14th International Research/Expert Conference
"Trends in the Development of Machinery and Associated Technology"
TMT 2010, Mediterranean Cruise, 11-18 September 2010

ANALYZING AND MODELING OF THE INFLUENCE OF CUTTING PARAMETERS ON THE CUTTING FORCE IN FACE MILLING

Dražen Bajić, Luka Celent, Sonja Jozić
Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture,
University of Split, Ruđera Boškovića bb, Split
Croatia

ABSTRACT
The general manufacturing problem can be described as the achievement of a predefined product quality with given equipment, cost and time constraints. This paper examines the influence of three cutting parameters on the cutting force components during face milling of steel 42CrMo4. The cutting speed, the feed per tooth and the depth of cut have been taken as influential factors. Two modeling methodologies, namely regression analysis and neural networks, have been applied to experimentally determined data. Results obtained by the models have been compared. The research has shown that whit small training dataset, neural networks modeling methodologies are comparable with regression analysis methodology and it can even offer better result, in this case average relative error of 2,62%.
Keywords: face milling, cutting force, regression analysis, radial basis function neural networks

1. INTRODUCTION

Complex manufacturing and technological process nowadays claim implementation of sophisticated mathematical and other methods for the purpose of their efficient control. Thus a research is needed to get the mathematical approximations of machining processes and appearing phenomena as better as possible [1]. Engineers are facing in manufacturing with two main practical problems. The first is to determine the values of the process parameters that will provide the desired product quality and the second is to maximize manufacturing system performance with available resources. The decisions made by manufacturing engineers are based not only on their experience and expertise but also on understanding the machining principles and mathematical relations among influential parameters.

Cutting force is one of the important physical variables that embody relevant process information in machining. Such information can be used to assist in understanding critical machining attributes such as machinability, tool wear fracture, machine tool chatter, machining accuracy and surface finish [2]. The researchers propose models that try to simulate the conditions during machining and establish cause and affect relationships between various factors and desired product characteristic.

The aim of this research is to find mathematical models which relate the surface cutting force components with three cutting parameters, the cutting speed (v_c), the feed per tooth (f_t) and the depth of cut (a_p), in face milling. Two different approaches have been used in order to get the mathematical models, design of experiment (DOE) with regression analysis and modeling by means of artificial neural networks (ANNs) [3, 4]. In this work, radial basis function neural networks (RBF) are used.

2. EXPERIMENTAL SETTINGS

Machining center VC 560 manufactured by Spinner was used for milling tests on samples made of steel 42CrMo4 with dimensions 110x220x100. The face milling experiments were executed by a tool CoroMill 390 with three TiN coated inserts, produced by Sandvik. The cutting forces were measured by utilizing dynamometer Kistler type 9271A produced in Winterhur Switzerland. The dynamometers signals were then processed via charge amplifiers and A/D converter to computer. Cutting parameters

as the cutting speed, the feed per tooth and the depth of cut were taken within their region of interest of 120 to 140 m/min, 0.10 to 0.20 mm/tooth and 1.0 to 1.5 mm, respectively.
All experiments were carried out without cooling and lubrication agents. Altogether 33 experiments were conducted, 20 experiments in order to allow performing ANOVA and RA and additional 13 experiments to obtain additional data for performing RBF modeling and verification of both models.
After the training, models were tested to their generalization ability. Testing was performed with the data that had not been used in training process. In order to conduct the training and testing of the neural network models, a neural network toolbox embedded in MATLAB [5] was used.

