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Examination and Modelling of the Influence of Cutting Parameters on the Cutting Force and the Surface Roughness in Longitudinal Turning

Dražen Bajić[1] - Branimir Lela[1] - Goran Cukor[2]
[1]University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, Croatia
[2]University of Rijeka, Faculty of Engineering, Croatia

This paper examines the influence of three cutting parameters on the surface roughness and the cutting force components in longitudinal turning. The cutting speed, the feed rate and the depth of cut have been taken as influential factors. Two modelling methodologies, namely regression analysis and neural networks, have been applied to experimentally determined data. Also, for both methodologies the ability of interpolation and extrapolation has been tested. Results obtained by neural network models have been compared to those obtained by regression models. Both methodologies give nearly similar results when interpolation is observed. However, regarding extrapolation neural network models give better results. In order to find the optimum values of the cutting parameters an optimization has been carried out.

Keywords: longitudinal turning, cutting forces, surface roughness, neural networks

0 INTRODUCTION

Chip-forming machining is a multi-disciplinary scientific area based on the theory of plasticity, thermodynamics, tribology and material science. Parameters that influence the machining process can be divided into two categories:
- physical phenomena during cutting, related to influence of material structure, chip compression ratio, appearance of friction, heat development, cutting angles, etc.,
- technique of machining along with the belonging cutting parameters (cutting speed, depth of cut and feed rate), cutting force, power, etc.

Complex technological and manufacturing processes nowadays demand implementation of sophisticated mathematical and other methods for the purpose of their efficient control. Therefore a research is needed to obtain the mathematical approximations of machining processes and appearing phenomena as better as possible. Understanding the machining principles and mathematical relations among influential parameters is an important prerequisite for:
- machine tool designing that corresponds to manufacturing optimum,
- achieving product quality besides the ever-growing demands in respect to the accurate production and quality of surface roughness,
- machine tool play an important role in the design of manufacturing processes, not only in fulfilment the demands for higher productivity, but also in the requirements for production economy.

The goal of this paper is to obtain a mathematical model that relates the cutting force components and the surface roughness with the cutting parameters in longitudinal turning. In this search two different approaches have been used in order to get the mathematical models. The first approach is a design of experiment (DOE) together with an analysis of variance (ANOVA) and regression analysis. The second approach is modelling by means of artificial neural networks (ANNs). In the past, the DOE approach has been used to quantify the impact of various machining parameters on various output parameters at turning [1] to [7]. But in the last decade neural networks have experienced real prosperity in their application to various complex problems in different engineering fields. A review of scientific researches dealing with the application of ANNs to turning process can be found in [1]. It has been reported that ANNs have

*Corr. Author's Address: University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, Ruđera Boškovića bb, HR-21000 Split, Croatia, dbajic@fesb.hr

ability for mapping very complex and nonlinear systems. Turning process is an example of such a system and that justifies the usage of ANNs.

1 THE SCOPE OF THE RESEARCH

It is estimated that of all machining processes about 40% pertain to turning. Turning is the most common way for processing rotational (symmetrical or non-symmetrical, round or non-round) surfaces with single-point cutting tool. Cutting force is the basic indicator of cutting process behaviour. Having knowledge of the cutting force it is possible to:

- calculate the necessary power for carrying out appropriate operation, i.e. choose appropriate drive motor,
- calculate systems of all main and auxiliary transmission mechanisms from motor to tool,
- calculate and design the elements and parts of machine tools,
- define the dimensions of auxiliary devices,
- choose dimensions and types of cutting tool and verify the stability of tool in entirety,
- determine cutting parameters and conditions in the design of economical variants of technological machining process,
- perform the calculation of accuracy and the ability of machining of a workpiece at an appropriate machine tool, cutting parameters and conditions.

On the basis of knowledge of the cutting force function, the rational construction and economical efficiency of production systems, the optimization of machining process and the development of particular concepts for adaptively controlled manufacturing systems are ensured.

Surface of a workpiece can be obtained with various machining processes and various machining parameters and the roughness depends on it. Surface roughness is one of the most important criteria for the quality of machine parts and products. As the competition grows and customers have the increased demands for quality, the surface roughness becomes one of the most important disciplines in market competition. Optimally smooth surface is needed at seat surface where a certain machine parts are permanently or periodically joined with other parts (pistons and cylinders, bearings and trunks, slide guides, couplings, etc.), and at parts where the surface loading is pronounced. For the first it is endeavoured to reduce the friction between parts and for the latter the appearance of notch effect that reduces the strength of dynamically loaded machine parts is avoided. Optimum surface quality is therefore needed due to the improvement of tribological properties, driving strength, resistance to corrosion and aesthetic appearance of products. The excessive surface quality requires considerably higher machining costs. This has to be taken into account when the optimally needful surface quality of machined parts is determined and therefore certain machining processes should be used when there is a valid reason. The accurate estimation of machined surface roughness has been brought into the focus of research for many scientists during a few decades.

2 INFLUENTIAL FACTORS ON CUTTING FORCE AND MACHINED SURFACE ROUGHNESS

2.1 Influential Factors on the Cutting Force

Figure 1 shows cutting force components during the longitudinal turning. The resultant force (cutting force) F_R can be decomposed into:

- tangential component of cutting force, F_c,
- feed component of cutting force, F_f,
- radial component of cutting force, F_p.

