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POSSIBILITY OF ANFIS APPLICATION FOR EVALUATION ROUGHNESS OF SURFACE DURING CNC MACHINING

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Abstract: *In this investigation was analyzed the surface roughness of Co29Cr6Mo medical alloy which is machines with a CNC machine. The method of ANFIS (adaptive neuro fuzzy inference system) was applied to estimate important factors of roughness of surface of the material during machining process. Than main goal was to evaluate the machining parameters for the surface roughness in order to optimize the machining process for the best conditions. Four machining parameters are considered. Average surface roughness Ra is considered as output since it is the only relevant measure of the surface quality.*

Key words: *Surface roughness, alloy, ANFIS, machining*

Mogućnosti primene ANFIS metdofologije za evaluaciju hrapavosti površine u toku CNC obrade. *U ovom radu je analizirana hrapavost površine od materijala Co29Cr6Mo koja je obrađovana na CNC mašini. ANFIS metodologija je korišćena kako bi bili određeni najuticajniji parameteri za određivanje hrapavosti površine date legure. Četiri ulazna parametra obrade su korišćena u analizu. Kao izlazni parametar je korišćena srednja aritmetička visina neravnina Ra.*

Ključne reči: *hrapavost površine, legura, ANFIS, obrada materijala*

1. INTRODUCTION

Chip based machining is still important engineering process since many engineering parts should be manufactured by the process. Therefore many factors need to be controlled and estimated during the process for the complex engineering parts to minimize tool wear, tool temperature, vibration, roughness of surface as the main indicator and etc.

Therefore metal cutting process is considered as the most important process since this process should manufacture machine elements to achieve geometric, dimensional and surfaces requirements. Hence there is need for accurate processes for precision machine components. Computer control machines (CNC) can control the machining quality of the elements. Small changes in the conditions or machine tool can produce high changes of the surface roughness.

The surface roughness estimation by the system simulations is very challenging task due to machine tool parameters [1]. Also surface estimation by analytical methodology is also very complicated because of high nonlinearities. However approximate estimation of surface roughness is not suitable since the surface should be used for precision manufacture.

In article [2] was investigated the modeling of experimental data of surface roughness of a medical alloy machines on a CNN lathe based on cutting parameters where the main goal was to obtain the best combinations of parameters to optimize the problem in order to acquire minimum roughness. Artificial neural network was used to predict surface roughness in investigation [3] where the prediction error if the surface roughness was 4.52%. In investigation [4] was used ball burnishing process. In articles [5, 6] was presented prediction of average surface roughness. In investigation [7] was indicated that the fuzzy-nets modeling technique for surface roughness prediction.

Lubricant viscosity can have high influence for coefficient of friction [8]. Several mathematical models were presented in article [9] for the estimation of surface roughness. Taguchi method was used in article [10] for the minimization of surface roughness.

In article [11] was found that increased spindle speed, decreased nozzle feed rate, increased abrasive flow rate and lower standoff distance resulted in smoother surfaces. The best results were obtained when spindle speed and abrasive flow rate were increased [11]. The global packet analysis (G-WPT) method was observed to be an ideal procedure for processing cutting force signals applied to the real-time monitoring of surface finish, and was estimated to be highly accurate and reliable at a low analytical-computational cost [12]. On-line monitoring of surface finish in machining processes has proven to be a substantial advancement over traditional post-process quality control techniques by reducing inspection times and costs and by avoiding the manufacture of defective products [12]. Analysis [13] was shown that Feed is the most evident factor for Surface Roughness.

Although surgical alloys obtain an extraordinary high accuracy of surface roughness and quality in the body environment, additional investigations are needed to determine the optimal machining conditions for such surgical alloys [14]. Even though there are models of the surface roughness in a CNC lathe, in this investigation the main aim is to overcome high nonlinearity by applying the soft computing method namely adaptive neuro-fuzzy inference system (ANFIS) [15] for selection of the most important parameters for surface roughness of surgical alloy Co29Cr6Mo [16, 17]. Than main goal was to estimate the optimal machining parameters for the surface roughness in order to optimize the machining process for the best conditions.

