30	9.5	9.09
5	6.5	2.5	70	3.3	3.21
6	6.5	2.5	110	6.4	0.79
7	6.5	4	30	6.4	5.62
8	6.5	4	70	9.5	4.05
9	6.5	4	110	3.3	0.09
10	10	1	30	6.4	8.70
11	10	1	70	9.5	6.65
12	10	1	110	3.3	0.69
13	10	2.5	30	9.5	11.61
14	10	2.5	70	3.3	4.86
15	10	2.5	110	6.4	3.23
16	10	4	30	3.3	7.24
17	10	4	70	6.4	5.99
18	10	4	110	9.5	4.63

Nine (9) samples (50%) were used for training, four (4) samples (20%) for validation and five (5) samples (30%) for testing purposes. The samples that were used for ANN training were selected following the L_9 Taguchi orthogonal array (i.e. experiments 1-3, 7-8, 13-15 and 17). For the validation process were used the samples 4, 12, 16, and 18. The rest ones (i.e. 5-6, and 9-11) were used for testing purposes (confirmation of model validity).

There are many possible types of architecture for ANN [21]. In this work, the feed-forward with backpropagation learning (FFBP) architecture has been selected for predicting the bevel angle (response variable). These types of networks have an input layer of X inputs, one or more hidden layers with several neurons and an output layer of Y outputs. In the selected ANN, the transfer function of the hidden layer is hyperbolic tangent sigmoid, while for the output layer a linear transfer function was used. The input vector consists of the four process parameters of Tab. 3. The output layer consists of the performance measure, namely the bevel angle. In order to compute the best number of neurons and hidden layers, several trial and errors have taken place for the initial learning phase. It was found that network architecture with one hidden layer of three (3) neurons (Fig. 4) exhibits a minimal error between the output estimated by ANN and the output provided by the experimental data. Back propagation ANNs are prone to the overtraining problem that could limit the generalization capability of the ANN [22]. Overtraining usually occurs in ANNs with a lot of degrees of freedom [23] and after a number of learning loops, in which the performance of the training data set increases, while the performance of the validation data set decreases. However, in this case, the size of the network is small with regards to the training data set and as depicted in Fig. 6, when the training of the ANN stops, the validation performance is adequate.

The performance of the network is measured by the Mean Squared Error (MSE) of the estimated output with regards to the values of the experimental data. Mean Squared Error is the average squared difference between outputs of the network and target (experimental) values. Lower values are better. Zero means no error. Another performance measure for the network efficiency is the regression (R). Regression values measure the correlation between outputs and targets. An R value of 1 means a close relationship (Fig. 5), 0 means a random relationship.

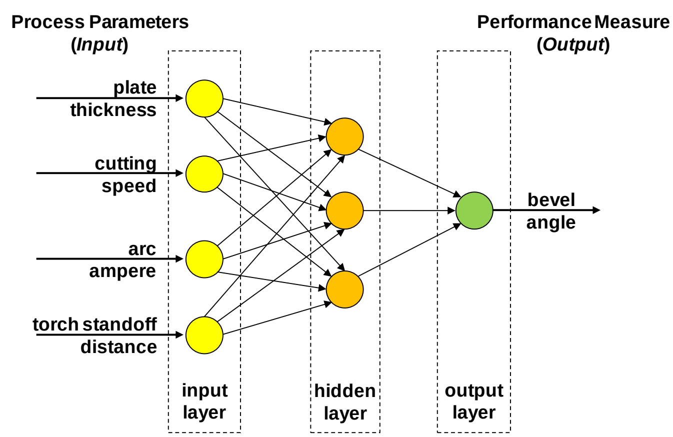

Figure 4. THE SELECTED ANN ARCHITECTURE (FEEDFORWARD WITH BACKPROPAGATION LEARNING)

The mathematical relation of the input parameters to the output parameter is presented in the following formula:

$$y = purelin\left(\sum_{i=1}^{S} w2_i * \tan sig\left(\sum_{j=1}^{X} w1_{i,j} * x_j + b1_i \right) + b2 \right) \quad (2)$$

Where:

y: is the output value
S: is the number of hidden neurons
X: is the number of inputs

w1: is the vector of weights between the input and the hidden layer. The size of w1 is S×X and $w1_{i,j}$ is the weight of the *i* neuron for the *j* input

w2: is the vector of weights from the hidden layer to the output. The size of w2 is S×1 and $w2_i$ is the weight of the *i* neuron to the output value

b1: is the vector of biases of the neurons in the hidden layer. The size of b1 is S×1 and $b1_i$ is the bias of the *i* neuron

b2: is the bias of the output neuron.

purelin: is the linear transfer function and *purelin*(x) = x

tansig: is the hyperbolic tangent sigmoid function and $tansig(x) = \frac{2}{\left(1+e^{-2x}\right)} - 1$

The weights and biases of Eq. 2 were calculated during the learning phase of the ANN, using the experimental data available (Tab. 3).