Expression for the resultant force is:

$$F_R = \sqrt{\left(F_c^{\,2} + F_f^{\,2} + F_p^{\,2}\right)} \quad (1).$$

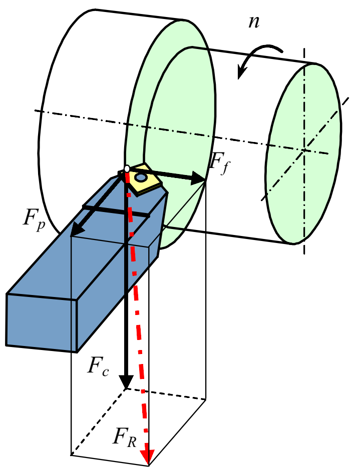


Fig. 1. *Cutting force components in the longitudinal turning process*

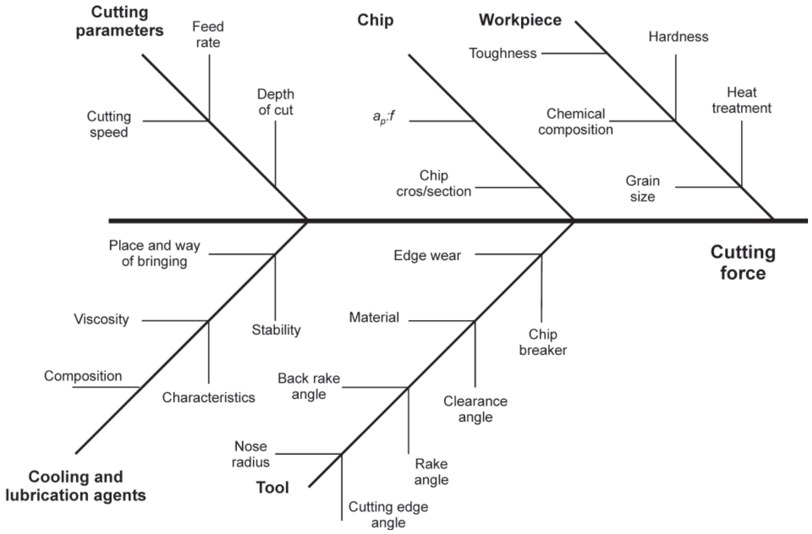


Fig. 2. *Fishbone diagram with the factors that influence the cutting force*

The tangential force component F_c always acts in the direction of cutting speed vector, the feed force component F_f is opposite to the feed rate and the radial force component F_p is perpendicular to these two force components.

The cutting force depends on:

- workpiece: hardness, toughness, heat treatment,
- tool: geometry (clearance angle α, rake angle γ, back rake angle λ, cutting edge angle κ, cutting tool nose radius r_ε), wear and chip breaker,
- size and shape of chip section,
- cutting parameters: speed v_c, dept of cut a_p, feed f,
- cooling and lubrication.

Figure 2 shows fishbone diagram with influential factors on the cutting force.

The values of feed rate and depth of cut define the undeformed chip cross-section. The larger chip cross-section follows the higher cutting force. The research [8] has shown that the cutting force is not increased proportionally with the increase of chip cross-section. The cause for that phenomenon is that lesser compression gives higher chip cross-sectional area.

Apart from the chip cross-section, considerable influence has the depth of cut to the feed rate ratio. The cross-section with the higher ratio gives the larger tangential component of the cutting force.

In the turning of steel it is observed that with the increase of cutting speed up to 0.83 m/s the cutting force rises a little and afterwards decreases. This phenomenon depends not only on the cutting force but also on the rake angle γ. With the further increase of cutting speed up to the value of 3.3 m/s the cutting force experiences decrement. The cutting speed values within interval 3.3 to 8.3 m/s almost have no influence on the cutting force [8]. These results are obtained for f = 0.74 mm/rev and a_p = 2 mm.

2.2 Influential Factors on the Surface Roughness

There are a great number of factors influencing the surface roughness. The most important of them are:

- machining parameters,
- build-up edge,
- tool geometry,
- machining time,
- tool and workpiece material,
- tool wear,
- dynamic behaviour of machining system,
- application of cooling and lubrication agent.

Fig. 3 shows influential factors on the machined surface roughness.

The influence of cutting speed is closely related to emergence of build-up edge (BUE) and that implies its effect on machined surface roughness. At lower cutting speed (within interval 0.16 and 0.6 m/s) the generation of BUE results with grater surface roughness. Increasing the cutting speed the influence of BUE is reduced and that entails the reduction of surface roughness. But exaggeration in the increase of cutting speed does

