Application of adaptive neuro fuzzy systems for grinding process modeling

Pavel Kovač*, Dragan Rodić*, Marin Gostimirović*, Borislav Savković*, Dušan Ješić**
*Univeristy of Novi Sad, Faculty of Technical Sciences, Trg Dositeja Obradovica 6, 21000 Novi Sad, Serbia
** Medjunarodna Tehnoloska-Menadzerska Akademija – MTMA, Trg Dositeja Obradovica 7, 21000 Novi Sad, Serbia
pkovac@uns.ac.rs; rodicdr@uns.ac.rs; maring@uns.ac.rs; savkovic@uns.ac.rs; dusanjesic@hotmail.com

***Abstract*—Modeling and prediction of cutting forces by intelligent techniques in grinding operations play an important role in the manufacturing industry. This paper proposes a method using an adaptive neuro-fuzzy inference system (ANFIS) to currently establish the relationship between the machining conditions and cutting force, and consequently can effectively predict cutting force using cutting parameters work speed, feed rate and depth of cut. The results indicate that the ANFIS modeling technique can be effectively used for the prediction of cutting force in grinding process.**

I. Introduction

The grinding process has been shown to be a good method as a final operation for heat-treated materials. The machining parameters of grinding process, such as feed-rate, cutting speed and depth of cut are usually selected before machining according to standard manuals or experience [1]. In setting the machining parameters, the main goal is the minimum cutting forces [2]. The main problem is how to currently obtain the actual cutting forces using various parameters of cutting operations. It is difficult to utilize the optimal functions of a machine owing to there being too many adjustable machining parameters. As a result, many machining systems are inefficient and run under the operating conditions that are far from optimal criteria [3]. To know the optimal criteria, it is necessary to employ intelligent models making it feasible to do predictions in function of response parameters [4]. In order to achieve the minimal cutting forces, machining parameters must be optimally set.

Artificial intelligent techniques, such as adaptive neuro fuzzy systems, has been successful applied to machining processes through recent years. A broad literature survey has been conducted on the application of artificial intelligence systems to machining processes [5-7]. As all these researches paid high attentions on the fuzzy correlation between the experimental results and influential factors. A lot of ANFIS methods were also developed and used for predicting cutting forces [8-10]. From the review of literature, it is observed that neuro-fuzzy systems have found wide applications in modeling of process parameters.

In solving problems of modeling and prediction of cutting forces, this study uses a more powerful learning tool known as a combination of fuzzy logic and neural networks. It is known that the adaptive neuro-fuzzy inference system (ANFIS) is efficient for non-linear mapping [11]. ANFIS is a fuzzy inference system implemented in the framework of an adaptive neural network. The main problem with fuzzy logic is that there is no systematic procedure to define the membership function parameters. ANFIS eliminates the basic problem in fuzzy system design, defining the membership function parameters and design of fuzzy if-then rules, by effectively using the learning capability of neural network for automatic fuzzy rule generation and parameter optimization.

In this paper an adaptive neuro-fuzzy inference system (ANFIS) is used to correlate the machining parameters to cutting force in grinding process using the data generated based on experimental observations. The results of the experiments were also compared with those of the ANFIS predictions [12].

II. Experimentals procedures

Cutting tests were performed on a 4 kW cylindrical grinder machine. Tool was cylindrical grinding wheel Ø 350x40x127 mm, type B60L6V. The working material was a cylindrical shaped of Ø 60 x 150 mm of steel EN 34Cr4 and was fixed on grinding machine table.

The experiment was carried out for different combinations of work speed, feed rate and depth of cut according to the planning of experiment. The workpiece was mounted on a three-component piezo-electric dynamometer. Output parameter was Tangential force F_t (N). Other parameters were kept constant: tool geometry, tool wear, cooling and lubricating fluid, dynamical system machine-tool-workpiece.

