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RESEARCH

Modeling of Surface Roughness in Plasma Jet Cutting Process of Thick Structural Steel

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A B S T R A C T

Today highly competitive market and demands for obtain high surface finish and machining of complex shape geometries replace conventional machining processes with non-conventional. Plasma jet cutting is one of these non-conventional processes that primary uses a thermal energy of highly ionized gas to cut specified material and blow molten metal away. Main advantages of plasma jet cutting process are high speed of cutting, cutting different types of materials, the quality of cut and moderate to low investment costs. This paper presents experimental results concerning the surface roughness variation at plasma jet cutting of structural steel S235JRG2 plate thickness of 15 mm. Using the experimental data artificial neural network (ANN) model was developed in order to predict the surface roughness in terms of two input parameters, cutting current and cutting speed. After the prediction accuracy of the developed model was validated, the model was used for analyzing influence of input parameters on process response values.

1. INTRODUCTION

Today, different non-conventional thermal processes can be found in many applications in metal processing and shipbuilding industry. These processes include oxy fuel cutting, laser cutting and plasma jet cutting. They can be used for the cutting various types of materials at various thicknesses. Plasma jet cutting process has many advantages which can help the modern company to survive in a turbulent market. Main benefits that characterize this process and position it in front of the laser and abrasive water jet cutting are optimal combination of cut quality, productivity and costs for mild steel, stainless and aluminium cutting. Competitive investments, high productivity, long consumables life and lower costs per part lead this technology to become a practical alternative to other processes such as laser and abrasive water jet cutting.

Plasma jet cutting process was developed at the end of 1950s. Plasma can be defined as the fourth state of substance which is obtained by supplying a tremendous amount of energy to gas or when a gas is subjected to a high electric field. In this process an electric arc is generated between the electrode and the workpiece. An electrode acts as an anode and the workpiece as a cathode. The plasma gas expandes with the high velocity through the nozzle at the same time an electric current passes through the gas with the help of a tungsten electrode due to which a high intensity plasma jet is generated. This jet is able to melt or vaporize the plate surface that should be cut and to blow the molten metal away from the cut. The most commonly used gases for this process are compressed air, nitrogen, argon-hydrogen, oxygen and their combinations. They can be used both as a plasma and shield gases.

Main components of plasma jet cutting system are power supply unit, an arc starting circuit and a torch. These units provide the electrical energy, ionization, and process control for cutting all ellectrically conductive materials to 180 mm thickness.

Today many of plasma jet cutting systems are supported by manufacturers recommendations. However these recommendations usually reflect the point of view of the manufacturers bussines but do not lead to the optimization of all cut quality features required by users. Because of that various experimental researches were conducted in order to describe and model plasma jet cutting process and to chose the optimal process parameters.

Kumar Das et al. [1] analyzed the influence of three process parameters, gas pressure, arc current and torch height on material removal rate and surface roughness parameters. They conducted experiments on EN31 steel according to Taguchi L_{27} orthogonal array. Parametric optimization was carried out using grey relational analysis. Salonitis et al. [2] used the regression analysis to describe the effect of cutting power, cutting speed, cutting height and plasma gas pressure process parameters on cut quality features such as kerf taper angle, the edge roughness and the size of the heat affected zone. Bini et al. [3] analyzed the influence of arc voltage, cutting speed, plasma and shield gas flowrates on kerf position and shape in 15 mm thick mild steel sheets cutting. They used a two-level fractional factorial design for design experiment and ANOVA (Analyisis of variance) for data analysis. Chamarthi et al. [4] cut a Hardox 400 plate thickness of 12 mm. They varied cutting speed, plasma gas flow rate and voltage as the process parameters in the 16 experiments and analyzed their influence on the unevennes of cut surface. ANOVA is performed later in order to identify the parameters that clearly define the unevenness quality attributes. Gullu et al. [5] investigated material structure changes that occurred after plasma jet cutting of AISI 304 stainless steel and St 52 carbon steel. Gariboldi et al. [6] cut titanium sheets using high tolerance plasma arc cutting process. They used free feed rate range with the adoption of oxygen and nitrogen as plasma and shield gases and analyzed cut quality features such as unevenness, kerf width, angle of cut and surface roughness. Also they conducted temperature measurements in the regions near to the cutting edge, microstructural investigations and measurements of geometric and surface atributes of the cutting edges. Adalarasan et al. [7] assesed te quality characteristics of the cut surface by measuring the surface roughness and kerf width while cutting the 304L stainless steel. Taguchi L_{18} orthogonal array and Grey Taguchi based respone surface methodology were used to design experiments and find optimal cutting parameters. Chen et al. [8] analyzed two process responses such as bevel magnitude and the hole diameter deviation. They conducted 36 experiments according to Taguchi L_9 experiment design and varied six process parameters, tip size, feed rate, voltage, amperage, air pressure and pierce time. Taguchi method was used to find optimal combination of process parameters that lead to the smallest bevel angle and diameter deviation of the hole. Thilak et al. [9] analyzed the influence of arc current, gas pressure, cutting speed and arc gap in plasma cutting of stainless steel 316L on process responses such as machining time, hardness and kerf width. They used Taguchi method for design experiment and Grey relational analysis for optimization. Radovanovic et al. [10] conducted experiments in which they varied three input process parameters, cutting current, plate thickness and cutting speed. They developed artificial neural network model to predict the ten point height of irregularities of cut surface (Rz) and to identify cutting parameters values that lead to optimal surface roughness. Kechagias et al. [11]