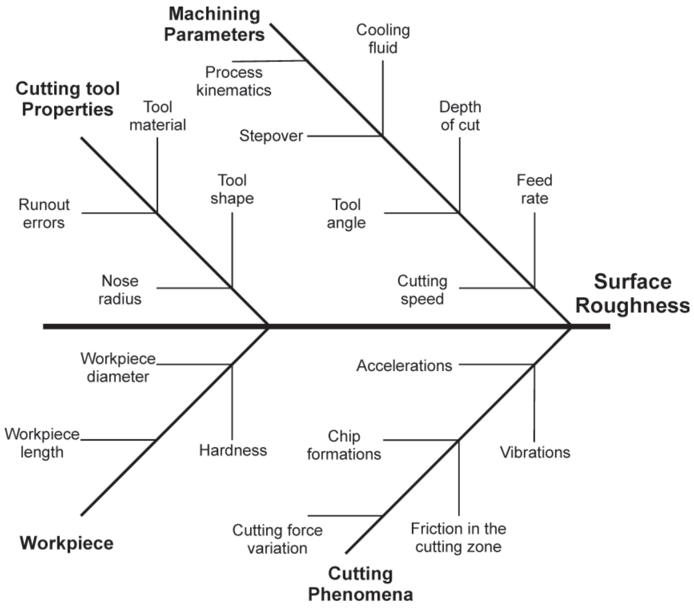


Fig. 3. *Fishbone diagram with the factors that affect the surface roughness* [9]

not influence the further reduction of surface roughness because tool wear is simultaneously increased and it keeps roughness nearly constant. Feed rate influence is directly proportional to surface roughness with the power of two. Larger feed rate causes higher machined surface roughness. The influence of feed rate is closely related to cutting tool nose radius. The reduction of feed even if its value is very small, does not result with the further reduction of surface roughness. At some boundary feed rate, which depends on cutting tool nose radius, roughness remains approximately constant at minimum possible level. Cutting tool nose radius influences surface roughness inversely proportionally, i.e. its increment causes the reduction of surface roughness. This reduction of roughness is also limited with some minimum value because the further increase of cutting tool nose radius causes vibrations that influence negatively on surface roughness. From a geometrical point of view, the depth of cut does not influence surface roughness because it has no influence on size and form of bumps. On the other hand, the depth of cut has the influence indirectly through the BUE generation, deformation of separated chips, cutting temperature, cutting force, vibrations, etc. [10].

3 DESIGN OF EXPERIMENTS

The planning of experiment means, on the basis of present cognition from the literature, experience or expected aim, beforehand prediction of all influential factors and actions that will result with new cognitions utilizing the rational researches. The experiments have been carried out using the factorial design of experiment. The turning is characterized with many factors, which directly or interconnected act on the course and outcome of an experiment. It is necessary to manage experiment with the statistical multifactor method due to statistical character of a machining process. In this search the design of experiment was achieved using the rotatory central composite design (RCCD). In the experimental research, modelling and adaptive control of multifactor processes the RCCD of experiment is very often used because it offers optimization possibility [11]. The aim of this search is to find mathematical models that describe the dependence of machined surface roughness and cutting force components on three cutting parameters:

- the cutting speed, v_c,
- the feed rate, f,
- the depth of cut, a_p.

The basis of the multifactor design of experiment can be visualized in the form of "black box". Figure 4 shows a "black box" for the longitudinal turning.

RCCD models the response using the empirical second-order polynomial:

$$y = b_0 + \sum_{i=0}^{k} b_i \cdot X_i + \sum_{1 \le i \lhd j}^{k} b_{ij} \cdot X_i \cdot X_j + \sum_{i=1}^{k} b_{ii} \cdot X_i^2 \quad (2),$$

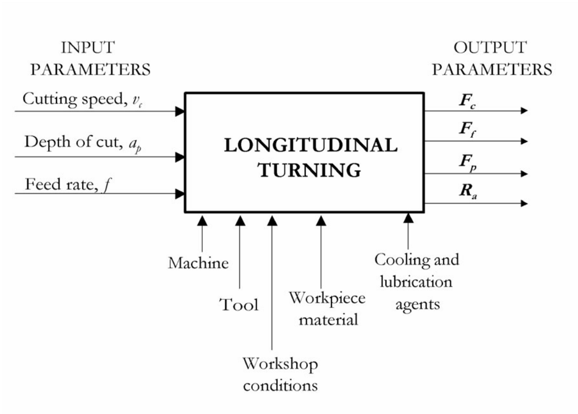


Fig. 4. *Form of "black box" for longitudinal turning*

where:
- b_0, b_i, b_{ij}, b_{ii} are the regression coefficients,
- X_i are the coded values of input parameters.

In order to determine the required number of experimental points for RCCD the following expression is used:

$$N = 2^k + 2k + n_0 = n_k + n_\alpha + n_0 \quad (3),$$

where:
- k is the number of parameters,
- n_0 is the repeated design number of the average level,
- n_α is the design number on the central axes.

RCCD of experiment demands 8 experiments (3 factors on two levels, 2^3), 6 experiments on the central axes and 6 experiments on the average level, what makes total of 20 experiments.

Adding the points to the central axes where $x_i = \pm\,\alpha_\alpha$, and $\alpha_\alpha = 1.682$, the 3-factorial RCCD of experiment is obtained. The minimum and maximum values of chosen cutting parameters as well as the coded input factors are presented in Table 1.