3. DESIGN OF EXPERIMENT

The experiments have been carried out using the factorial design of experiment. The milling is characterized by 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 [6]. In this work, the design of experiment was achieved by the rotatable central composite design (RCCD). The RCCD models the response using the empirical second-order polynomial:

$$y=b_0+\sum_{i=0}^{k} b_i \cdot X_i + \sum_{1\leq i<j}^{k} b_{ij} \cdot X_i \cdot X_j + \sum_{i=1}^{k} b_{ii} \cdot X_i^2 \tag{1}$$

where b_0, b_i, b_{ij}, b_{ii} are regression coefficients and X_i, X_j are the coded values of input parameters.
In order to collect data for RA, software Design-Expert 6.0 was used to generate experimental points.
By applying the regression analysis the coefficients of regression, multi-regression factors, standard false evaluation and the value of t-test have been assessed. After omitting insignificant factors the mathematical models for components of cutting force F_x, F_y, F_z are obtained as follows:

$$F_x = 1526{,}97 - 15{,}69 \cdot v_c + 882{,}34 \cdot f_t - 654{,}16 \cdot a_p + 7743{,}04 \cdot f_t^2 + 162{,}64 \cdot a_p^2 \tag{2}$$

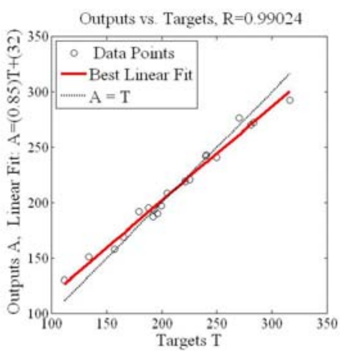
$$F_y = 796{,}95 - 9{,}379 \cdot v_c + 357{,}74 \cdot f_t - 144{,}91 \cdot a_p + 0{,}042 \cdot v_c^2 + 86{,}925 \cdot a_p^2 + 660{,}0 \cdot f_t \cdot a_p \tag{3}$$

$$F_z = -63{,}8142 + 379{,}5651 \cdot f_t - 3{,}25 \cdot v_c \cdot f_t - 0{,}75 \cdot v_c \cdot a_p \tag{4}$$

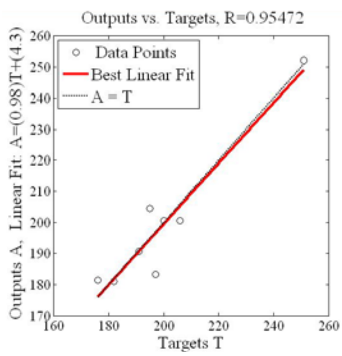
The squares of regression coefficient (r^2) for F_x, F_y, F_z are 0.9547, 0.9607 and 0.9402 respectively.

4. NEURAL NETWORK MODELING

Artificial neural networks (ANNs) are non-linear mapping system that consists of simple processors, called neurons, linked by weighted interconnections. Using a large amount of data out of which they build knowledge bases, ANNs establish the analytical model to solve the problem prediction, decision-making and diagnosis. Fitting neural network parameters as foreground learning task, allow mapping of given input on known output values. After the learning has been finished, computation of response of the ANN is computation of value of approximated hyper-plane for given input vector.
Interpolation with RBF is one of the most successful method for solving the problem of continuity multi-variable function, with main advantages like its simplicity, ease of implementation and extremely good learning and generalization ability [7].



a)



b)

Figure 1. Results of RBF for F_x component of cutting force for training (a) and testing (b)

In this work RBF model is used for approximation of three-variable function $f(x)$, $x=[x_1, x_2, x_3]^T$.
The construction of RBF network involves input layer composed of three neurons, output layer with one neuron and hidden layer with number of neurons equal to the number of the sample of learning test. The same network architecture has been used for modeling the each of three physical relations separately. The network setups relate cutting parameters and F_x, F_y, F_z components of cutting force.
Results of training and testing, in the form of regression analysis, for F_x are shown in Figure 1.
R is a measure of agreement between the outputs and targets, and the aim is to get R-value close or equal to 1. In example in Figure 1, it is close to 1 and that indicates good fit.

