10th INTERNATIONAL SCIENTIFIC CONFERENCE
ON DEFENSIVE TECHNOLOGIES
OTEH 2022
Belgrade, Serbia, 13 – 14 October 2022

ANFIS PREDICTION IN PLASMA ARC CUTTING

MADINA ISAMETOVA
Institute of Energy and Mechanical Engineering, Satbayev University, Almaty, Kazakhstan
isametova69@mail.ru

MILOŠ MLOVANČEVIĆ
Faculty of Mechanical Engineering, University of Nis, Niš, Serbia
milovancevic@masfak.ni.ac.rs

DALIBOR PETKOVIĆ
Pedagogical Faculty in Vranje, University of Niš, Serbia
dalibortc@gmail.com

Abstract: *Plasma arc cutting process is very sensitive process which has to be optimized before application. There are different input factors which need adjustment in order to find the optimal combinations for the best final product. Therefore the main aim of the study was to establish predictive models for the plasma arc cutting in order to determine the cutting quality before real application of the plasma arc cutting. As cutting material Quard-400 was used. Input factors cutting speed and gas pressure were used during experimental procedure and for the predictive models crating. As the output quality parameters, mean surface roughness – Ra and material removal rate – MRR were used. Higher material rate means more profit for industry and vice versa. In the same time higher removal rate could increase surface roughness which is not desirable. Surface roughness needs to be minimized as much as possible which depends on the product application purpose. Predictive models were created based on adaptive neuro fuzzy inference system – ANFIS, which is suitable for nonlinear and redundant dataset. Results shown high predictive accuracy for the both output parameters.*

Keywords: *plasma arc cutting; prediction; surface roughness; ANFIS*

1. INTRODUCTION

Plasma state is the fourth state of material after solid, liquid and gaseous states. Plasma state occurs after very high heating of the material. In other words the first state is solid state which converts in the liquid state after heating. The liquid state converts further in gaseous state after more heating. And finally the gaseous state converts into plasma state after more heating. Plasma represent in ionized gas which is electro conductive and operated on temperatures between 10000ºC and 14000ºC. Plasma arc cutting is based on the ionized gas and it represents one type of thermal cutting process which uses a jet of the plasma gas in order to melt and cut material. The plasma arc cutting is very attractive process for material removal or cutting because of high quality of the final product. However the plasma arc cutting process is very expensive process in comparison to laser cutting or cutting by oxygen fuel.

Plasma arc cutting (PAC) is well recognized non-conventional machining processes widely used to fabricate intricate part profiles for diverse electrically conductive materials including superalloys and composites [1]. Plasma arc cutting process is frequently used to cut stainless steel, alloy steel, aluminum and other materials [2]. The application of teaching learning based optimization (TLBO) algorithm in order to analyze the effect of process parameters on surface roughness in plasma arc cutting of AISI D2 steel has been performed in article [3]. The optimum selection of process parameters is essential for smoother and faster cutting and in research work [4], experimental investigation of plasma arc cutting has been carried out where Taguchi based desirability analysis (TDA) was observed to find the optimal cutting conditions for improving the quality characteristics of the plasma arc cutting process. The quality of the cut of the plasma arc cutting procces has been monitored by measuring the kerf taper angle (conicity), the edge roughness and the size of the heat-affected zone (HAZ) [5]. Results in paper [6] have been shown that this fuzzy control and PID neural network improves the precision, ripples, finish and other comprehensive indexes of the workpiece compared with conventional PI control, and the plasma arc cutting power supply based on the fuzzy-neural network has excellent control performance. Plasma arc cutting (PAC) is a thermal cutting process that makes use of a constricted jet of high-temperature plasma gas to melt and separate (cut) metal [7]. In work [8], the microstructural modifications of the Hf insert in plasma arc cutting (PAC) electrodes operating at 250 A were experimentally investigated during first cycles, in order to understand those phenomena occurring on and under the Hf emissive surface and involved in the electrode erosion process where macrocracking was observed in the oxide layer, while microcracking and grain growth were detected in the remelted Hf. The paper [9] pointed out that high quality parts of the plasma arc cutting can be obtained as a result of an experimental investigation aimed at selecting the proper values of process parameters. There is need to develop and optimize novel plasma arc heat source such as cross arc and coupling arc [10]. In study [11] has been studied the influences of plasma arc remelting on the microstructure and properties of thermal sprayed Cr_3C_2-NiCr/NiCrAl composite coating. To reduce the kerf width and to improve the kerf quality, the hydro-magnetically confined plasma arc was used to cut engineering ceramic plates [12]. The quality of cuts performed on titanium sheets using high tolerance plasma arc cutting (HTPAC) process was investigated under different process conditions and a comparison between predicted thermal cycles, experimental measurements and microstructural observations confirmed the reliability of the estimation in terms of extension of microstructural modifications [13].