4 NEURAL NETWORK MODELING

Artificial neural networks grew out of attempts to mimic the ability of biological nervous system to learn from the environment. Biological nervous systems perform extremely complex tasks using a very large number of simple processing units (called neurons) and their numerous interconnections. Similar structure uses ANN. The units in an ANN are arranged in a layered feed forward topology. Artificial neuron receives numerous inputs (either from original data, or from the output of other neurons in the neural network). Each input comes via a connection that has strength (or *weight*). Each neuron also has a threshold value that is subtracted from the calculated weighted sum of the inputs. In this way the activation signal of the neuron is obtained. The activation signal is passed through an activation function (also called transfer function) in order to produce the output of the neuron. If the number of layers and the number of units in each layer are sufficiently large, multilayer perception (the most popular architecture) can model functions of arbitrary complexity [12] to [15]. For both systems (biological and artificial) the learning process is achieving by altering the "strength" of synaptic connections (weights). ANN learns the relationship between input and output through training. In supervised learning a set of training data needs to be collected. The training data contains examples of input/output pairs. Once the number of layers, and number of units in each layer, has been selected, the weights and thresholds of network must be adjusted, using one of the training algorithms, so as to minimize the prediction error made by the network. The error of the network is determined by comparing the outputs of the network with the targets and then calculating an error function. The most common error function is the sum-squared error, where the individual errors of output units on each training pair are squared and summed together [14]. The network error is used to adjust the weights, and then the process repeats. The learning algorithm progresses through a number

Table 1. *Physical values and coded indexes of input factors*

Input factors	**Coded values of input parameters**				
	$x_{-i\alpha}$	$x_{-i,\min}$	x_{-i0}	$x_{i,\max}$	$x_{+i\alpha}$
	-1.682	-1	0	+1	+1.682
$x_1 = v_c$, m/min	115.9	150	200	250	284.1
$x_2 = a_p$, mm	0.4	0.6	0.9	1.2	1.4
$x_3 = f$, mm/rev	0.12	0.16	0.22	0.28	0.32

of epochs. The training process stops when a given number of epochs is exceeded, or when the error reaches a desirable value, or when the error stops improving. The most desirable property of a network is its ability to generalize to new (unseen) cases. A network with more weights models a more complex function, and is therefore prone to over-fitting. A network with fewer weights may not be sufficiently powerful to model the underlying function [12], [13] and [15].

In order to mathematically model the influence of cutting parameters on the cutting force components and the surface roughness a three layer feed-forward ANN has been chosen. In accordance with the aim of this research the chosen ANN model had three neurons in the input layer, twenty neurons in the hidden layer and one neuron in the output layer (Fig. 5).

The same network architecture has been used for modelling the each of four physical relations separately. Namely, in this way the three cutting parameters (cutting speed, depth of cut and feed) are related with the tangential component of cutting force, feed component of cutting force, radial component of cutting force and surface roughness. The network models are named as follows:

- Model 1 - relates cutting parameters and tangential component of cutting force,
- Model 2 - relates cutting parameters and feed component of cutting force,
- Model 3 - relates cutting parameters and radial component of cutting force,
- Model 4 - relates cutting parameters and surface roughness.

In the hidden and output layer sigmoid and linear activation function has been used, respectively. The resilient back-propagation (Rprop) learning algorithm [16] and [17], with supervised learning mechanism, was used for all models. During the training, the initial weight change value for Rprop learning algorithm was taken 0.07 for all models. Before training, input and output variables were normalized within the range of –0.9 and 0.9. In order to avoid over-fitting or under-fitting the weight decay regularization [18] have been applied to all models. The choice of appropriate values for the regularization parameter is essential since it determines the degree of fitting. The leave-one-out cross-validation procedure was used to estimate the regularization parameter of all models. Data set for training and testing the network consisted of 22 data pairs for each of the models. The 15 data pairs were taken from the conducted design of experiment and 7 additional data pairs were measured separately. Out of the data set 4 data pairs were selected randomly and the testing data set was obtained. Training data set consisted of 18 training pairs. After the training, all models were tested to their generalization ability. Testing was performed with the testing data that had not been used in the training process. Results of training and testing, in the form of regression analysis, for Model 1 are shown in Figure 6.

R is a measure of agreement between the outputs and targets. The aim is to get R-value very close or equal to 1. In the example on Figure 6, R-values are very close to 1 and that indicates very good fit. For the other models the R-values are 0.98 or higher for both training and testing. In order to conduct the training, testing and simulation of the neural network models, a neural network toolbox embedded in MATLAB [19] was used.

