



ARTIFICIAL INTELIGENCE APPROACHE TO MODELING OF CUTTING FORCE AND TOOL WEAR RELATIONSHIPS DURING DRY MACHINING

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Abstract: In the paper numerical and experimental study for different cutting conditions according planning of experiment was carried out. Contribution was made during dry face milling process what contributes to sustainability of manufacturing processes. Cutting force components and parameters of tool wear versus time were pointed out. It was observed that cutting force components increase with time and/or tool wear. The relationships for cutting force components versus cutting depth, feed and tool wear parameters were expressed by regression analyse and artificial neural network.

Key words: cutting force, tool wear, experimental dry study machining, neural network, regression analyse.

Modeliranje zavisnosti sila rezanja i habanja alata pomoću veštačke inteligencije pri suvoj obradi. U radu je sprovedeno numeričko i eksperimentalno istraživanje za različite uslove rezanja prema planu eksperimenta. Dobit rada je prikazana tokom procesa suvog čeonog glodanja što doprinosi održivosti proizvodnih procesa. Istaknute su komponente sila rezanja i parametri habanja alata u odnosu na proteklo vreme obrade. Uočeno je da se komponente sila rezanja povećavaju sa vremenom odnosno habanjem alata. Odnosi komponenti sila rezanja sa dubinom rezanja, pomakom i parametarom habanja alata su obrađeni preko regresione analize odnosno veštačke neuronske mreže.

Ključne reči: sile rezanja, habanje alata, eksperimentalna suva obrada, neuronska mreža, regresiona analiza.

1. INTRODUCTION

Cutting fluids have a direct influence on the environment and in recent times are being questioned in the light of ecological and economic manufacture. The criterion of minimization of cutting fluids use makes it's important; as range from 7 – 17 % of manufacturing costs can be attributed to the cutting fluids. Consequently, it is interesting for researches to develop sustainable manufacturing processes like dry machining [1, 2, 3].

A dry cutting process must be designed to minimize the amount of heat flowing into the workpiece. This may be achieved by minimizing the cutting forces and also by influencing the heat distribution. Cutting forces can be reduced by positive cutting-edge geometries. The introduction of dry machining necessitates measures to compensate for the primary functions of the fluid, cooling, lubricating, chip transport and adhesive interaction between tool and workpiece [4].

Tool wear is of great significance in manufacturing because it effects the quality of the components, tool life and machining costs. For this reason, many papers on tool wear can be recognise in literature. Many of them are mainly based on empirical models [5], experimental studies [6] and only few regards the simulation of tool wear [7].

The purpose of work [8] was to study the influence of the tool entering angle on the stability of the process and on tool life based on a time and frequency domain analysis of the cutting forces.

The work [9] utilizes the mechanistic modeling approach for predicting cutting forces and simulating

the milling process of fiber-reinforced polymers. Model predictions were compared with experimental data and were found to be in good agreement.

This study develops a combined numerical and experimental approach based on response surface methodology suggested by authors [10]. For experimental study, series of tests have been performed during concerning the case dry milling operation.

2. CUTTING FORCE MODELLING

For cutting force components presentation of Kienzle-Victor relationship, which is based on unit cutting force k_{i1} and is used very often:

$$F_i = b \cdot h^{1-C_i} \cdot k_{i1} \quad (1)$$

where $b \cdot h$ is chip cross section and $i = 1,2,3$

If tool wear taken in to consideration equation (1) is extended with parameter l which represent cutting length:

$$F_{iw} = b \cdot h^{1-C_{iw}} \cdot k_{i111} l^{C_{il}} \quad (2)$$

where i is unit cutting force determined for cutting length $l = 1 \text{ m}$

$$k_{i111} = k_i (b = 1\text{mm}, h = 1\text{mm}, l = 1\text{m}) \quad (3)$$

Constants C_{iw} and C_{il} depend of work material and cutting conditions [11, 12].