also used artificial neural network approach for prediction of bevel angle that appear after CNC plasma arc cutting of St37 mild steel sheets. They conducted a L_{18} Taguchi orthogonal array experiment. Input parameters whose influence was analyzed are plate thickness, cutting speed, arc current and torch standoff distance.

In the present research paper experiments were conducted on structural steel S235JRG2 plate thickness of 15 mm. It was analyzed the influence of input process parameters, cutting current and cutting speed on surface roughness. Artificial neural network approach was used for mathematical modeling and to identify cutting parameters ranges that lead to minimal surface roughness values.

2. EXPERIMENTAL PROCEDURE

Experimental work was conducted on a CNC Steel Taylor plasma cutting machine (Fig. 1). Test specimens were cut on 15 mm thickness structural steel plate S235JRG2 with the use of compressed air as plasma gas. Input process parameters levels that were varied in experiments were shown in Table 1. Fixed input parameters are: nozzle diameter 1.5 mm, gas pressure 6 bar, cutting height 5 mm. Every experiment was conducted one time. During the experiments it was noticed that some combinations of cutting parameters lead to not penetrated workpieces such as those in runs number 3 and 8. In Figures 2 and 3 it was shown look of well cut specimen and one not penetrated. Measurements of surface roughness were performed on three places of cut surface: near to upper cut edge (g), in the middle (s) and near to lower cut edge (d) (Fig. 4). Results of measured surface roughness were shown in Table 2.

Fig. 1. CNC Steel Taylor plasma jet cutting machine.

Table 1. Plasma jet cutting parameters.

No. of Experiment	Input parameters	
	Cutting current, I (A)	Cutting speed, v (mm/min)
1	60	425
2	60	530
3	60	635
4	80	490
5	80	610
6	80	730
7	80	870
8	80	1055
9	100	530
10	100	695
11	100	870
12	100	1055
13	120	730
14	120	870
15	120	1055
16	120	1320
17	120	1585

Table 2. Experimental results.

No. of Exp.	Measurement places	Measured surface roughness, Ra (μm)	Mean value of surface roughness, Ra (μm)
1	g	10.50	19.00
	s	17.00	
	d	30.70	
2	g	12.40	24.70
	s	21.30	
	d	40.40	
3	g	Workpiece is not penetrated	
	s		
	d		
4	g	17.50	24.50
	s	29.40	
	d	26.60	
5	g	15.20	24.67
	s	35.80	
	d	23.00	
6	g	14.10	21.03
	s	24.30	
	d	24.70	
7	g	14.00	36.67
	s	41.00	
	d	55.00	
8	g	Workpiece is not penetrated	
	s		
	d		

9	g	35.00	28.67
	s	19.00	
	d	32.00	
10	g	13.00	11.93
	s	13.00	
	d	9.80	
11	g	12.40	11.40
	s	8.80	
	d	13.00	
12	g	12.00	11.50
	s	12.40	
	d	10.10	
13	g	16.00	16.00
	s	14.00	
	d	18.00	
14	g	17.00	17.00
	s	14.00	
	d	20.00	
15	g	10.30	7.10
	s	11.00	
	d	-	
16	g	10.80	11.20
	s	9.90	
	d	12.90	
17	g	8.30	9.40
	s	10.10	
	d	9.80	

Fig. 2. Look of penetrated specimen.

Fig. 3. Look of not penetrated specimen.

Fig. 4. Surface roughness measurement places.