In order to decrease price of the plasma arc cutting process there is need to establish predictive models of the process. In other words the models could suggest future quality of the plasma arc process for the given combination of the input parameters. In order to do the predictive models there is need for an advanced computational models like soft computing or computational intelligence. Therefore in this article is used adaptive neuro fuzzy inference system or ANFIS [14-18] in order to predict laser arc cutting output parameters based on the input processing factors like cutting speed and plasma gas pressure. The output factors are mean surface roughness and material removal rate.

2. METHODOLOGY

2.1. Experimental procedure

Figure 1 shows the total experimental procedure of the plasma arc cutting. As can be seen there are nine main steps of the procedure. The torch body contains cathode which is non-melting. Working material represent anode or positive electrode where high temperature plasma gas or primary gas will be impinged. Kerf represent width of material removal during cutting process where molten metal is removed. For the cooling purpose secondary gas is used.

As working material Quard-400 is used which is abrasion resistant steel. This material has optimal combination of hardness, ductility and strength and it is very suitable for cutting process. Chemical composition of the material has following elements: C, Mn, P, Si, Al, Cu, Nb, Ni, Cr, V, Ti, N_2, B and Fe.

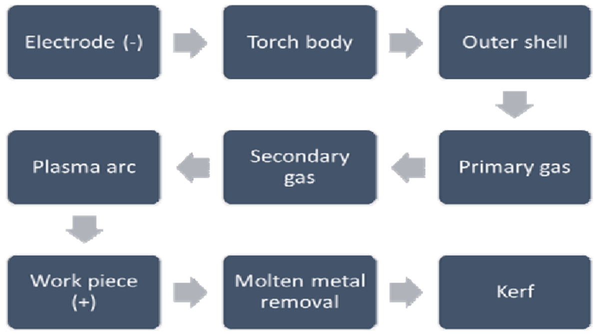


Figure 1. Experimental procedure of the plasma arc cutting process.

For the experimental procedure CNCN plasma arc cutting machine is used. Cutting specimens are dimension of 20×20×10mm. As cutting gas oxygen is used. Table 1 shows the numerical values (minimum and maximum) of the input and output factors which are used and obtained during cutting process.

Material removal rate or MRR is calculated based on the weight of the final product after cutting process. Surface roughness is measured by surface roughness tester and Ra value is measured based on three positions of the work piece. Based on the three measurements mean surface roughness is calculated.

Table 1: Input and output factors of the plasma arc cutting process

Input factors		Output factors	
Cutting speed (mm/min)	Pressure (psi)	Mean surface roughness, Ra (μm)	Material removal rate (gm/sec)

2.1. ANFIS methodology

ANFIS network has five layers as it shown in Figure 2. The main core of the ANFIS network is fuzzy inference system. Layer 1 receives the inputs and convert them in the fuzzy value by membership functions. In this study bell shaped membership function is used since the function has the highest capability for the regression of the nonlinear data.

Figure 2. ANFIS layers.

Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (1)$$

where $\{a_i, b_i, c_i\}$ is the parameters set and x is input.