For reasons of economy, tool life tests in a face and end milling operation are often made with single tooth cutters. It is possible to use the results of these tests for

multi-tool cutters if the radial and axial throw is very small ($\leq \pm 0,002$ mm). This is valid for cutting force and tool wear. According to this, in the paper experiments were made with single tooth cutter. Cutting tests demonstrate that the predictive model of the cutting force components has good correlation to the cutting conditions and actual tool flank wear.

In the mathematical model was taken width of flank wear land VB as the most important tool wear parameter which is the easiest to measure.

In the paper the artificial neural network and 3 factorial experimental design for cutting force relationships determination was used. Based on the investigation cutting force is a function of cutting conditions and cutting time:

$$F_i = f_1(s_z, a, t) \quad (4)$$

Any of tool wear parameter is function of cutting conditions and cutting time

$$W_i = f_2(s_z, a, t) \quad (5)$$

When from equation (4) cutting time is put in equation (5) relationships for cutting force components versus cutting conditions and chosen parameter of tool wear can be predicted

$$F_i = f_3(s_z, a, W_i) \quad (6)$$

In the paper relationships for cutting force components were predicted in the form:

$$F_i = C_i \cdot s_z^{x_i} \cdot a^{y_i} \cdot VB^{z_i} \quad (7)$$

Face milling process particularity like multi tooth that simultaneously cutting and difference in chip cross section that one tooth cut influenced development of

variety of models for cutting force calculation. Variation in chip cross section gives difference in intensity of cutting forces and thermal load of single tooth.

3. EXPERIMENTAL APPROACH

For measurement of cutting force components, tool wear parameters, measuring were arranged. Cutting forces were sensed using the Kistler 3-axes piezoelectric force dynamometer (type 9257A). The dynamometer signals are then processed to make them suitable for computer capture. This is achieved via charge amplifier and an analogue to digital (A/D) converter. The output electric charges (in pC) delivered from the measuring platform are converted by Kistler multi-channel charge amplifier (type 5001) into proportional voltages. Simultaneously, data acquisition and A/D conversion depend on ED 428 card. The ED 428 multifunction board can be used for analogue input, analogue output, and digital input/output and counting applications. It has 16 single-ended or 8 differential analogue input channels and provides analogue input gains of 1, 10 or 100. The board has jumper-selectable input ranges of $\pm 5V$, $\pm 10V$, 0-5V and 0-10V. Measurement was supported by computer and adequate software.

Work material was steel C 1730 (AISI 1060). The bar of this steel ($100 \times 120 \times 600$ mm³) was fixed on two Kistler piezoelectric platforms for measuring cutting force components in three directions as it is shown in Fig. 1. Cutting tests were performed on a 14-kW vertical milling machine without coolant. A face milling cutter of 125 mm diameter, with the cemented carbide P 25 inserts SPAN 12 03 ER with 8-th tooth positions was used, but cutting tests were performed with a single tooth.