3. ARTIFICIAL NEURAL NETWORK MODELING OF SURFACE ROUGHNESS

The Artificial Neural Network (ANN) is an artificial system similar to the biological nervous system able to intelligently process the information simulating the biological intelligence. The artificial neural networks are applicable today in various areas such as process modeling and optimization, design and simulation, classification, robotics, etc. [12-14].

Architecture of artificial neural networks is parallel-distributed and it consists of a large number of neurons distributed in several layers. Each ANN must have at least three layers: input layer, hidden layer and output layer [15-17]. Neurons of one layer are connected by specific synapses to the neurons of their neighbouring layers. Interconnections between particular neurons by the layers are characterized by weights and biases, which change during the ANN training. By proper adjustments of weights and biases in the training process ANN is more capable to better describe the relationships between input process parameters and output responses. Prior to ANN training process optimal number of hidden layers and the number of neurons in each of them should be properly defined. These numbers change during training and can be defined empiricaly or by using some existing equations that take in consideration number of input and output neurons and training data. Training is carried out on the exmples data usually obtained by the experiments. This process should be repeated until the ANN is stabilized or error is defined below a previously defined treshold. Validation and testing process of developed ANN are performed on data subsets that are not included in the training data subset. The trained, validated and tested ANN can be used for modeling and prediction various processes [15-22].

In this paper, the three layered feed-forward backpropagation ANN architecture has been selected for modeling surface roughness in plasma jet cutting process of thick structural steel plate. The input layer of the ANN model consists of two neurons corrsponding to the two process parameters that were varied in the experiments, cutting current (I) and cutting speed (v) and the output layer has one neuron for prediction of surface roughness values (Fig. 5).

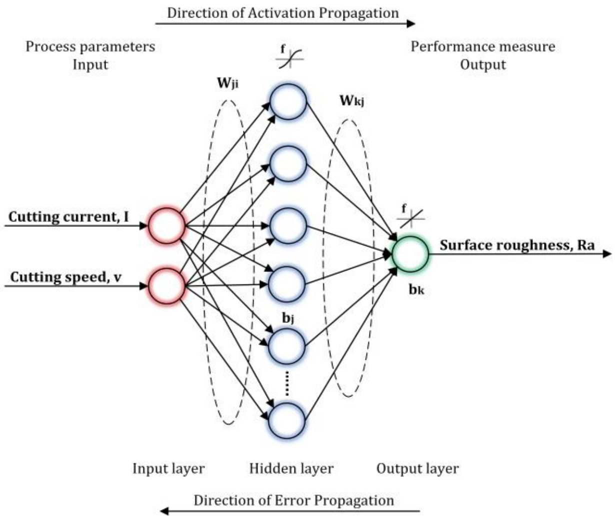

Fig. 5. Selected ANN architecture for modeling surface roughness in plasma jet cutting process.

The whole experimental data set (N_{tot}=17) is divided into a data subset for training, a data subset for validation and a data subset for testing. 90 % randomly selected data of the whole experimental data have been employed for training, 5 % for validation and 5 % for testing.

Main problems that occure in backpropagation ANNs are overfitting and overtraining. Overtraining means that ANN only memorizes the training data set and excellent learns these data but doesn't have an ability to generalize to new data and because of that performance of the validation set decreases. According to this, the goal is to find the simplest ANN model that has the total error considerably low [23-24]. In this paper ANN architecture with one hidden layer and ten neurons was used for process modeling and prediction. It was found out that this architecture gives a minimal difference between the predicted values and real experimental data. Transfer functions that were used in the network are tangent sigmoid function in the hidden and linear function in the output layer. Prior to ANN training the training data were normalized to a range of (-1,1) and the initial values of weights were set according to Nguyen-Widrow method. As it was already mentioned backpropagation algorithm with momentum was used for ANN training.

The performance of the network was measured by the Mean Squared Error (MSE) of the predicted outputs with regards to the real experimental data. The goal is to get MSE as close as possible to zero. The zero means that there is no error between outputs of the network and experimental values. In this case, ANN training was initially set to terminate after a maximum number of epochs, but it was stopped at 15 iterations since no further improvement in the MSE was achieved. MSE values obatined after training, validation and testing of ANN are shown in Table 3.

Table 3. MSE values of ANN model.