Second layer multiplies the fuzzy signals from the first layer and provides the firing strength of as rule. The third layer is the rule layers where all signals from the second layer are normalized. The fourht layer provides the inference of rules and all signals are converted in crisp values. The final layers sumarized the all signals and provied the output crisp value.

3. RESULTS

3.1. Accuracy indicies

Performances of the proposed models are presented as root means square error (RMSE), Coefficient of determination (R^2) and Pearson coefficient (r) as follows:

1) RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{2}$$

Pearson correlation coefficient (r)

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right)\cdot\left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \tag{3}$$

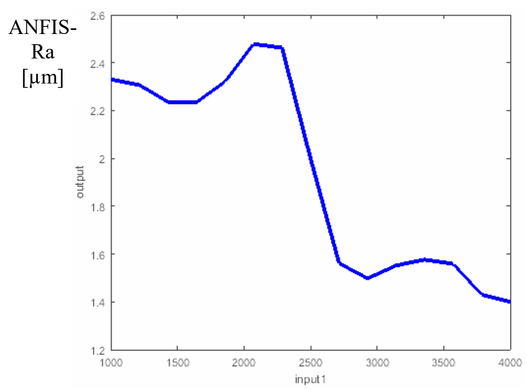
2) Coefficient of determination (R^2)

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \tag{4}$$

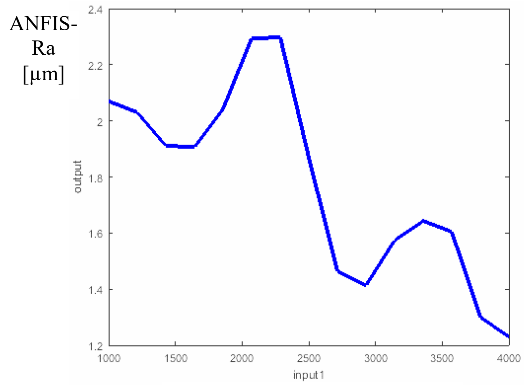
where P_i and O_i are known as the experimental and forecast values, respectively, and n is the total number of dataset.

3.2. ANFIS prediction

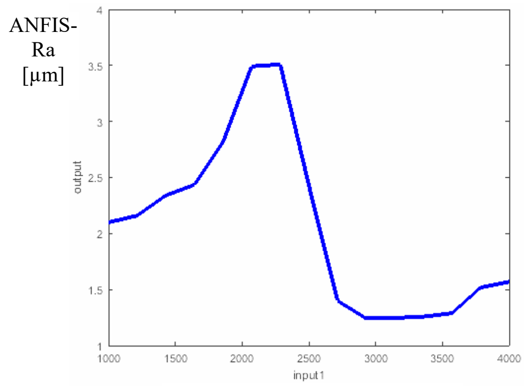
Figure 3 shows ANFIS prediction of mean surface roughness (Ra) based on cutting speed and for three different values of pressure, 65, 80 and 90 (psi). Figure 4 shows ANFIS prediction of Ra based on pressure and for six different values of cutting speed, 1000, 1500, 2500, 3000, 3500 and 4000 (mm/min). Figure 5 shows ANFIS-Ra prediction based on the both inputs simultaneously.



Cutting speed (mm/min)
(a)

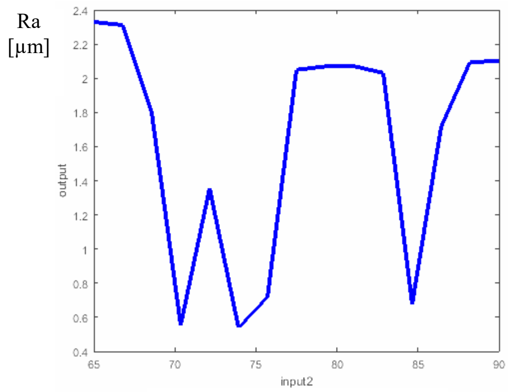


Cutting speed (mm/min)
(b)

