MODELING THE PLASMA ARC CUTTING PROCESS USING ANN

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Abstract: This paper deals with modeling of plasma cutting process using artificial neural network (ANN). The objective was to develop an ANN model in order to predict the ten-point height of irregularities (R_z) in terms of three input parameters, cutting current, plate thickness and cutting speed. To this aim, a feed-forward backpropagation ANN was developed and trained using the experimental data. After the prediction accuracy of the ANN was validated, ANN model was used to generate contour plots from which optimal cutting regions were identified.

Keywords: *plasma arc cutting, surface roughness, artificial neural networks, modeling*

1. INTRODUCTION

The efficient manufacture of high-quality plate components is quite difficult task. Mechanical processes for contour cutting thin sheets, such as punching, shearing, and sawing, are characterized by the need for rigid clamping of the part, difficulty in handling hardened or brittle material, cut edge deformation or burring and the need for constant sharpening and replacement of the cutting tool. One of the easiest methods of contour cutting steel is oxy-fuel cutting. With respect to oxy-fuel cutting, laser cutting, abrasive water jet cutting, and plasma cutting are new attractive advanced processes for contour cutting of plate. They have numerous advantages, namely, a narrow cut, a proper cut profile, smooth and flat edges, minimal deformation of a workpiece, the possibility of applying high feed rates, intricate profile manufacture and fast adaptation to changes in manufacturing programs.

Plasma cutting, Figure 1, is practical alternative to laser cutting and abrasive water jet cutting. Plasma cutting was developed primarily for cutting stainless steel and aluminum. Plasma is often described as the fourth state of matter. If energy is added to a gas, it can be shown that its physical properties change drastically. A highly ionized, hot gas is formed composed up of ions, electrons and neutral particles – plasma. Many of the laws of electrical current flow through a metal can also be applied to the plasma arc. High temperature of the plasma arc is used with its kinetic energy for plasma cutting. The plasma cutting process, as used in the cutting of electrically conductive metals, utilizes electrically conductive gas to transfer energy from an electrical power source through a plasma cutting torch to the material being cut. It uses a high-velocity jet of electrically charged gas to cut metal at up to 50.000 degrees Kelvin.

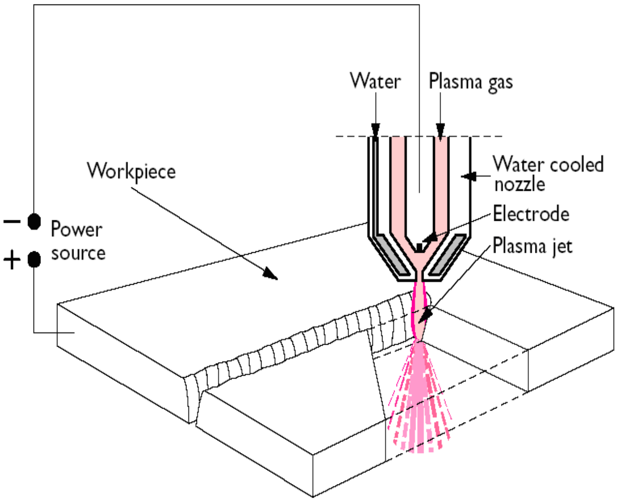


Fig.1. Plasma cutting

The basic plasma cutting system consists of a power supply, an arc starting circuit and a torch. These system components provide the electrical energy, ionization capability and process control that is necessary to produce high quality, highly productive cuts on a variety of different materials. Plasma cutting can be used to cut plate to 180 mm thick. Plasma cutting is less expensive than laser cutting. Nitrogen based systems are well suited for high performance materials such as stainless steel, aluminum and nickel. Oxygen based systems are better for carbon steels and leave no nitride deposits, which complicate further processing. Plasma consumables can be short lived depending on gas selection, operator proficiency and water selection. Heat affected zones appear in the area surrounding the cut. Dross can occur. Under water cutting helps reduce the size of the heat affected zone. Fine plasma cutting (high tolerance plasma arc cutting) is used for cutting metals from 5 to 10 mm thickness. This system uses a nozzle with a smaller orifice diameter so the flow rate of the spinning plasma gas is much higher. The cut quality is nearly as good as laser cutting, but at a lower cost.