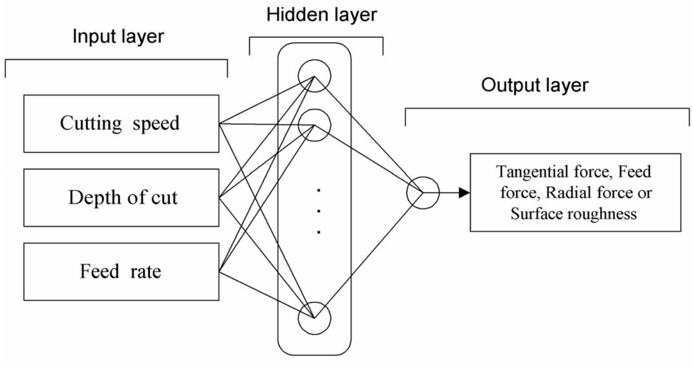
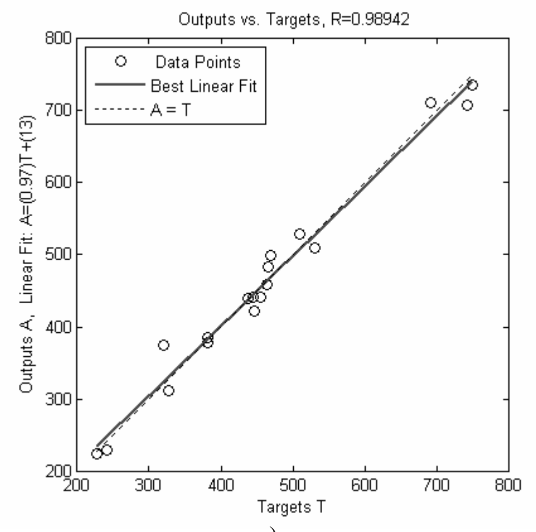
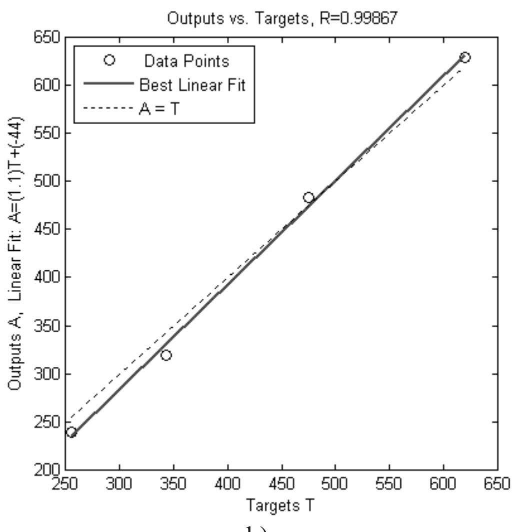


Fig. 5. *Neural network model*



a)



b)

Fig. 6. Result of training (a) and testing for generalization ability (b) of Model 1

5 EXPERIMENT PERFORMANCE

The experiments for measuring the cutting force components and surface roughness were carried out on the universal lathe "Prvomajska" D-420/1500. The cutting force components were measured utilizing force transducer KISTLER (Type: 9257 A) produced in Winterthur Switzerland. The roughness measurements were performed with the "SURTRONIC 3+" instrument, produced by Rank Taylor Hobson. Before the measurements had been carried out all the measuring instruments were calibrated. The longitudinal turning experiments were performed by a tool for the external machining. The tool has been composed of the tool holder PTGNR2020K16 and the cutting insert TNMG160408–PF4015, produced by SANDVIK Coromant. The material of workpiece was carbon steel Ck45. The workpiece was in a form of axle with bored centering holes. On the lathe the workpiece was prepared in order to remove rust, grooves and all damages from the surface and to obtain the workpiece with wanted dimensions. All experiments were carried out without the cooling and lubrication agents.

Altogether 33 experiments were conducted. Twenty experiments were conducted in order to allow performing ANOVA and regression analysis, and additional 13 experiments to obtain additional data for neural network training and verification of modelling.

6 RESULTS OF BOTH STATISTICAL ANALYSIS AND NEURAL NETWORKS SIMULATION

The twenty measured values of cutting force components and surface roughness, (Table 2), are input data for the second-order regression models and ANOVA. The ANOVA and regression analysis have been carried out using program package "Design Expert 6". The ANOVA has shown which factors and interactions had an important influence on the cutting force components and the surface roughness.

Applying the regression analysis the coefficients of regression, multi-regression factors, standard false evaluation and the value of *t*-test have been determined. After omitting insignificant factors and interactions the mathematical models for the tangential component of cutting force, feed component of cutting force, radial component of cutting force and surface roughness are obtained as follows:

Tangential component of cutting force:

$$\begin{gathered} F_c = -144.76 + 0.595 \cdot v_c + 198.91 \cdot a_p + \\ +559.714 \cdot f - 2.526 \cdot v_c \cdot f + 366.041 \cdot a_p \cdot f \end{gathered} \quad (4).$$

Feed component of cutting force:

$$\begin{gathered} F_f = 353.15 - 0.808 \cdot v_c - 180.064 \cdot a_p - \\ - 817.523 \cdot f + 152.182 \cdot a_p^2 + 3047.996 \cdot f^2 \end{gathered} \quad (5).$$

Radial component of cutting force:

Table 2. *Experimental data*

Exp. number	v_c (m/min)	a_p (mm)	f (mm/rev)	F_c (N)	F_f (N)	F_p (N)	Ra (µm)
1	284.1	0.90	0.224	456	175	155	2.23
2	250	0.60	0.160	242	94	120	1.81
3	250	1.20	0.280	743	260	230	3.65
4	250	1.20	0.160	466	210	170	1.96
5	250	0.60	0.280	382	126	178	3.13
6	200	0.90	0.125	327	162	145	1.43
7	200	0.40	0.224	227	78	163	2.39
8	200	1.40	0.224	692	300	234	2.44
9	200	0.90	0.315	620	209	225	4.43
10	200	0.90	0.224	464	184	165	2.38
11	200	0.90	0.224	459	181	160	2.34
12	200	0.90	0.224	465	185	168	2.41
13	200	0.90	0.224	468	188	162	2.40
14	200	0.90	0.224	466	182	164	2.39
15	200	0.90	0.224	460	180	169	2.36
16	150	1.20	0.280	750	320	250	3.60
17	150	0.60	0.160	255	105	150	1.65
18	150	0.60	0.280	447	160	218	3.44
19	150	1.20	0.160	470	230	208	1.71
20	115.9	0.90	0.224	475	193	178	2.39

$$F_p = 17.237 - 0.184 \cdot v_c + 2.599 \cdot a_p + 769.93 \cdot f + 1560.196 \cdot a_p \cdot f \quad (6).$$

Surface roughness:

$$Ra = 2.67 - 1.81 \cdot a_p - 14.875 \cdot f + 73.662 \cdot f^2 - 0.0285 \cdot v_c \cdot f \quad (7).$$

The squares of regression coefficient (r^2) for F_c, F_f, F_p and Ra are 0.9827, 0.978, 0.9935 and 0.993 respectively.