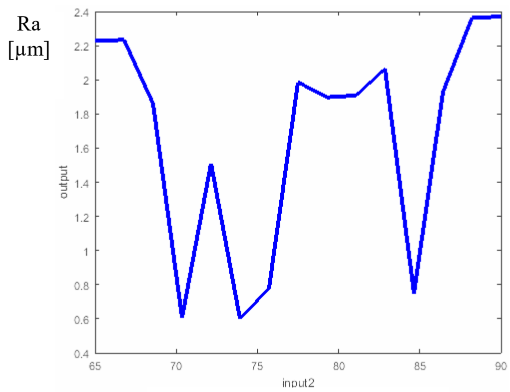


Cutting speed (mm/min)
(c)

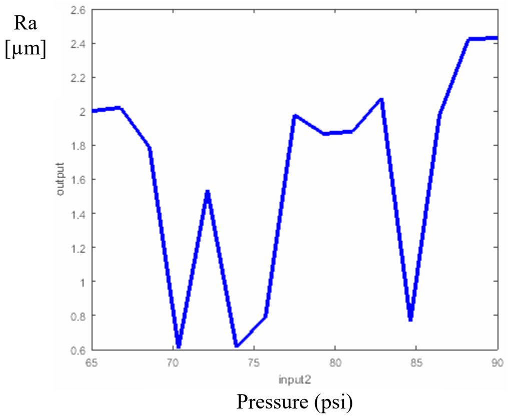
Figure 3. ANFIS-Ra prediction based on cutting speed and for pressure of: (a) 65, (b) 80 and (c) 90 (psi).



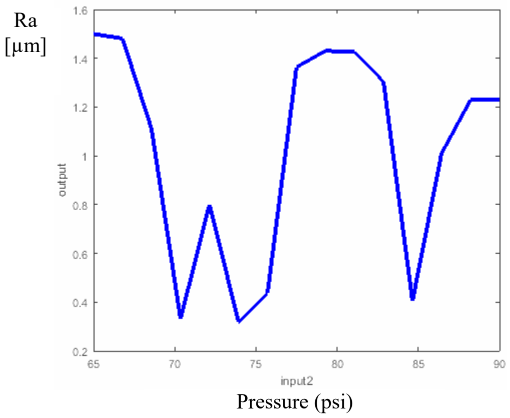
Pressure (psi)
(a)



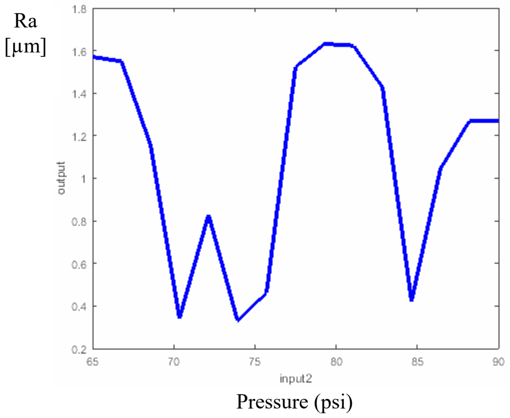
Pressure (psi)
(b)



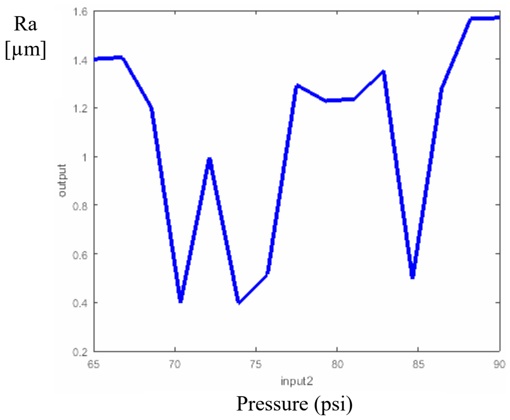
(c)



(d)



(e)



(f)

Figure 4. ANFIS-Ra prediction based on pressure and for cutting speed of: (a) 1000, (b) 1500, (c) 2500, (d) 3000, (e) 3500 and (f) 4000.