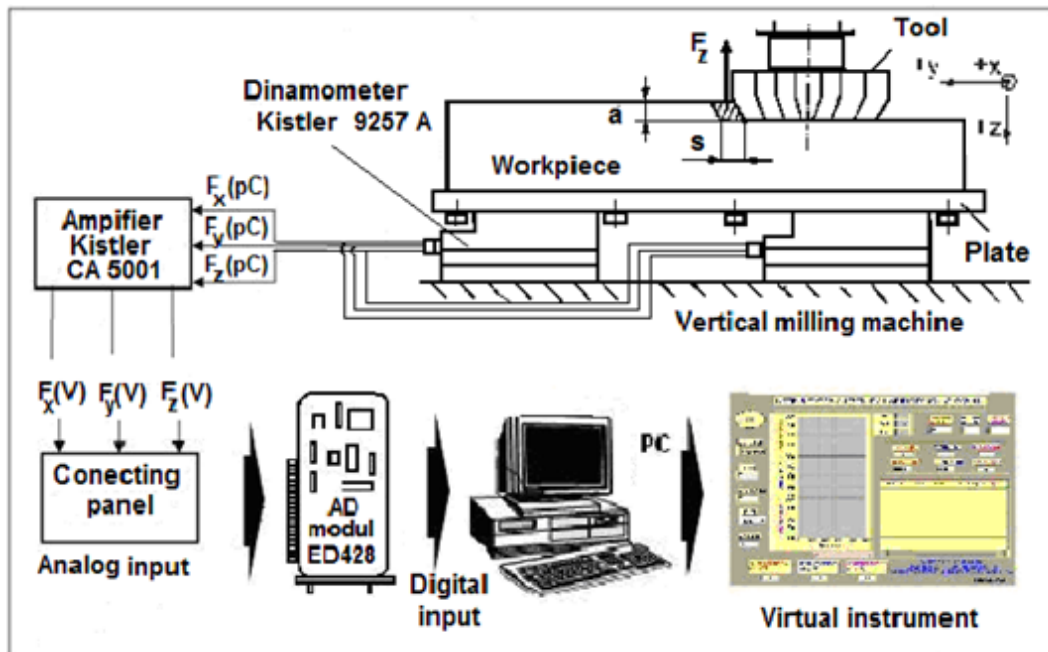


Fig. 1 Experimental arrangement

The cutting tool wear parameters were measured on a tool microscope when cutting was interrupted. The measured values of cutting forces and tool wear

parameters were finally stored and processed by the PC. All functional relationships and graphs were made processing the data by appropriate software.

The experiment was carried out for different combinations of feed (s_z) per tooth, depth of cut (a) and width of flank wear land WB , according to the 3-factorial planning of experiment [10] and artificial neural network methodology [13]. The width of cut was $B=100$ mm and with central position of cutting tool refer to the workpiece.

3.1 Neural network methodology

The basic architecture of a Neural Network typically consists of an input function, which can take the form of binary, continuous or normalized data: a processing architecture which consists of transfer function description, summation function, and relative learning strategy: a method for identifying and learning from past errors in estimates: and finally a mechanism for feeding error corrections back into the network [14]. Figure 2 shows the schedule of data that is used for network training, validation or test data.

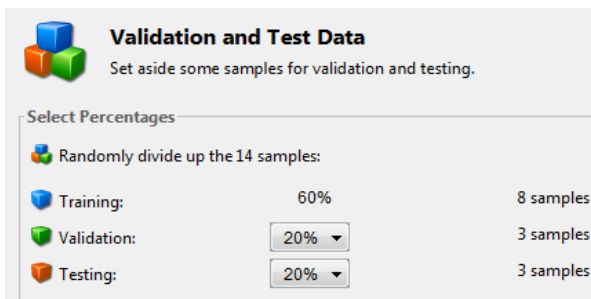


Fig. 2. Percentage distribution of data in the creation of a neural network

A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (*fitnet*), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer.

The network are trained with Levenberg-Marquardt backpropagation algorithm (*trainlm*), unless there is not enough memory, in which case scaled conjugate

gradient backpropagation (*trainscg*) will be used.

Elected as Levenberg-Marquardt, back propagation networks. This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

The architecture of the designed network comprises three inputs parameter and three output parameter at a time, and a single hidden layer of six neurons. With the help of back propagation training data set (Input parameter related to output parameters) is set to utilize to train the neural network. Three input parameter and three output parameter are considered. The selected input parameters should be easily variable and can be easily changed by the operator, Figure 3.

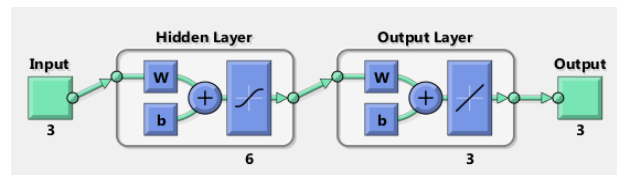


Fig. 3. The window created by a neural network

4. EXPERIMENTAL RESULTS AND DISCUSSION

The results of the experimental investigation are presented in a graphical form. In Fig. 4 to 6 cutting force components F_x , F_y and F_z width of flank wear land VB , depth of crater wear KT and width of crater KB versus cutting time, for selected cutting conditions are presented.