2. ARTIFICIAL NEURAL NETWORKS: AN OVERVIEW

The appearance of ANNs is related to the attempt to form an artificial system based on mathematical models which will be, in its structure, function and information (signal) processing, similar to biological nervous systems, and thus be able to process “intelligently” information (signals), that is, simulate biological intelligence [2].

ANNs consist of a larger number of neurons (as basic processing units) distributed in several layers. Each ANN usually have three layers: input layer, hidden layer, and output layer. The greatest number of ANNs used for modeling machining processes have one or two hidden layers though there may be more of them. Neurons of one layer are connected by specific synapses to the neurons of their neighboring layers. Apart from specific types of ANNs, there are no interconnections between the neurons belonging to the same layer. The interconnections between particular neurons by the layers are characterized by weights, which change during the ANN training. By tuning a set of weights and biases in the training process, ANN learns the relationship between given inputs and related outputs.

The ANN based modeling is not a straight-forward process and numerous decisions related to ANN architecture and training processes have to be made. The methodology and basic steps in ANN modeling of machining processes and derivation of mathematical equations from ANNs is presented in [3,4].

After selecting the ANN architecture and adopting the ANN with the best performance achieved during training and testing, created ANN may be used for simulation, prediction or can be used as a objective function for optimization.

3. MODELING THE PAC PROCESS

The objective of the plasma arc cutting (PAC) process is to concentrate a large amount of energy on a small surface of a workpiece which leads to intensive heating of the material surface. The source of energy is high temperature and high speed ionised gas. The gas is ionised using a direct current passing between the cathode (inside the nozzle) and anode (workpiece). The plasma jet cuts the material by releasing the energy spent for the plasma gas ionisation upon hitting the workpiece surface. The removal of the melted material from the cutting zone is done by the action of plasma jet kinetic energy. The characteristics of plasma jet can be significantly altered by changing the type of gas, gas flow, cutting current, and nozzle size, etc.

Even though it is the case of a complex process, which is characterized by a large number of influential factors, the previous analysis has shown that this number can be reduced to three main influential factors: cutting current (I), cutting speed (V), and plate thickness (s). Influential factors were varied on a great number of levels. The ten-point height of irregularities (R_z), which is one of the basic characteristics of the surface quality, was selected as the target function (output value). The experiment was described in more detail in [1] and experimental data are given in Table 1.