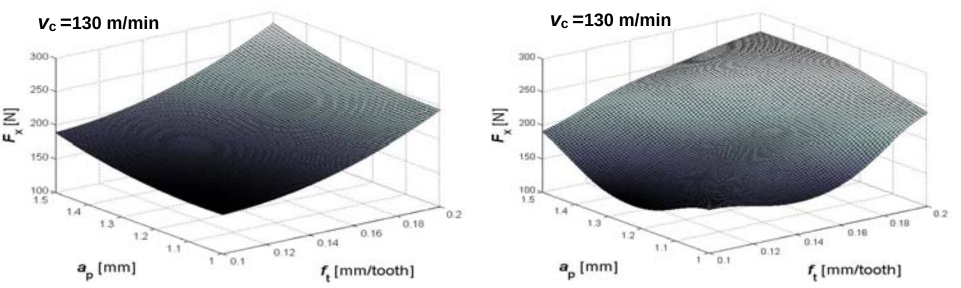
5. ANALYSIS OF RESULTS OF RA AND RBF SIMULATION

In order to test which modeling method gives better prediction, a relative error of deviations from measured values have been calculated. Validation of both models was performed with randomly selected eight data pairs that had not been used in training process. Relative errors obtained using RA and RBF methodologies have been compared, and the results of testing are presented in Table 1. The results from Table 1 indicate that RBF model offers the best prediction capability with total average relative error of 2,62%.

Table 1.Testing the capability of both models for predictions of cutting force components

Exp. Number	v_C [m/min]	f_t [mm/tooth]	a_p [mm]	Experiment			Average relative error [%]					
							RA			RBF		
				F_x [N]	F_y [N]	F_z [N]	F_x	F_y	F_z	F_x	F_y	F_z
21	135	0,13	1,2	176,0	136,0	42,0	4,80	3,52	6,25	6,50	1,39	0,12
23	131	0,14	1,4	200,0	148,0	45,0	3,25	3,01	9,39	0,26	0,36	3,65
27	129	0,17	1,1	206,0	143,0	48,0	0,56	0,81	8,40	2,66	0,06	5,94
28	121	0,12	1,2	182,0	135,0	41,0	2,05	0,05	7,50	0,57	2,05	2,81
30	138	0,15	1,3	195,0	149,0	44,5	4,26	5,53	7,71	4,85	1,08	0,28
31	135	0,10	1,5	191,0	134,0	40,8	0,17	4,62	10,88	0,16	1,29	6,37
32	120	0,12	1,2	197,0	143,0	42,0	8,55	4,76	9,67	6,99	3,28	4,81
33	127	0,18	1,4	251,0	171,0	52,0	3,58	3,51	8,69	0,47	5,25	1,71
						Average:	**3,40**	**3,23**	**8,56**	**2,81**	**1,84**	**3,21**
						Total average relative error:	**5,06%**			**2,62%**		

Figures 2-4 shows the results obtained from both models in form of graphical representation for the F_x, F_y, F_z components of cutting force and its dependence on depth of cut and feed per tooth. Cutting speed has been kept constant at 130 m/min.
It can be seen that RA method predicts that the cutting force components almost linearly depends on both, depth of cut and feed per tooth. In graphical representation of RBF method it can be seen nonlinearity, which better describes the reality state of milling process. Nonlinearity can be caused by lot of factors that influence the cutting force [1].



a) *b)*

Figure 2. Response surface for F_x obtained from regression analysis (a) and neural network (b)