ANN architecture	Mean Squared Error (MSE)		
	Training	Validation	Testing
2-10-1	0.0218	0.0697	0.0043

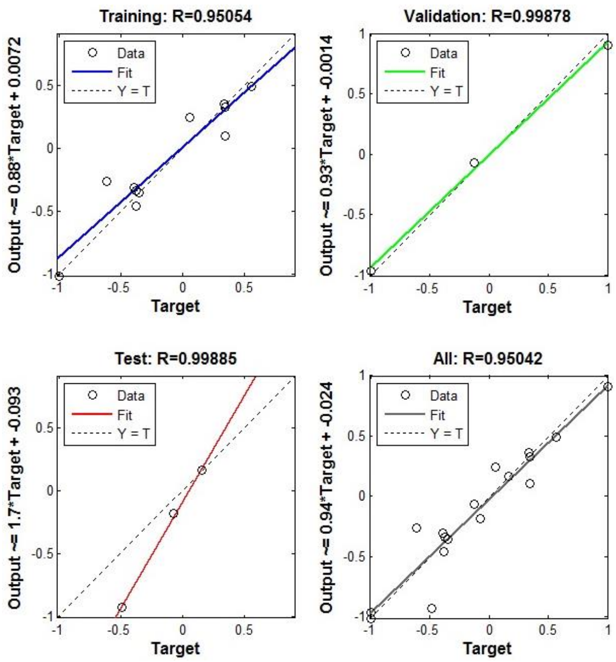

Fig. 6. Correlation between predicted and experimental data during training, validation and testing of the developed ANN model.

Except MSE another performance measure for ANN model is correlation coefficient (R). This is a statistical measure of the strength of correlation between predicted and experimental values. A perfect correlation is obtained when R=1. In real manufacturing processes this case is very rare. A good ANN model should have the correlation coefficient greater than 0.8. Correlation coefficients of the developed ANN model for all three datasets are shown in Fig. 6. Also, it was carried out comparison of actual data and those predicted by developed ANN model. Results were shown in Fig. 7.

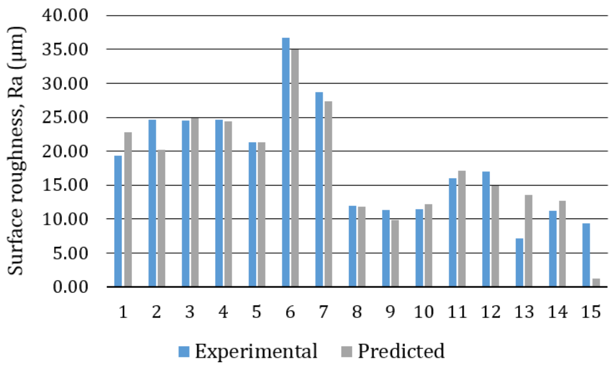

Fig. 7. Comparison of actual and predicted surface roughness values.

The weights and biases of the ANN model that were determined in training process are given in Table 4-5.

Table 4. The weights w_{ji} of developed ANN model.

Weights					
w_{ji}					
I	-3.2376	2.829	0.85764	4.8486	4.7737
I	3.0145	5.2474	-5.1114	-5.6098	2.7624
w_{ji}					
II	0.46901	-1.7208	6.2266	-0.64648	3.1856
II	2.4687	3.2077	6.0504	-2.4774	-3.535

Table 5. The weights w_{kj} and biases of developed ANN model.

Weights	Biases	
w_{kj}	b_j	b_k
-1.4067	5.4031	-0.13449
1.2101	-4.6788	
-0.65194	3.9649	
-0.73323	-0.877	
0.16832	-2.7303	
2.3098	1.534	
-0.53875	0.83182	
-2.6379	-1.9525	
0.85298	-0.49454	
0.077574	4.2281	

Using the weights and biases from Table 4-5 and in accordance with selected ANN architecture the exact mathematical relationship between process response, surface roughness (*R*a) and input cutting parameters, cutting current (I) and cutting speed (v) can be expressed following the Equation 1. In this equation X is the column vector which contains normalized values of v and I and Ra_{norm} is the normalized value for the *R*a. To obtain actual values of surface roughness it is necessary to denormalize the data:

$$Ra_{norm} = \left[\frac{2}{1+e^{-2(X \cdot w_{ji} + b_j)}} - 1 \right] \cdot w_{kj} + b_k \qquad (1)$$

4. RESULTS

Using Equation 1 and by varying value of both or just one parameter while the other was kept at specified level the effects of input process parameters on the surface roughness were analyzed. In Figs. 8-9 were shown their individual impacts while in Fig. 10 was shown impact of their interaction on process response values.