Table 3 shows 13 additional measured experimental data. Data marked with asterisk (*) were not used either in the network training or in the regression analysis. These data were utilized for the validation of both regression analysis and ANN modelling.

Table 4 shows the values of cutting force components and surface roughness obtained from the both type of modelling, i.e. from the regression

Table 3. *Additional measured experimental data*

Exp. number	v_c (m/min)	a_p (mm)	f (mm/rev)	F_c (N)	F_f (N)	F_p (N)	Ra (µm)
21*	300	1.60	0.400	1105	392	425	5.80
22*	280	0.50	0.315	355	95	201	3.97
23	240	0.70	0.200	343	123	128	2.04
24	230	1.10	0.160	445	200	160	1.63
25*	225	1.00	0.250	555	207	190	2.90
26	220	0.85	0.280	510	194	198	3.43
27	210	0.65	0.250	320	120	185	2.63
28*	190	1.00	0.280	610	230	216	3.48
29	170	0.80	0.200	381	161	173	2.05
30	160	1.00	0.180	438	204	170	1.82
31*	150	0.70	0.180	325	130	160	1.80
32	140	1.30	0.140	530	250	205	1.45
33*	100	0.30	0.125	117	29	110	1.60

Table 4. *Values obtained by regression analysis and neural network models*

Exp. numb.	Regression				Neural network			
	F_c (N)	F_f (N)	F_p (N)	Ra (µm)	F_c (N)	F_f (N)	F_p (N)	Ra (µm)
21	1272.31	367.04	447.5	7.76	1064.67	399.87	433.77	6.19
22	336.2	91.64	218.53	3.84	369.67	100.02	196.8	3.91
23	333.79	130.22	134.05	2	329.18	112.88	124.91	2
24	434.55	198.12	161.69	1.78	441.88	198.36	162.86	1.77
25	560.81	211.76	181.17	2.83	549.4	213.94	215.04	2.82
26	532.53	188.92	192.28	3.39	529.11	188.47	208.72	3.4
27	385.12	136.47	166.73	2.73	374.59	132.79	172.47	2.7
28	624.43	236.62	209.64	3.51	629.88	235.51	224.3	3.52
29	391.57	160.48	155.61	2.02	377.71	159.32	173.88	2.06
30	434.76	196.57	169.31	1.79	440.09	199.39	182.81	1.84
31	324.89	131.77	153.81	1.81	316.97	135.58	161.39	1.83
32	444.41	239.51	222.44	1.42	510.06	254.3	219.86	1.47
33	143.18	17.78	188.84	1.68	111.22	37.85	125.63	1.58

Table 5. *Relative error for data taken within interval limited with the min and max values of cutting parameters*

Exp. number	Relative error using regression (%)				Relative error using neural network (%)			
	F_c	F_f	F_p	Ra	F_c	F_f	F_p	Ra
25	1.05	2.30	4.65	2.41	1.01	3.35	13.18	2.76
28	2.37	2.88	2.94	0.86	3.26	2.40	3.84	1.15
31	0.03	1.36	3.87	0.56	2.47	4.29	0.87	1.67
Average:	1.15	2.18	3.82	1.28	2.25	3.35	5.96	1.86
	Total average: 2.11 %				Total average: 3.35 %			

Equations (4) to (7) and from the simulation of neural network models.

In order to test which modelling method gives better prediction, a relative error of deviations from measured values have been calculated. In these calculations only experimental data that were not used for modelling either the regression equations or neural network models were utilized.