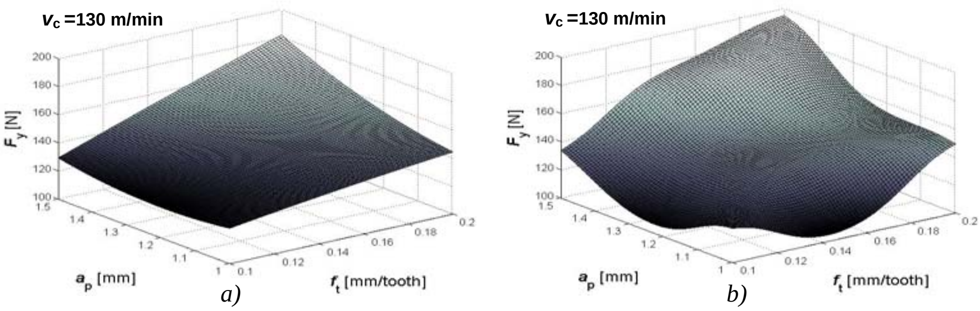


Figure 3. Response surface for F_y obtained from regression analysis (a) and neural network (b)

The minimum values of cutting force components are achieved when feed per tooth and depth of cut nearly reach their minimum values. Figure 4 shows that both methods predict that depth of cut has not at all or slight influence on the F_z component of cutting force. At the end it is evident that the feed per tooth has the dominant influence on cutting force.

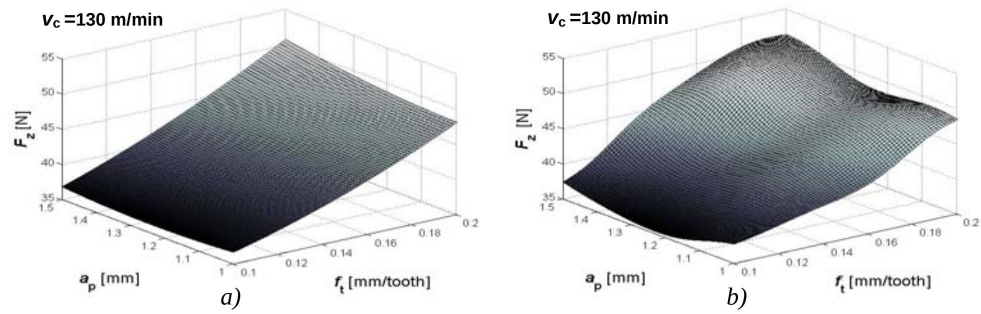


Figure 4. Response surface for F_z obtained from regression analysis (a) and neural network (b)

6. CONCLUSION

The purpose of this study is the research of possibility of the cutting force components modeling. The influence of the cutting speed, the feed per tooth and the depth of cut on cutting forces in face milling process have been examined in the study, and in order to model dependency between those parameters regression analysis and neural network methodology were used. Regarding the results, both methodologies are found to be capable for accurate predictions of the cutting force components, although neural network models give somewhat better predictions, with approximately relative error of 2,62%. The research has shown that when training data set is relatively small neural network models is comparable with RA methodology and furthermore it can offer even better results.

7. REFERENCES

[1] Bajić D., Cukor G., Lela B.: Examination and Modeling of the Influence of Cutting Parameters on the Cutting Force and the Surface Roughness in Longitudinal Turning, Strojniški vestnik – Journal of Mechanical Engineering, 2008., 322-333,

[2] Yawei Li, Steven Y., Vosniakos: Cutting force analysis in Transient State Milling Processes, Journal of Machine Tools & Manufacture, 2002., 833-844,

[3] Lela B., Bajić D., Jozić S., Regression analysis, support vector machines and Bayesian neural network approaches to modeling surface roughness in face milling International Journal of Advanced Manufacturing Technology, Vol. 42, No. 11-12, 2009., pp. 1082-1088**,**

[4] Živković D., Bajić D., Lela B., Modelling of machined surface roughness and optimization of cutting parameters in face milling, Metalurgija - Metallurgy, Vol. 47, No. 4, 2008, pp. 331-334, Zagreb,

[5] MATLAB User's Guide: The Mathworks, 2003, Neural Network Toolbox,

[6] Montgomery D. C.: Design and analysis of experiments, New York: John Wilwy & Sons, Inc., 1997.,

[7] Novaković B., Majetić D., Široki M., 1998, Artificial neural network, University of Zagreb, FSB, Zagreb.