Cutting forces components in investigated range change due to varying cutting conditions and on-going wear of cutting tool. From the graphs can be seen that cutting force components increase versus the cutting time and/or tool wear and this time progress is similar like tool wear curves.

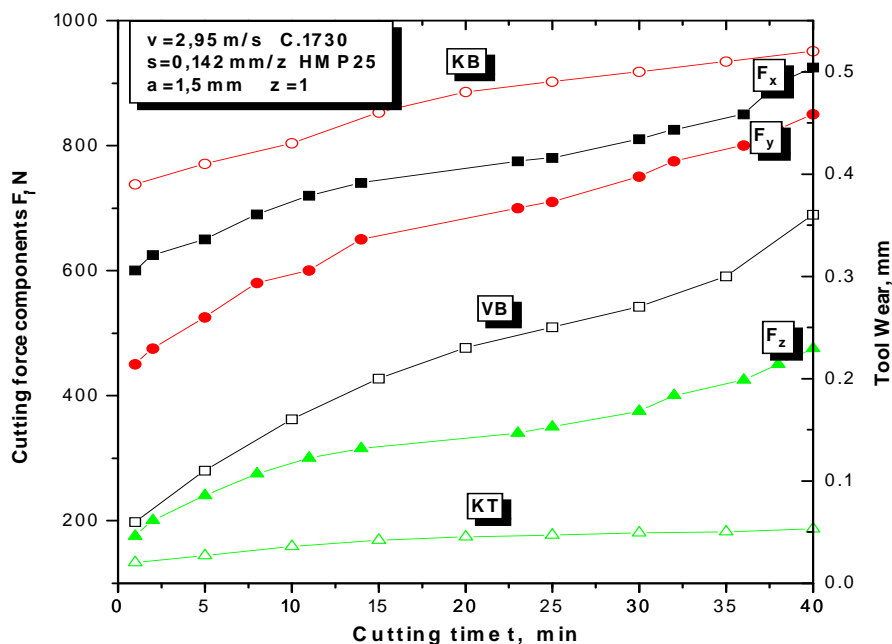


Fig. 4. Cutting force components and parameters of tool wear versus time

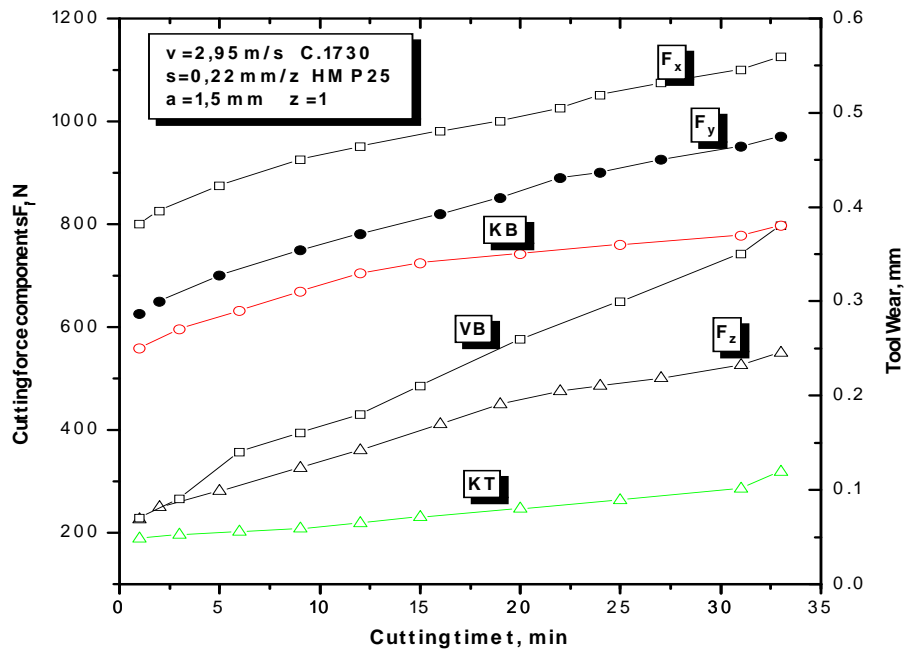


Fig. 5. Cutting force components and parameters of tool wear versus time

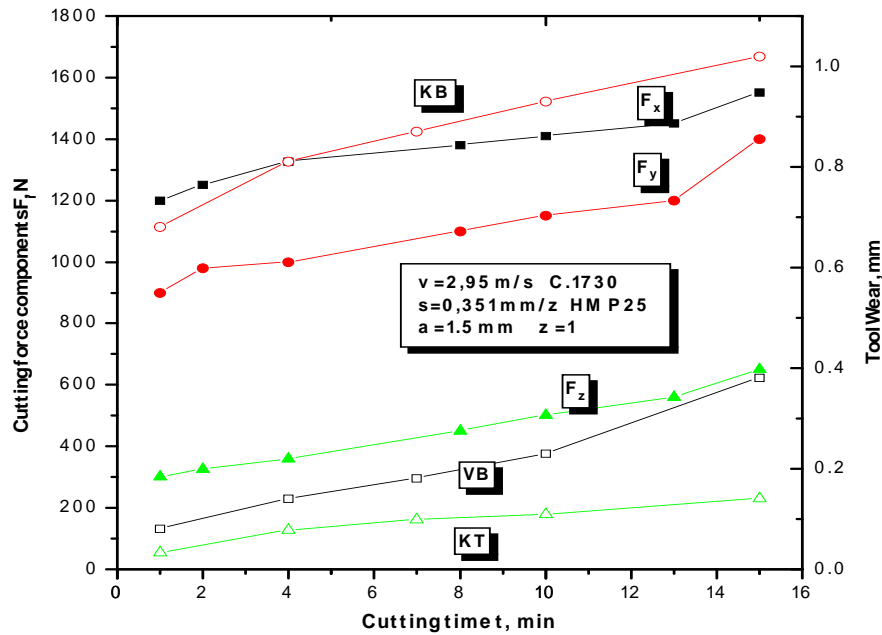


Fig. 6. Cutting force components and parameters of tool wear versus time

The time progression of the investigated cutting force components can be divided into three distinctive stages. The first is initial stage during which a very rapid increase occurs. The second or normal stage occurs generally vary at a constant tool wear rate. The final stage of time progression often happens rapidly with a greater possibility of tool failure

The effect of feed per tooth can be seen in Fig. 7. It can be noticed that when feed increases, tool life decreases until cutting force components increase.

The effect of the depth of cut can be seen in Fig. 8. When the depth of cut during cutting increase cutting force components significantly increase.