Table 1 Data for training and testing of the ANN

No	Cutting current I (A)	Plate thickness s (mm)	Cutting speed V(m/min)	Surface roughness R_z (μm)
1.	80	4	1.3	2.13
2.	80	4	1.4	2.15
3.	**80**	**4**	**1**	**2.25**
4.	**80**	**4**	**0.9**	**2.3**
5.	80	4	1.2	2.4
6.	80	4	1.7	2.42
7.	80	4	2.1	3.2
8.	80	4	2.2	3.15
9.	80	4	2.3	3.4
10.	**80**	**4**	**2.4**	**3.5**
11.	80	4	2.5	3.55
12.	80	4	2.6	3.58
13.	80	4	2.8	3.7
14.	**45**	**4**	**1.05**	**3.2**
15.	45	4	1.1	3.4
16.	45	4	1.15	3.6
17.	45	4	1.2	3.67
18.	**45**	**4**	**1.25**	**4.1**
19.	45	4	0.95	3.4
20.	**45**	**4**	**0.9**	**3.5**
21.	45	4	0.85	3.3
22.	**45**	**4**	**0.8**	**3.1**
23.	45	4	1.1	3.5
24.	45	4	1.3	3.82
25.	45	4	1.4	3.8
26.	**45**	**4**	**1.5**	**4**
27.	80	6	1.225	2.15
28.	**80**	**6**	**1.275**	**2.21**
29.	80	6	1.3	2.25
30.	80	6	1.375	2.25
31.	80	6	1.425	2.28
32.	**80**	**6**	**1.475**	**2.3**
33.	80	6	1.175	2.22
34.	80	6	1.125	2.35
35.	**80**	**6**	**1.075**	**2.35**
36.	80	6	1.025	2.38
37.	80	6	0.9	2.45
38.	80	6	1.7	2.5
39.	**80**	**6**	**1.9**	**2.6**
40.	80	6	2.1	2.65
41.	80	6	2.3	2.8
42.	**45**	**6**	**0.85**	**2.55**
43.	45	6	0.9	2.48
44.	45	6	1	3.1
45.	45	6	1.1	3.15
46.	45	6	0.8	3.1
47.	**45**	**6**	**0.75**	**3.05**
48.	45	6	0.7	2.9
49.	45	6	0.65	2.6
50.	**45**	**6**	**0.6**	**2.52**
51.	45	6	1.300	3.1
52.	80	8	0.9	3.29
53.	**80**	**8**	**0.95**	**3.42**
54.	80	8	1	3.3
55.	**80**	**8**	**1.05**	**3.25**
56.	80	8	1.1	3.2
57.	80	8	1.15	3.2
58.	**80**	**8**	**1.2**	**3.3**
59.	80	8	1.25	3.42
60.	80	8	1.3	3.6
61.	80	8	1.35	4.05
62.	**80**	**8**	**1.4**	**4.22**
63.	80	8	1.5	4.32
64.	**80**	**8**	**1.7**	**4.3**
65.	80	8	2	4.5
66.	130	12	0.82	1.79
67.	**130**	**12**	**0.87**	**1.85**
68.	130	12	0.92	1.86
69.	130	12	0.97	1.9
70.	**130**	**12**	**1.02**	**2.06**
71.	130	12	1.07	2.22
72.	130	12	0.77	2.1
73.	130	12	0.72	2.15
74.	**130**	**12**	**0.67**	**2.12**
75.	130	12	0.62	2.2
76.	130	12	0.57	2.25
77.	130	12	1.2	2.1
78.	**130**	**12**	**1.4**	**2.18**
79.	130	12	1.6	2.2
80.	130	12	1.8	2.27
81.	130	15	0.58	2.16
82.	130	15	0.63	2.2
83.	130	15	0.68	2.22
84.	**130**	**15**	**0.73**	**2.3**
85.	130	15	0.78	2.42
86.	130	15	0.83	3.05
87.	130	15	0.53	2.2
88.	**130**	**15**	**0.48**	**2.42**
89.	130	15	0.43	2.62
90.	**130**	**15**	**0.38**	**3.23**
91.	130	15	0.33	3.78
92.	130	15	0.9	3.15
93.	**130**	**15**	**1.1**	**3.1**
94.	130	15	1.3	3.05
95.	**130**	**15**	**1.6**	**2.5**
96.	130	15	1.7	2.25

The series of 29 input-out data for ANN testing is marked with bold numbers

3.1. ANN design and training

In this paper, the three layered feed-forward backpropagation (FFBP) architecture has been selected for modeling. The input layer of the ANN model consists of the three neurons corresponding to the three process parameters (*I*, s, *V*) whereas the output layer has one neuron for calculating the R_z

(response variable). For the needs of training and testing the created ANN the whole experimental data set (N_{tot} = 96) is randomly divided into a data subset for training (N_1 = 67) and a data subset for testing the ANN (N_2 = 29). Approximately, two-thirds of the whole data set have been employed for training and one-third of the whole data set has been used for testing the trained ANN. Since there is 67 data for ANN training, different small and large scale ANN architectures could be developed. However, ANNs are prone to the overfitting and overtraining problem that could limit the generalization capability of the ANN. Overfitting usually occurs in ANNs with a lot of degrees of freedom (a huge number of neurons) and when overtrained the ANN only memorizes the training set and loses its ability to generalize to new data. In both cases the performance of the training data set increases, while the performance of the validation data set decreases. This is well known bias-variance problem, and the the goal is to find simplest ANN model that has the total error considerably low. To this aim, in searching for ANN which generalizes well different ANN architectures were developed. It was found that ANN architecture with 3 hidden neurons (Figure 2) represents optimal solution (after trade-off).

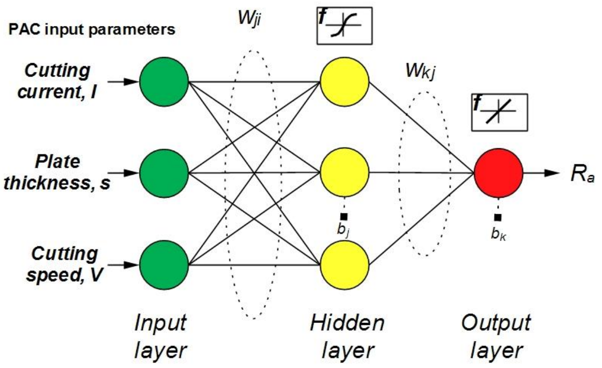


Fig. 2. The selected ANN architecture for modeling the PAC process

For all developed ANN models linear transfer function and tangent sigmoid transfer function were used in the output and hidden layer, respectively. In order to stabilize and enhance ANN training the data was normalized to a range of [-1, 1].