III. ANFIS modeling of grinding

The architecture of the ANFIS used in the proposed method is shown in Fig. 1. The process followed in this study is illustrated in Fig. 2. There are three input parameters (v, f, a) and one output value, the predicted cutting force (F_t). Denote the output node i in layer l as $O_{l,i}$. The used five-layer ANFIS is described as follows:

Layer 1:

Every node in this layer is an adaptive node with a node output defined:

$$\begin{aligned} O_{1,i+1m} &= m_{vi}(v),\ i=1,\ldots,m; \\ O_{1,i+2m} &= m_{fi}(f),\ i=1,\ldots,m; \\ O_{1,i+3m} &= m_{ai}(a),\ i=1,\ldots,m; \end{aligned} \quad (1)$$

Where $\boldsymbol{v}$, $\boldsymbol{f}$, $\boldsymbol{a}$ *are the inputs to the nodes*, $\boldsymbol{v_i}$, $\boldsymbol{f_i}$, $\boldsymbol{a_i}$ are the i^{th} fuzzy sets associate with the membership functions of this nodes, and ***m*** is the number of fuzzy sets for each input parameter. In other words, $O_{1,i}$ which are outputs of this layer, are the membership values of the premise part v_i, f_i, a_i. Here, we choose the membership function to be *Gaussian* shaped with maximum equal to 1 and minimum equal to 0.

$$O_i^1 = \mu_{Ai}(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (2)$$

where x, c and σ is the parameter set.

Layer 2:

Every node in this layer is a fixed node labeled Π, which multiplies the incoming signals and outputs the product. For instance:

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad i = 1,\, 2 \qquad (3)$$

Each node output represents the firing strength Π of a rule.

Layer 3:

Every node i in this layer is a fixed node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rule's firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_i w_i} = \frac{w_i}{w_1 + w_2 + w_3} \quad i = 1,\, 2,3 \qquad (4)$$

For convenience, outputs of this layer are called *normalized firing strengths.*

Layer 4:

Every node i in this layer is an adaptive node with a node function:

$$O_i^4 = \overline{w}_i\, f_i = \overline{w}_i\left(p_i v + q_i f + r s_i\right) \quad i = 1,2 \qquad (5)$$

Where $\overline{w}_i$ is the output of layer 3 and {*pi*, *qi*, *ri*} is the parameter set. Parameters in this layer are referred to as *consequent parameters.*

Layer 5:

This layer is called as the output nodes. The single node in this layer computes the overall output as the summation of contributions from each rule.

$$O_i^5 = f(x.y) = \sum_i \overline{w}_i \cdot f_i = \overline{w}_i\, f_1 + \overline{w}_i\, f_2 = \frac{\sum_i w_i\, f_i}{\sum_i w_i} \qquad (6)$$

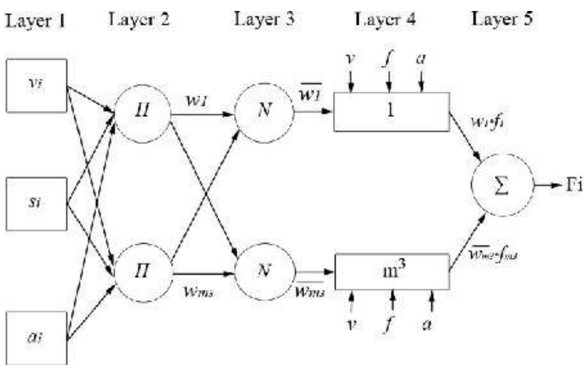

Figure 1. ANFIS architecture

TABLE I.
EXPERIMENTAL DATA

No.	Machining factor			Experimentally measured values
	v	f	a	F_t
	[m/min]	[mm/o]	[mm]	[N]
1	18,4	20	0,01	10,9
2	36,8	20	0,01	11,8
3	18,4	30	0,01	13
4	36,8	30	0,01	13,2
5	18,4	20	0,02	17,4
6	36,8	20	0,02	17,9
7	18,4	30	0,02	18,8
8	36,8	30	0,02	20
9	26	25	0,014	12,3
10	26	25	0,014	13,5
11	26	25	0,014	12,2
12	26	25	0,014	14
13	16	25	0,014	12,6
14	42,4	25	0,014	13,6
15	26	18,4	0,014	12,4
16	26	32,6	0,014	14,1
17	26	25	0,0086	10,8
18	26	25	0,023	18,1
19	16	25	0,014	12,1
20	42,4	25	0,014	13,9
21	26	18,4	0,014	12,6
22	26	32,6	0,014	14,6
23	26	25	0,0086	11
24	26	25	0,023	18,5

IV. RESULTS

In this study, an ANFIS model based on both ANNs and FL has been developed to predict cutting force in grinding process. Four machining parameters namely work speed, feed rate and depth of cut were taken as input features.