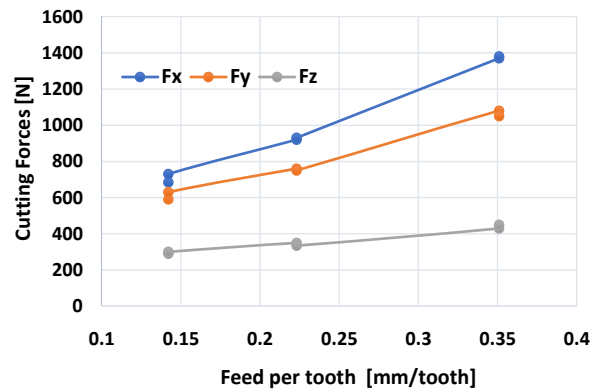


Fig. 7. Cutting forces versus feed per tooth

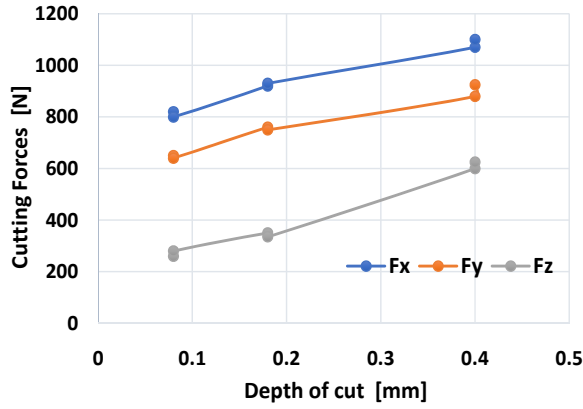


Fig. 8. Cutting forces versus depth of cut

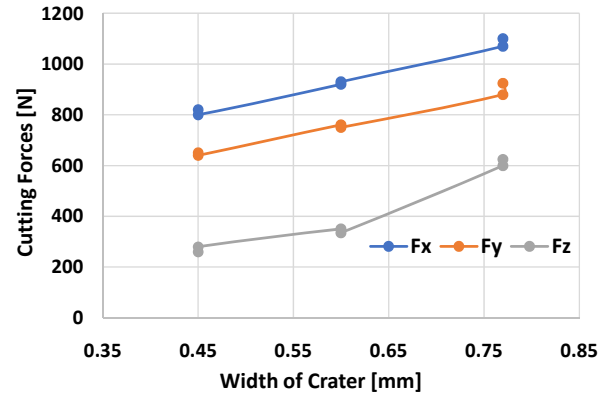


Fig. 10. Cutting forces versus width of crater

The effect of width of flank wear land on components of cutting force is visible on Figure 9. The effect of width of crater wear on components of cutting force is visible on Figure 10. The effect of width of crater depth wear on components of cutting force is visible on Figure 11.

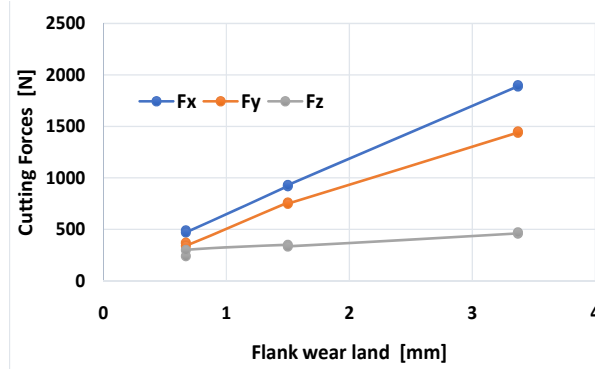


Fig. 9. Cutting forces versus width of flank wear land

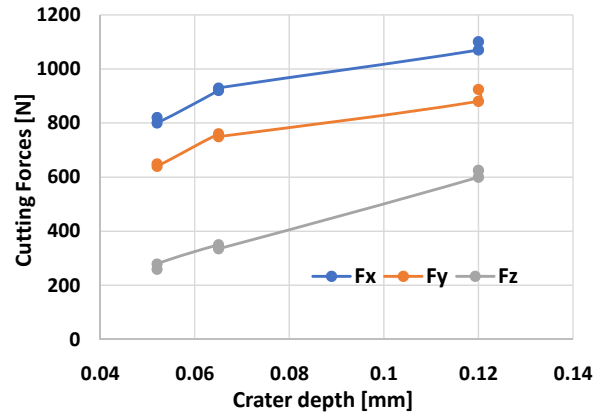


Fig. 11. Cutting forces versus crater depth

In Table 1. for different cutting conditions (constant cutting speed $v=2.95$ m/sec) according factorial experimental plan and the cutting force components (measured and estimated values and NN), and width of flank wear land are shown.