2. METHODOLOGY

2.1 Experimental measurement

In this investigation three cutting parameters are selected as the inputs. There are 1000 tests in total. Table 1 shows four input and output parameters which are used in this investigation. Output parameter of surface roughness is determined by measurements. The test are performed on a CNC lathe. The same cutting conditions are used for all of the test.

In the study the surgical alloy Co28Cr6Mo is used with harness of 45 HRC. The alloy specimen is with radius of 50mm and length of 600 mm. The turning tests are performed on a CNC lathe Model VDF-D480 10KW. During the turning tests the surface measurements are done by roughness meter, Perthometer M1 by Mahr Company. The experimental procedure of surface roughness measurement was performed on the Talysurf 6 (*Taylor Hobson*) system as it shown in Figure 1. This system could measure micro-geometric characteristics of the surface. The average surface roughness is measured on the three sections on the working piece. The surface roughness was measured on the three specimen's sections – upper, lower and middle section and average values were determined. The roughness was measured 0.1 mm from the upper and lower edges of the specimen.

Fig. 1. Surface roughness measurement system Talysurf 6

Inputs	Parameters description	Parameters range
input 1	Rotational speed (rpm)	320-640
input 2	Feed rate (mm/rev)	0.1-0.2
input 3	Depth of cut (mm)	0.5-1
input 4	Tool tip radius (mm)	0.5-1.5
output	Average surface roughness: *R*a (μm)	0.8-4.1

Table 1. Input and output parameters

The all tests are performed in dry conditions. Tool holder us MTJNR-L 2525 M26 and the cutting bit is TNMG 160412 by Taegutec. The cutting bit is cladded by TiCN.

2.2 ANFIS methodology

The structure of ANFIS network with two inputs is shown in Figure 2.

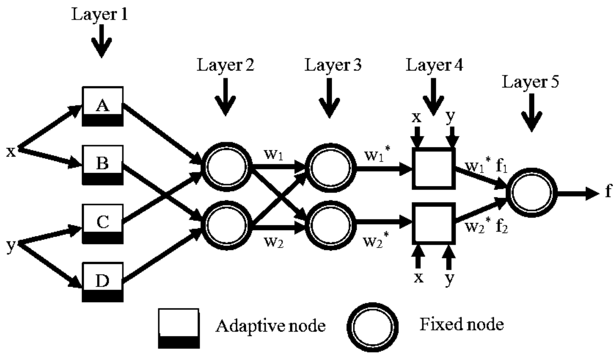

Fig. 2. ANFIS structure with two inputs

The first ANFIS layer presents inputs of membership function (MF). Each node here is considered an adaptive node having a function which is dependable on MF. The second layer is the membership layer where firing strength of rules are determined. In the third layer the fuzzy inference is made based on the training data. The fourth layer provides inference of fuzzy rules. The fifth layer gives the final output which is crisp number.

The ANFIS network is trained by hybrid methodology in order to ensure the best regression of the data. One part of the methodology optimize the ANFIS parameters in forward direction. The second part of the methodology optimize the ANFIS parameters in backward direction from the last up to the first ANFIS layer.

3. RESULTS

A deep search was established from the given inputs in Table 1 in order to choose the set of the optimal combination of the inputs for the machining process of the surgical alloy (Table 1) with the most effect on the output parameter (surface roughness in a CNC lathe). ANFIS model is built for each combination of the inputs and the model was trained. The ANFIS performance are reported and compared for each model separately. The most impactful input parameters in the prediction of the output surface roughness was identified and determined, as depicted in Table 2. The input parameters with the smallest RMSE training error have the most relevance or importance for the given outputs.

Table 2 shows the most effective parameter for Ra prediction is feed rate (input 2) since the training RMSE is the smallest for the input 2 – feed rate (0.6873). The combination of feed rate and cutting deep is the most influential for Ra prediction since the training RMSE is the smallest for the combination of inputs 2 and 3 – feed rate and cutting deep (0.1673). Figure 3 shows the ANFIS prediction of Ra based on separate input.