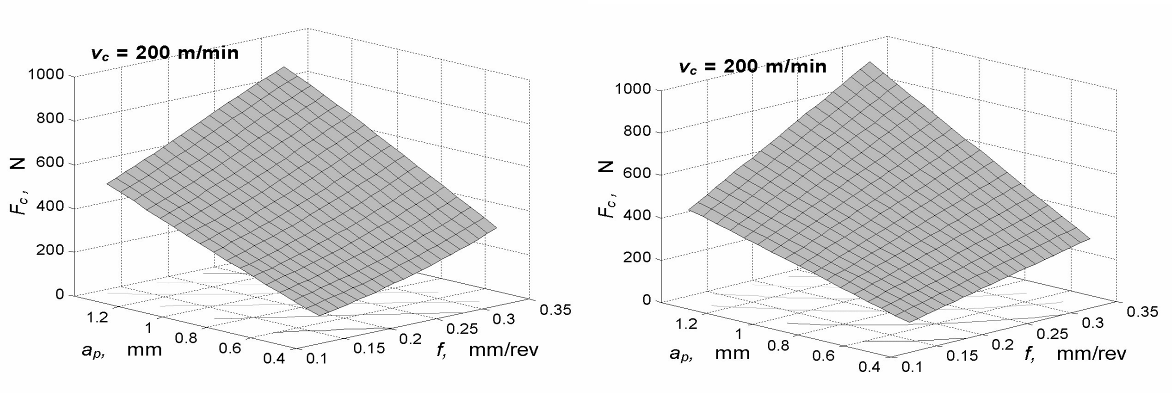
These experimental data have been also divided into two sets. The first data set consists of three randomly chosen experiments (experiments 25, 28 and 31) for which the values of the cutting parameters (Table 4) have been taken from the interval limited with maximum and minimum values (Table 1) used in this study. The second data set consists of randomly chosen experiments 21, 22 and 33 for which the cutting parameters have been taken outside the min/max interval. In this way the both methods of modelling have been tested for the possibility of both interpolation and extrapolation. The reason for choosing the only three experiments in both sets is the costs reduction and the attention to show that with the small number of experiments neural network modelling is able to give similar results as the DOE approach. The results of relative error calculations for the values of the cutting parameters inside and outside the interval are shown in Table 5 and Table 6, respectively.

From the presented results it can be seen that the modelling with regression analysis gives the lesser total average relative error for the data taken within the interval. Although the total error for both modelling is quite low, the regression analysis is able to give somewhat better prediction when the interpolation is considered. It should be noticed that ANN models have learned and tested from only 22 data pairs. This implies that more data pairs would give better results. Regarding the extrapolation, the neural network modelling gives much better results, although the total average relative error is much larger when comparing to the results obtained in the interpolation.

Fig. 7 shows the tangential component of cutting

Table 6. *Relative error for data taken outside the interval limited with the min and max values of cutting parameters*

Exp. number	**Relative error using regression (%)**				**Relative error using neural network (%)**			
	F_c	F_f	F_p	Ra	F_c	F_f	F_p	Ra
21	15.14	6.37	5.29	33.79	3.65	2.01	2.06	6.72
22	5.30	3.54	8.72	3.72	4.13	5.28	2.09	1.51
33	22.38	38.69	71.67	5.00	4.94	30.52	14.21	1.25
Average:	14.27	16.20	28.56	14.02	4.24	12.60	6.12	3.16
	Total average: 18.26 %				Total average: 6.53 %			



a) b)

Fig. 7. *Response surface for tangential component of cutting force as a function of feed rate and depth of cut obtained from neural network (a) and regression analysis (b); for constant cutting speed of 200 m/min*

force as a function of feed rate and depth of cut. The shown results have been obtained from neural network simulation (Fig. 7a) and regression analysis (Fig. 7b) with the constant cutting speed of 200 m/min. Response surfaces on Fig. 7 show that in both cases similar results are obtained. Namely, both modelling predict the minimum value of the tangential component of cutting force when both feed rate and depth of cut are minimized.

Figure 8 shows the results obtained from neural network simulation (Fig. 8a) and regression analysis (Fig. 8b) for the feed component of cutting force and its dependence on feed rate and depth of cut. Again it can be seen that both methods predict that the feed component of cutting force linearly depends on both, feed rate and depth of cut. The minimum value of the feed component of cutting force is achieved at minimum both feed rate and depth of cut.

On Figure 9 it can be seen the response surfaces for radial component of cutting force as a function of feed rate and depth of cut obtained from neural network (Fig. 9a) and regression analysis (Fig. 9b). Cutting speed has been kept constant at 200 m/min. Both modelling methodologies predict similar behaviour of the radial component of cutting force with change in feed rate and depth of cut. Again the minimum value of the radial component of cutting force is achieved when feed rate and depth of cut reach their minimum values.

Figure 10 shows the dependence of surface roughness on feed rate and depth of cut for neural network (Fig. 10a) and regression analysis (Fig. 10b) modelling methodology when cutting speed is constant 200 m/min. Both methodologies give the similar results. They both predict that dept of cut has no at all or has slight influence on the surface roughness. Feed rate has dominant influence on *Ra*. It is evident that the minimum surface roughness is obtained at minimum feed rate.

From the conducted optimization the optimum values of cutting parameters that give the minimum values for the cutting force components and surface roughness were obtained. The optimization was carried out using Genetic algorithm [20] and the results of optimization are presented in Table 7.