In Table 2. constants in cutting force components models with feed, depth of cut and width of flank wear land VB are shown.

$$F_i = C s^x a^y VB^z \quad (10)$$

	C	x	y	z
F _x	2701.77	0.735	0.847	0.182
F _y	1923.20	0.616	0.870	0.208
F _z	1511.56	0.442	0.340	0.509

Table 2. Constants in cutting force models with speed, depth of cut and VB

No.	Feed s mm/tool	Depth a mm	Wear VB mm	Measured, N			Estimated, N			Neural network, N		
				F _x	F _y	F _z	F _x	F _y	F _z	F _x	F _y	F _z
1	0.142	1.5	0.18	685	590	290	664	575	305	691.4	585.9	291.8
2	0.351	1.5	0.18	1370	1080	430	1291	1003	456	1387.7	1065.7	440.2
3	0.223	0.67	0.18	490	370	240	467	376	284	378.7	392.8	326.6
4	0.223	3.37	0.18	1890	1440	460	1837	1535	492	1895.5	1484.9	478.8
5	0.223	1.5	0.08	820	650	260	798	540	247	739.6	577.4	268.6
6	0.223	1.5	0.40	1070	880	600	1069	897	561	1075.3	877.0	604.1
7	0.223	1.5	0.18	920	760	350	925	760	373	928.3	756.5	349.1
8	0.145	1.55	0.185	730	630	300	664	575	305	699.6	574.5	296.7
9	0.355	1.55	0.185	1380	1050	450	1291	1003	456	1393.3	1042.1	446.7
10	0.228	0.69	0.185	475	340	300	467	376	284	409.2	413.0	327.5
11	0.228	3.3	0.185	1900	1450	470	1837	1535	492	1900.4	1449.9	470.7
12	0.228	1.55	0.085	800	640	280	798	540	247	812.7	642.5	279.9
13	0.228	1.55	0.405	1100	925	625	1069	897	561	1104.5	926.1	621.1
14	0.228	1.55	0.185	930	750	335	925	760	373	1010.9	817.8	372.0

Table 1. Cutting conditions, width of flank wear land and cutting forces measured and estimated and NN model values

The sensors for adaptive control of milling process can be developed based on these relationships' equations (8), (9) what agree with [1, 8].

The regression plot of the ANN for cutting force is shown in figure 12. The regression plots display the network outputs with respect to targets for training. From this plot, the value of the regression coefficient is found to be more than 99.9% which strongly justifies the acceptability in the prediction capability of the models. In case of the dry ANN model, the regression coefficient has a higher value; hence, it can be concluded that this model is accurate.

Figure 12 shows graphic coefficients of regression for training, test and validation data.

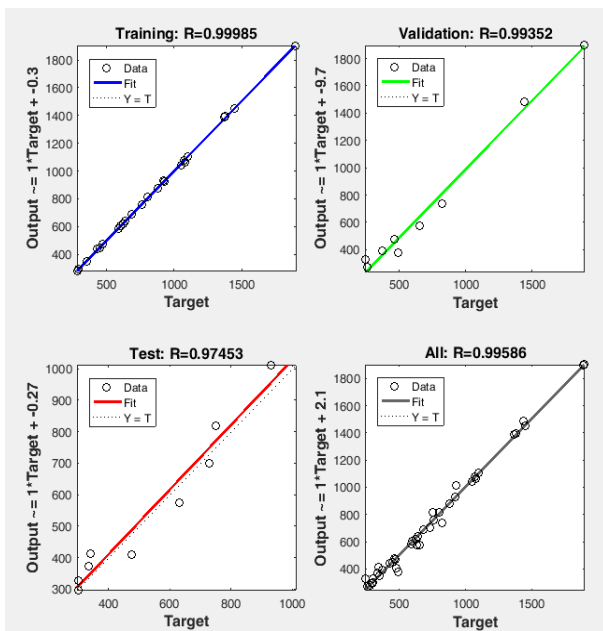


Fig. 12. Coefficient of Regression (plot regression)

5. CONCLUSIONS

Based on upper presented next conclusion can be drawn:

- Time progression of the cutting force components is similar to the time progression of tool wear.
- Strong correlation relationships for the cutting force components versus cutting conditions and the width of flank wear land VB are determined during dry milling.
- Investigated cutting force components relationships can be used for indirect tool wear monitoring.

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