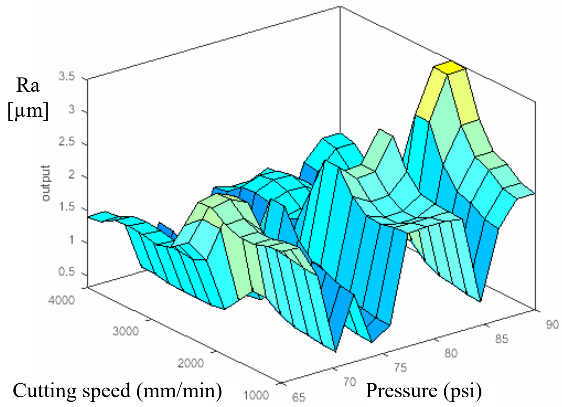
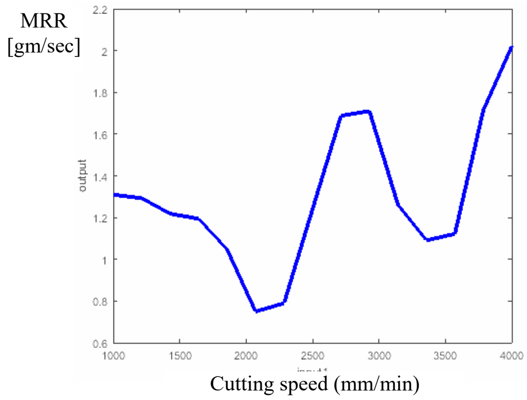
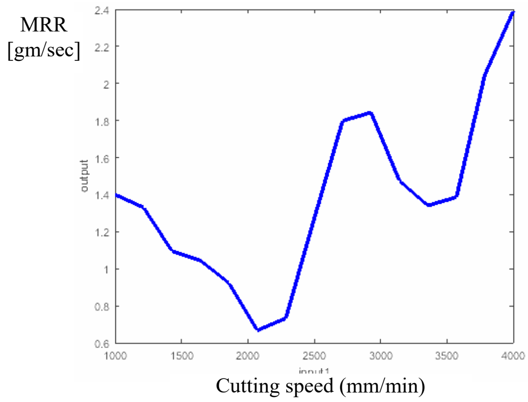


Figure 5. ANFIS-Ra prediction based on pressure and for cutting speed.

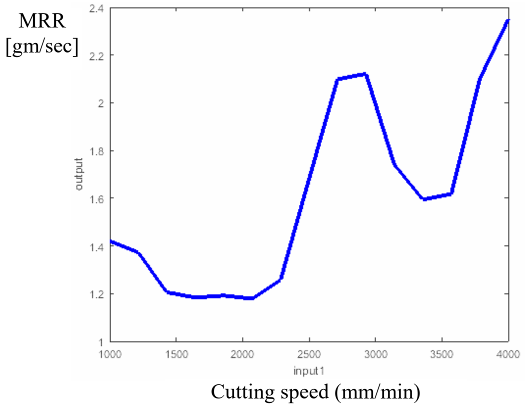
Figure 6 shows ANFIS prediction of material removal rate (MRR) based on cutting speed and for three different values of pressure, 65, 80 and 90 (psi). Figure 7 shows ANFIS prediction of MRR based on pressure and for six different values of cutting speed, 1000, 1500, 2500, 3000, 3500 and 4000 (mm/min). Figure 8 shows ANFIS-MRR prediction based on the both inputs simultaneously.