A full factorial experimental design was adopted to study to collect cutting force values. The data set was used as inputs of ANFIS in training and testing stage. The experiments were divided into two group for training (the first 16 experiment) and testing (remaining) of ANFIS. According to the experimental results, the proposed method is efficient for estimating of the cutting force in grinding process. The average deviation of the testing data for cutting force is 7.81 % (Table 2).

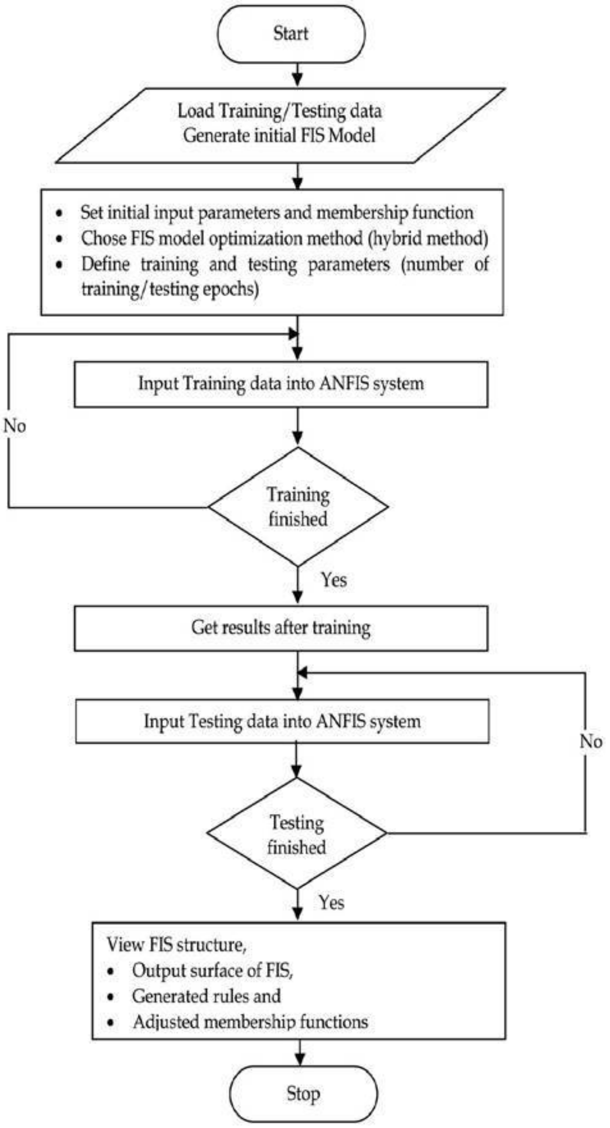

Figure 2. Comparison Flowchart of cutting force prediction of ANFIS system [13]

TABLE II.
TEST DATA

No.	Machining factor			Tangential force		
	v [m/min]	*f* [mm/o]	*a* [mm]	F_t [N]	*Fanfis* [N]	*Error* [%]
1.	36.8	20	0.02	16.6	15.8855	4.4978
2.	18.4	30	0.02	17.2	15.9767	7.6568
3.	26	25	0.014	12.6	14.5713	13.5286
4.	26	25	0.014	12.8	14.5713	12.1561
5.	26	25	0.0086	11.0	11.1825	1.6320
6.	26	25	0.023	17.1	15.6066	9.5690
7.	26	25	0.0086	11.1	11.1825	0.7378
8.	26	25	0.023	17.6	15.6066	12.7728
Average error:						**7.81**

In solving problems of modeling and prediction of cutting force in grinding process, this study uses a more powerful learning tool known as a combination of fuzzy logic and neural networks. On Fig. 3. is shown ANFIS system for prediction cutting force in grinding process. Figs. 4 depict the comparison of experimental and ANFIS results for the cutting force, respectively. It proved that the method used in this paper is feasible and could be used to predict the Fc in an acceptable error rate for grinding process. The compared lines seem to be close to each other indicating with good agreement.