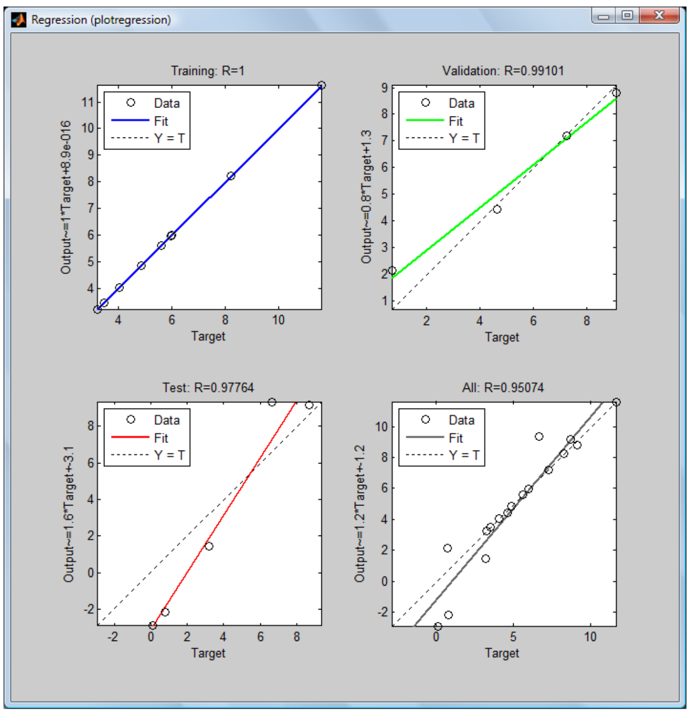

Figure 5. CORRELATION BETWEEN OUTPUTS AND TARGETS DURING THE TRAINING, VALIDATION AND TESTING OF THE NEURAL NETWORK

The trained ANN model can be used for the optimization of the cutting parameters during CNC plasma-arc cutting. This can be done by testing the behavior of the response variable (bevel angle) under different variations in the values of plate thickness, cutting speed, arc ampere, and torch standoff distance. In order to ensure accurate prediction of the bevel angle, the values concerning the four input parameters should be inside the range of values defined during the experimental setup (i.e. plate thickness: [6.5, 10], cutting speed [1, 4], arc ampere: [30, 110], and torch standoff distance: [3.3, 9.5]).

As depicted in Fig. 6, the prediction error, measured by the Mean Square Error (MSE), is very low (i.e. 0.29263). Consequently, the ANN can accurately estimate the right bevel angle once the plate thickness, cutting speed, arc ampere, and torch standoff distance are given values inside the valid range.

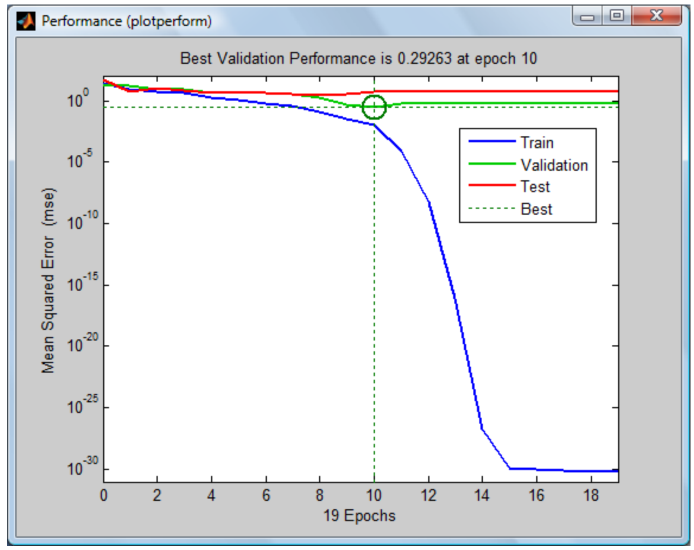

Figure 6. ANN TRAINING, VALIDATION AND TEST PERFORMANCE GRAPH

The surface response of the performance of the bevel angle for all the combination of arc ampere and torch standoff distance keeping constant the plate thickness (6.5mm and 10mm) can be seen below.