(a)

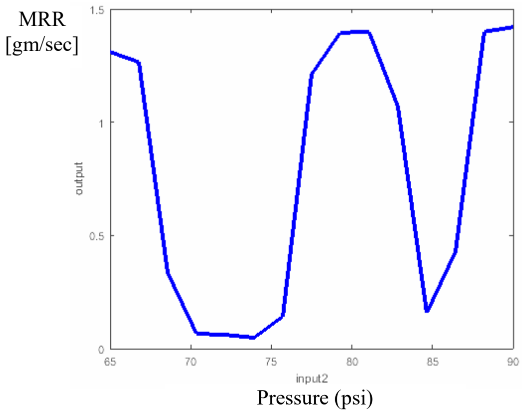


(b)

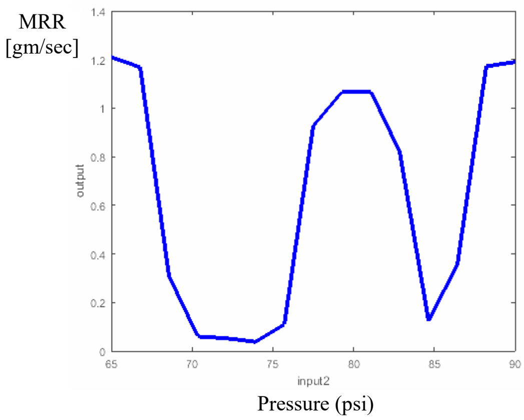


(c)

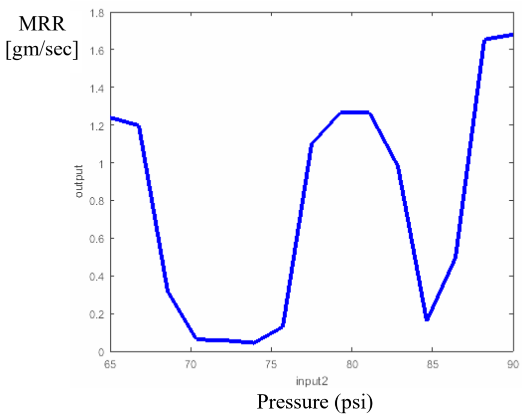
Figure 6. ANFIS-MRR prediction based on cutting speed and for pressure of: (a) 65, (b) 80 and (c) 90 (psi).



(a)



(b)



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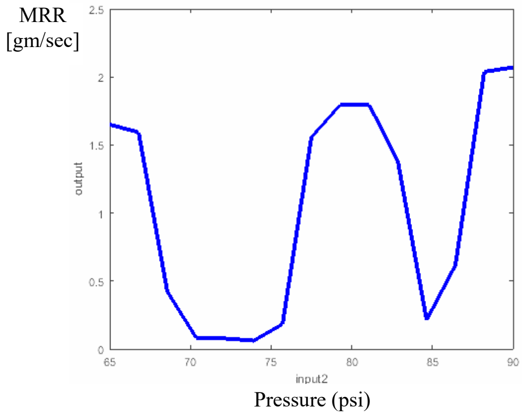
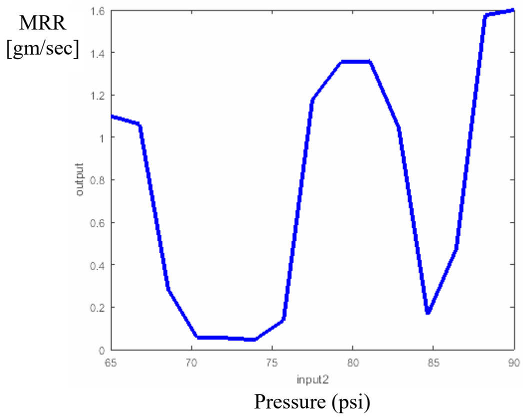


(d)



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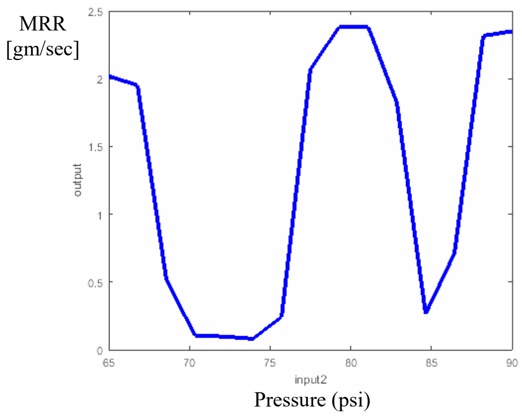

(f)

Figure 7. ANFIS-Ra prediction based on pressure and for cutting speed of: (a) 1000, (b) 1500, (c) 2500, (d) 3000, (e) 3500 and (f) 4000.