One input	Two inputs
ANFIS-1: in1 RMSE training=1.2627, RMSE testing=2.4169	ANFIS-1: in1 in2 RMSE training=0.6526, RMSE testing=2.1914
ANFIS-2: in2 RMSE training=0.6873, RMSE testing=2.1425	ANFIS-2: in1 in3 RMSE training=1.1286, RMSE testing=2.7129
ANFIS-3: in3 RMSE training=1.1549, RMSE testing=2.6035	ANFIS-3: in1 in4 RMSE training=0.5216, RMSE testing=2.7796
ANFIS-4: in4 RMSE training=1.0452, RMSE testing=2.0356	ANFIS-4: in2 in3 RMSE training=0.1673, RMSE testing=2.4737
	ANFIS-5: in2 in4 RMSE training=0.4804, RMSE testing=1.5459
	ANFIS-6: in3 in4 RMSE training=0.7818, RMSE testing=2.9532

Table 2. Input parameters influence on Ra

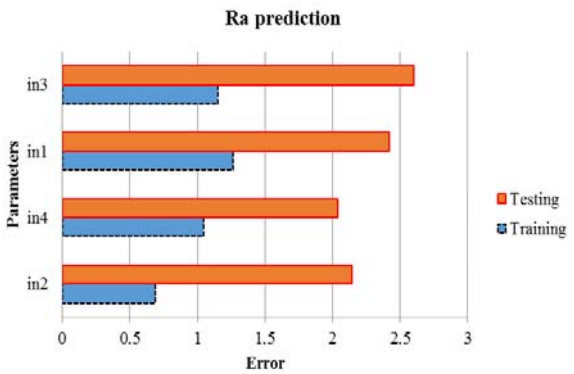

Fig. 3. Surface roughness prediction by ANFIS methodology

The two parameters are extracted to make prediction models with the ANFIS network. Figure 4 shows scatter plots of ANFIS prediction of roughness of surface Ra for the optimal combination of the two selected input parameters 2 and 3 – feed rate and tool tip radius. The determination coefficient is acceptable for the data. Also number of underestimated values are also limited.

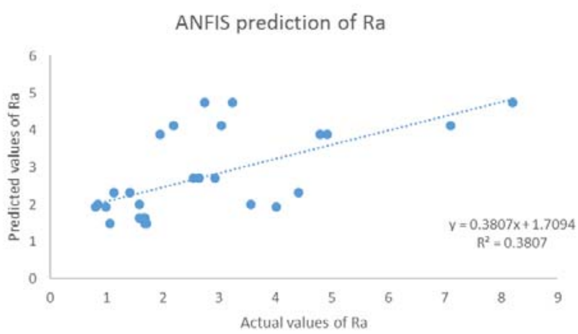

Fig. 4. ANFIS scatter plots for prediction of surface roughness in a CNC lathe for Ra

Table 3 summarize the prediction accuracy results for the selected two inputs for Ra value.

Ra prediction	r	0.6170
	R^2	0.3807
	RMSE	2.4737

Table 3. Statistical indicator for surface roughness prediction

4. CONCLUSION

The study carried out an approach to analyse the surface roughness prediction of Co29Cr6Mo medical alloy by the ANFIS methodology.

The effects of several factors on roughness of surface machined have been investigated and modeled. Understanding of surface topography can provide key data about the mechanism of the surgical alloy machining. In conducted experiments, machined material was surgical alloy Co29Cr6Mo.

Selected most influential machining parameter, determining surface roughness, which at the same have greatest practical usability in terms of selecting process parameters, are feed rate. The aim of the study was to examine the possibilities of efficient application of ANFIS in modeling roughness of the surface machined of the given surgical alloy. Relations between input variables and output values (surface roughness) were formed on the basis of the measured experimental values, while experiments were organized to follow practically usable trend of change in value of surface roughness with the change of machining parameters.

Understanding of surface quality of surgical alloy can be of great assistance in managing and improving the process of analysis, which makes the process more efficient and cost effective.

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