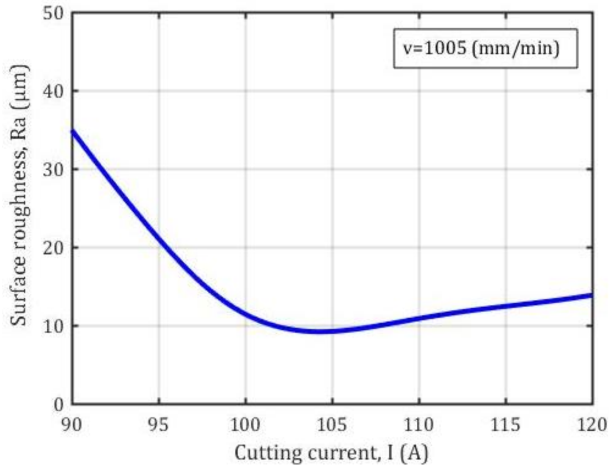

Fig. 8. Influence of the arc current (I) on the surface roughness (*R*a).

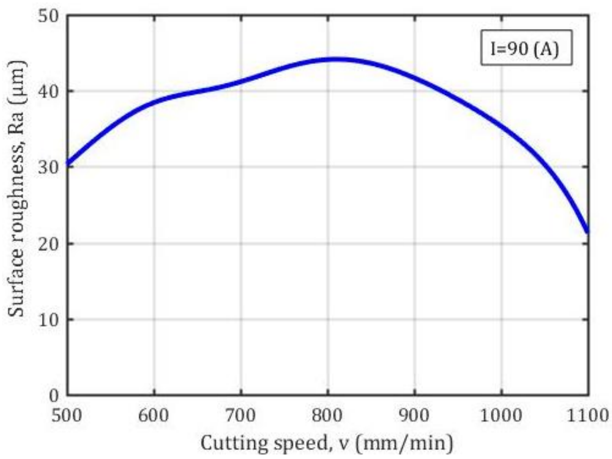

Fig. 9. Influence of the cutting speed (v) on the surface roughness (*R*a).

Analyzing the experimental data the area of parameters combinations within certainly comes to sheet metal cutting was defined. This area was shown in Figs. 8-10.

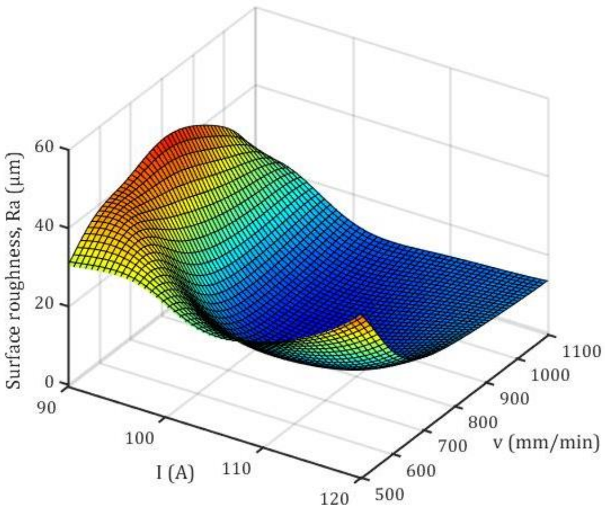

Fig. 10. Influence of the I-v interaction on the surface roughness (*R*a).

From Figs. 8-10 it can be concluded that higher values of cutting speed (>800 mm/min) and cutting current (>100 A) lead to smoother surface of the cut. At lower cutting current levels cutting speed has an inappreciable effect on the surface roughness values. At cutting speed values to 700 mm/min better surface can be obtained if the cutting current is set at 100-110 A.

5. CONCLUSION

In this paper a mathematical modeling of surface roughness in plasma jet cutting of thick structural steel was shown. This was performed using artificial neural networks. Neural networks have proven more suitable due to their potential to learn nonlinear features of any system from incomplete experimental data regardless of external noise. Model was verified using statistical measures such as R and MSE. Beside that a comparison between experimental and predicted values was conducted. These indices showed that model is quite acceptable. Created model was used to describe the influence of input parameters such as cutting current and cutting speed on analyzed process response. According to this the plots were created that can be used to identify cutting conditions that lead to minimal surface roughness values.

Future research will take in consideration other cut quality responses such as kerf width, dross width, dross height that occur during plasma jet cutting. Their values will be included in mathematical modelling procedure to obtain a complete view of output process quality.

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