Prior to ANN training, the initial values of weights were set according to Nguyen-Widrow method. In ANN modeling it is often advisable to perform and analyze the training of the given ANN model starting with different initial weights rather then changing the ANN architecture or adding more hidden neurons. The MATLAB's Neural Network Toolbox software package is used for training and testing the ANN models. BP algorithm with momentum was used for ANN training ("traingdm" procedure in MATLAB). After some preliminary investigations, learning rate 0.3 and momentum constant of 0.7 were chosen for ANN training. The ANN's performance during training was measured according to the mean of squared errors (MSE). MSE is the average squared difference between outputs of the network and target (experimental) values. Training was initially set to terminate after a maximum number of epochs (10000), but it was stopped at 5000 iterations since no further improvement in the MSE was achieved. As depicted in Figure 3, the prediction error, measured by the MSE, is low (i.e. 0.0379163).

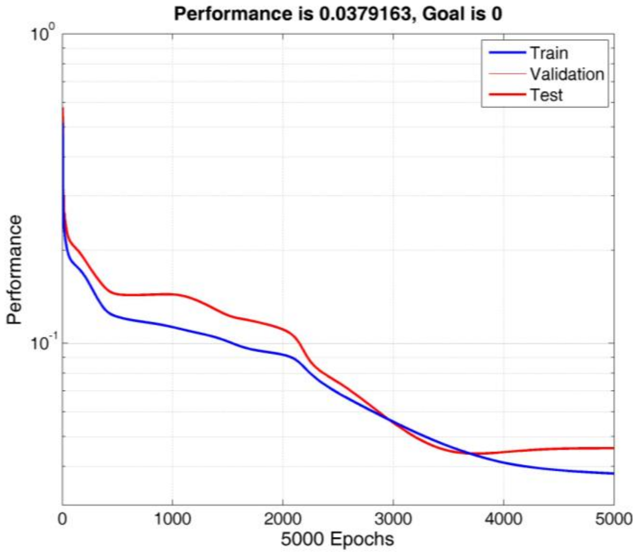


Fig. 3. ANN training and test performance graph

Another performance measure for the network efficiency is the correlation coefficient (R). The correlation coefficient is a statistical measure of the strength of correlation between actual versus predicted values. For example, the value of + 1 indicates perfect correlation. In that case, all points should lie on the line passing through the origin and inclined at 45°. The performance of the developed ANN model for PAC process is given in Table 2.

Table 2 Correlation coefficients for ANN model

ANN model	R		
	train	test	train+test
3-3-1	0.916	0.91	0.914

3.2. ANN mathematical model

The weights and biases of the ANN were determined during the training process and are given in Table 3.

Table 3 The weights and biases of the developed ANN model

Weights			Weights	Biases	
w_{ji}			w_{kj}	b_j	b_k
-0.99524	-1.4129	-1.793	-0.92501	-1.3197	0.966
3.5288	-1.5491	0.97196	-0.31493	-1.3197	
-0.8393	3.1402	0.06699	3.0174	-1.3197	

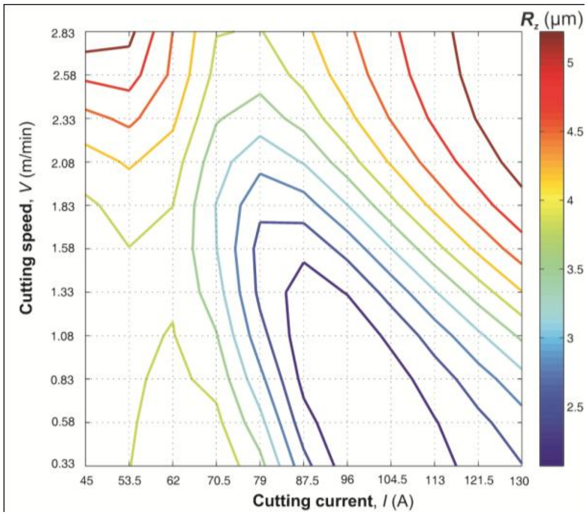
Regarding the architecture of the developed ANN, the used activation functions, and by using the weights and biases from Table 3, the exact mathematical relationship between R_z and input cutting parameters can be expressed by the following equation:

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

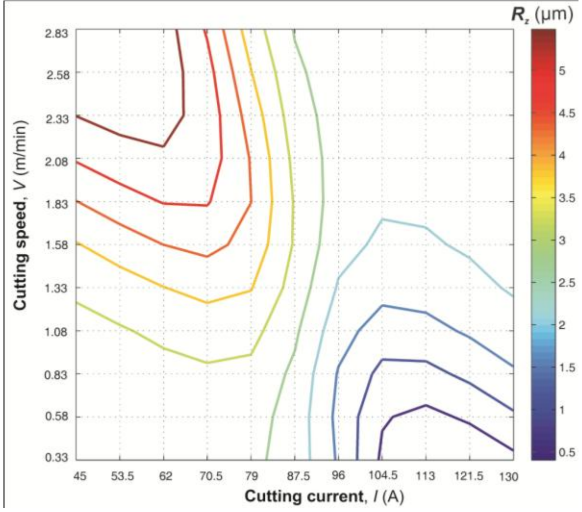
where X is the column vector which contains normalized values of I, s and V and $R_{z|norm}$ is the normalized value for the R_z. In order to obtain the actual values for R_z, one needs to perform denormalization knowing that the data was normalized to [-1, 1] range.

4. SIMULATION AND OPTIMIZATION

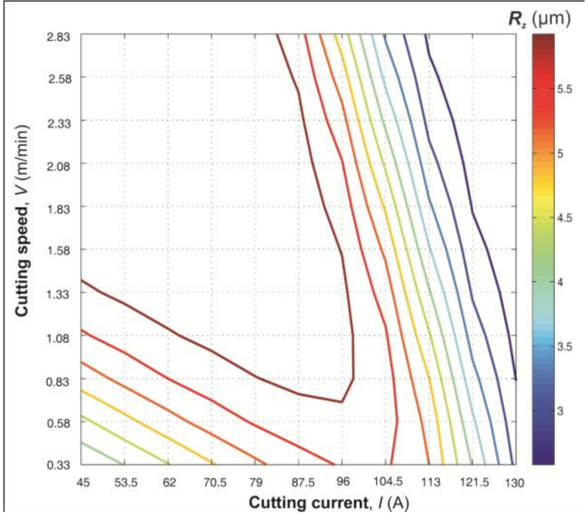
The trained ANN model can be used for the simulation and optimization of the cutting parameters during PAC process. This can be done by testing the behavior of the response variable (R_z) under different variations in the values of cutting current (I), plate thickness (s) and cutting speed (V) using Eq. 1.



a) *s* = 4 mm



b) *s* = 8 mm



c) *s* = 15 mm

Fig. 4. Surface roughness contour in cutting speed and cutting current plane at different plate thicknesses

In order to ensure accurate prediction of the R_z, the values concerning the three input parameters should be inside the experimental range (i.e. cutting current [45 130] A, plate thickness [4, 15] mm and cutting speed [0.33, 2.8] m/min). The contour plots of the R_z for all the combination of cutting current (I) and and cutting speed (V) keeping constant the plate thickness (4, 8 and 15 mm) can be seen in Figure 4.

The combined effect of cutting speed and cutting current as presented in Figure 4 shows that surface roughness increases with an increase in cutting speed, and decreases as cutting current increases. It can be seen that very good surface finish can be achieved in PAC process of 8 mm thick plate when cutting current and cutting speed are set nearer to their high and low level of the experimental range, respectively.

5. CONCLUSIONS

This paper presented an approach for development of mathematical models of the plasma arc cutting process based on artificial neural networks. For that purpose, the three layered feed-forward backpropagation architecture was used. Three input cutting parameters and one output process parameter were considered in the ANN model. The ANN model with 3-3-1 architecture proved to be able to represent the underlying relationships of the process. The ANN model was represented in the form of mathematical equation by which the contour plots of surface roughness were generated. Using these plots one can select machining conditions which corresponds to cutting regions with minimal surface roughness.

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