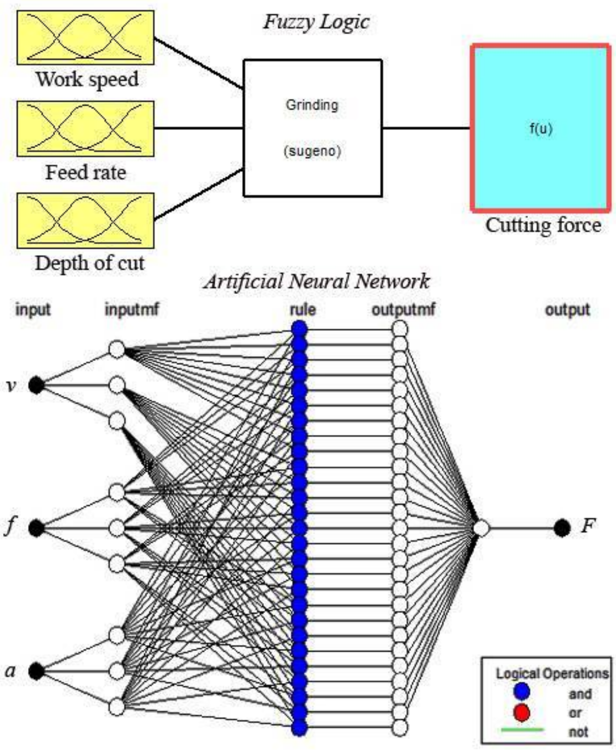

Figure 3. ANFIS architecture for prediction cutting force in grinding process

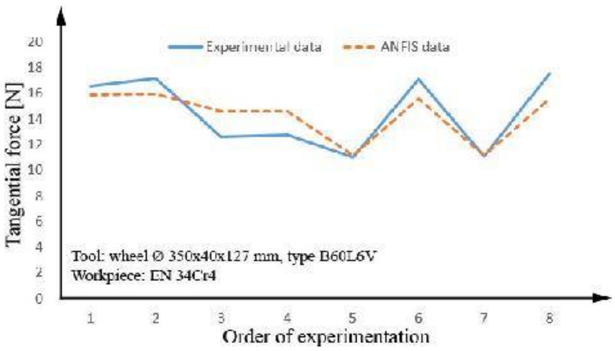

Figure 4. Comparison of predicted results with actual values for Tangential force.

Fuzzy 3D surface viewer give a good overview of the process behavior, displaying how the response vary with two different parameters, where remaining three of the inputs must be held constant. The form of the surface viewer depends of the membership functions and their parameters. The selection of most influential parameters was based on fuzzy logic.

At medium and high feed rate levels from 26 to 32 mm/o and depth of cut is constant 0.014 mm, the cutting force decrease with decreasing work speed for all cutting speed ranges, Fig. 5. At work speed ranging from 15 to 40 m/min, the cutting force increase with increasing depth of cut for ranging from 0.01 to 0.02 mm, Fig 6.

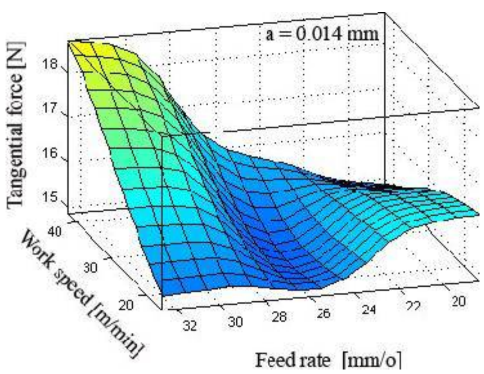

Figure 5. Fuzzy 3D surface viewer, effect of work speed and feed rate on the tangential cutting force, where a=const.

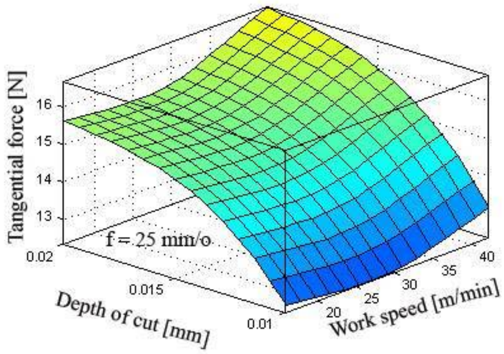

Figure 6. Fuzzy 3D surface viewer, effect of work speed and depth of cut on the tangential cutting force, where f=const.

V. Conclusion

This paper proposes a method using an adaptive neuro-fuzzy inference system (ANFIS) to currently establish the relationship between machining conditions and cutting force, and consequently can effectively predict cutting force using cutting parameters work speed, feed rate and depth of cut. The advantages of the proposed method is obtain the actual cutting force using various parameters of cutting operations. Experimental results have shown that the proposed ANFIS based method outperforms the existing polynomial network based method in terms of modeling and prediction accuracy.

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