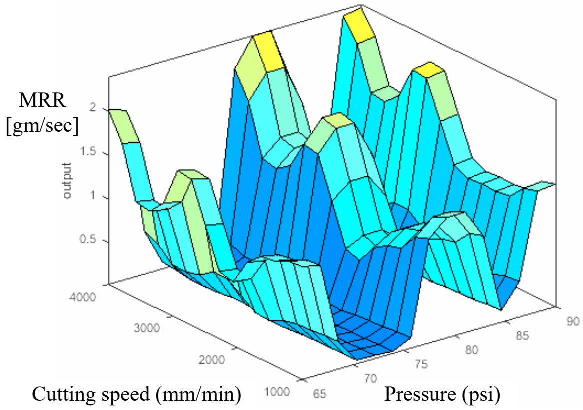

Figure 8. ANFIS-MRR prediction based on pressure and for cutting speed.

Figure 9 shows scatter plots of the ANFIS prediction of Ra based on the experimental measured data. It can be noted high predictive accuracy based on R^2 coefficient. Also, Pearson coefficient (r) is 0.873243 and root mean square error (RMSE) is 0.873243 for the Ra prediction.

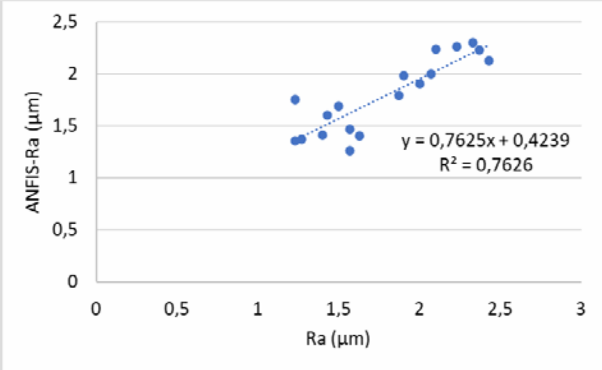

Figure 9. Scatter plot of ANFIS-Ra prediction.

Figure 10 shows scatter plots of the ANFIS prediction of MRR based on the experimental measured data. It can be noted high predictive accuracy based on R^2 coefficient. Also, Pearson coefficient (r) is 0.804839 and root mean square error (RMSE) is 0.173676 for the Ra prediction.

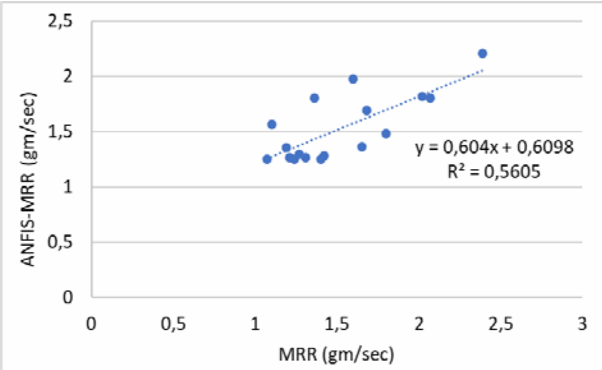

Figure 10. Scatter plot of ANFIS-MRR prediction.

4. CONCLUSION

In this paper was investigated predictive performance of adaptive neuro fuzzy inference system or ANFIS for prediction of output factors of plasma art cutting process. The output factors are mean surface roughness and material removal rate. The main purpose of the ANFIS predictive models was to determine which cutting quality will be obtained for different set of input parameters. ANFIS can eliminate the vagueness in the process in order to produce the best prediction conditions. In other words ANFIS network was used to convert the multiple performance characteristics into the single performance index.

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