Figure 7 presents an example of the bevel angle's surface response in relation to the arc ampere and torch standoff distance. The specific example refers to the bevel angle's response, while the plate thickness and the cutting speed were kept constant at the values of 10 *mm* and 1 *m/min* accordingly. This figure shows that when the arc ampere is increased the bevel angle decreases. In addition, when the torch standoff distance increases the response variable deteriorates.

Moreover the surface responses of the bevel angle in relation to the plate thickness and cutting speed were created. In these graphs the arc ampere and torch standoff distance were kept constant. An example of such a diagram (for arc ampere = 30 *amp* and torch distance = 9,5 *mm* accordingly) is presented in Fig. 8. This figure shows that when the cutting speed is increased the bevel angle deteriorates, as well as in the case of the plate thickness' increment.

Finally, using the ANN model, all the combinations of the parameter levels were predicted and the process was optimized. It was found that the best (optimum) combination that produces the minimum bevel angle is for: plate thickness = 6.5 *mm*, cutting speed = 1 *m/min*, arc ampere = 110 *amp*, and torch standoff distance = 3.3 *mm*.

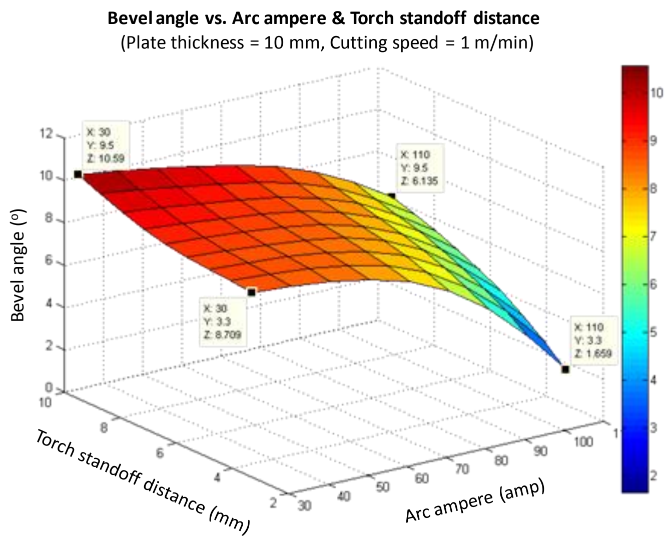

Figure 7. SURFACE RESPONSE OF BEVEL ANGLE FOR PLATE THICKNESS=10 mm AND CUTTING SPEED=1 m/min

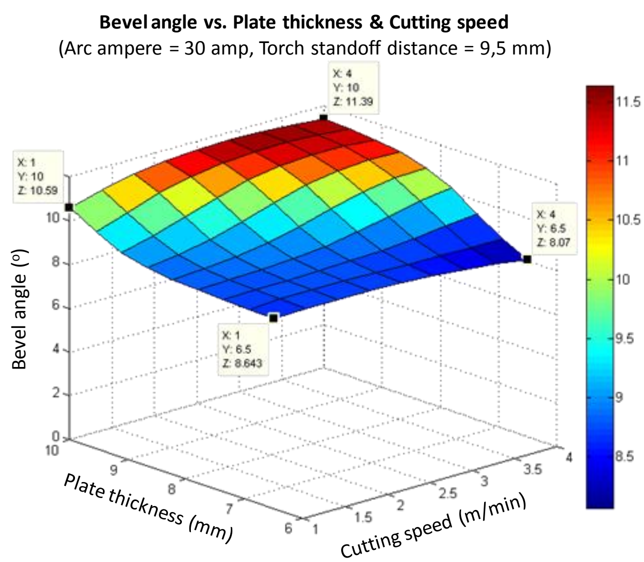

Figure 8. SURFACE RESPONSE OF BEVEL ANGLE FOR ARC AMPERE=30 amp AND TORCH STANDOFF DISTANCE=9,5 mm

CONCLUSIONS AND FUTURE WORK

The experimental data used for the ANN modeling procedure was acquired by a set of experiments that was properly selected, according to the Taguchi's design of experiments. However, using additional training data (experimental data sets) a more efficient (fine-tuned) ANN model could be achieved.

Multi-parameter optimization of the process according other quality indicators, such as kerf width, cut surface hardness, top edge rounding, dimensional accuracy, accumulation of metal underneath the part (dross build up), and surface quality parameters will be studied and analyzed in future work.

Finally, in order to highlight ANN efficiency in comparison to other modelling approaches, future work will include the modelling of the same procedure using additive models and functional regression. The results will be compared with the ones presented in this investigation. However, the main advantage of neural networks in comparison to the other modelling approaches is that ANN could be efficiently used for adaptive control of the CNC plasma arc cutting machine.

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