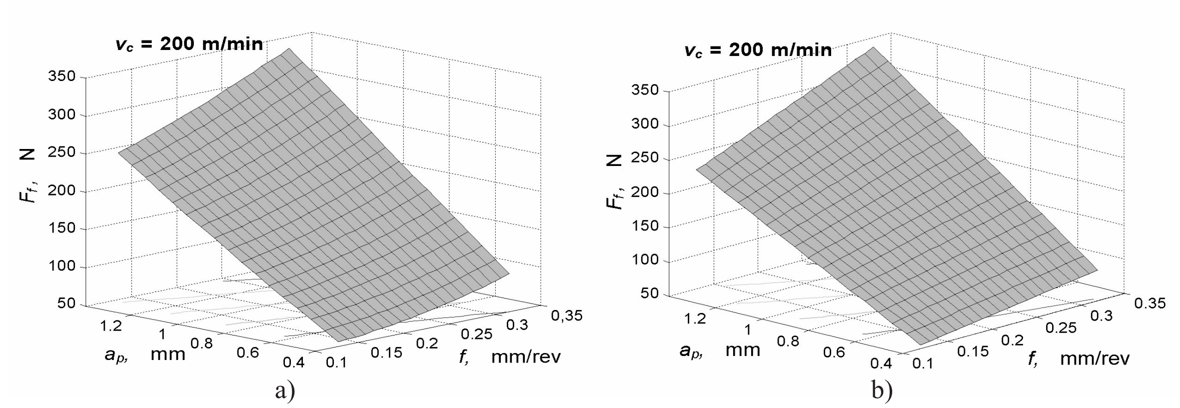


Fig. 8. Response surface for feed component of cutting force as a function of feed rate and depth of cut obtained from neural network (a) and regression analysis (b); for constant cutting speed of 200 m/min

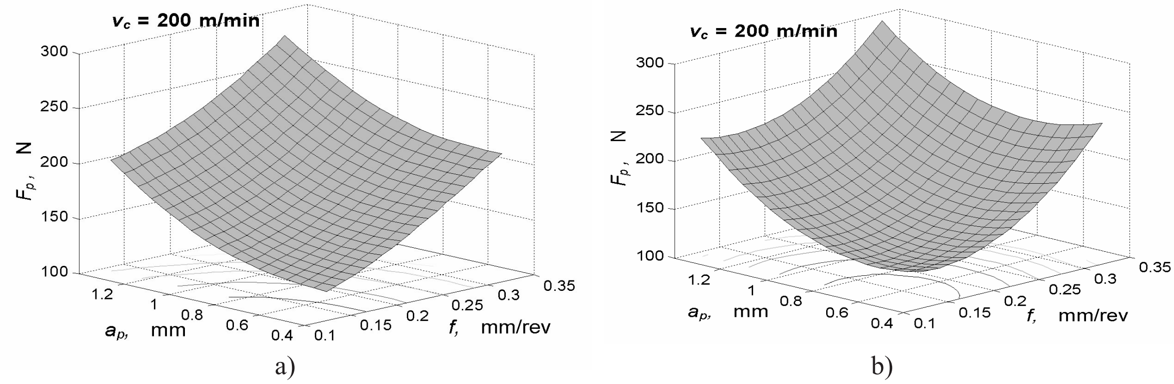


Fig. 9. Response surface for radial component of cutting force as a function of feed rate and depth of cut obtained from neural network (a) and regression analysis (b); for constant cutting speed of 200 m/min

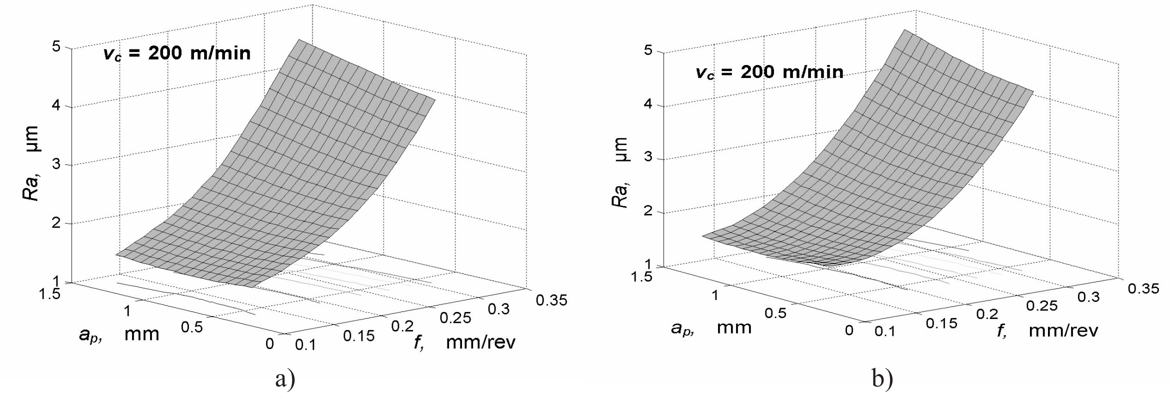


Fig. 10. Response surface for surface roughness as a function of feed rate and depth of cut obtained from neural network (a) and regression analysis (b); for constant cutting speed of 200 m/min

7 CONCLUSION

The aim of this paper is the examination of possibility of the cutting force components and the surface roughness modelling. In order to model dependency of the cutting force components and the surface roughness on the cutting speed, the depth of cut and the feed rate, regression analysis and neural network methodology were used. Both methodologies were tested for interpolation and extrapolation capability. Regarding the interpolation, both methodologies are found to be capable for accurate predictions (approximately relative error of 3%) of the cutting force components and the surface roughness, although regression models give somewhat better predictions. In the case of the extrapolation neural

Table 7. *Optimum cutting parameters*

Optimum cutting parameters			Minimum values of output parameters
v_c (m/min)	a_p (mm)	f (mm/rev)	
206.3	0.6	0.16	F_c = 249.2 N
192	0.6	0.16	F_f = 102 N
250	0.6	0.16	F_p = 120 N
150	1.11	0.16	Ra = 1.59 μm

network models give significantly better predictions. Neural network models were trained with 18 experimental data so even with the small data set ANNs are capable to achieve predictions nearly as accurate as regression models.

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