U.P.B. Sci. Bull., Series D, Vol. 77, Iss. 4, 2015 ISSN 1454-2358

THE MILLING MOMENTS PREDICTION USING A NEURAL NETWORK MODEL

Elena Luminița OLTEANU[1], Daniel Petru GHENCEA[2], Claudiu Florinel BÎȘU[3]

This paper presents an approach to optimize cutting parameters during milling by using the artificial neural networks (ANN). The aim is to analyze the cutting parameters influence (feed and cutting speed) on the torsor of mechanical actions, on the cutting moments respectively. To highlight the cutting moments generated by the milling process was developed a complex experimental protocol based on three-dimensional dynamometric measurements. The cutting moments are integrated and predicted using back-propagation neural networks method. Finally it is proposed a model that provides a good agreement between the measured values and calculated numerical values.

Keywords: cutting parameter prediction, cutting moments, milling, artificial neural network (ANN), cutting power.

1. Introduction

The development of the CNC machine tools with high speed machining (HSM), of the cutting tools that have high wear resistance, of the metal materials with high hardness or of the composite materials, requires the adjustment of the cutting parameters.

There is also a close interdependence between the choice of cutting parameters and power consumption. The feed, cutting speed and depth of cut are the cutting process parameters that have direct influence on power consumption.

In order to determine the cutting power, a detailed analysis is required for the mechanical actions arising from contact tool/chip/workpiece [1, 2, 3, 4, 5, 6]. The cutting forces were intensively studied [7, 8, 9], but the cutting moments still have need further research [10, 11] demonstrating that they have a large influence on the power consumption [11, 12]. The calculating formula of cutting power contains both the forces and cutting moments. The term that includes the cutting moments can represent up to 50% of the total mechanical power consumed during the cutting process [3, 12, 13].

[1] Ph.D. Eng., Romanian Academy - Institute for World Economy, Romania, e-mail: lumyole@yahoo.com
[2] Ph.D. Student, Eng., University POLITEHNICA of Bucharest, Romania, e-mail: daniel.ghencea@blackseasuppliers.ro
[3] Assoc. Prof., PhD. Eng., Dept. of Machine Tools and Manufacturing Systems, University POLITEHNICA of Bucharest, Romania, e-mail: claudiu.bisu@upb.ro

The cutting moments have been taken into account in studies 18 years ago [1, 14], where the researchers demonstrated the existence of a moment vector applied directly to the tool tip, and this moment it isn't the exclusive result of an arm. With the development of the six components dynamometer designed in the Research Laboratory of the University Bordeaux 1, the moments at the cutting tools tip have been observed.

The cutting moment's importance in the cutting processes has been shown through various studies. The mechanical actions theory is based on the torsor theory being validated by highlighting of the moments at the tool tip, during turning [1, 15, 16], drilling [17] and milling [11]. These studies demonstrate that the power consumed by the M_{zE} moment is considerable. Especially for high speed machine tools, it is necessary to take into account the moments, because their importance in the assessment of the cutting power is directly dependent on the rotational speed of the workpiece in turning or the spindle speed in milling [2].

A theoretical analysis on the cutting moments is difficult to perform and there are problems in establishing mathematical models and handling of these models, therefore it is proposed an approach using the artificial neural networks (ANN) [8].

In recent years, artificial neural networks (ANN) proved to be one of the most powerful computer modeling techniques and it is successfully used in various fields of engineering for modeling complex relationships that are difficult to describe with physical models. Artificial neural networks have been widely applied in modeling many cutting operations such as turning, drilling and milling [8]. Several researchers have used artificial neural networks (ANN) to predict the influence of cutting parameters on the rate of production, the cost of production [18] or to predict the influence of cutting parameters on surface roughness [19, 20, 21, 22], the tool wear [23, 24] or the cutting force [8, 9].

In this paper, the evolution of the cutting moments with the purpose of developing a mathematical model able to integrate the complete torsor of the mechanical actions, it is highlighted. Experimental optimizing of the cutting parameters involves numerous experimental tests and a solution to this can be ANN. Neural networks enables the possibility of the mechanical actions prediction for modeling complex physical phenomena generated in the cutting process. Regarding this issue, ANN does not require the specific wording of physical relations with other words they just need the experimental results. Neural networks are a solution for optimizing the cutting parameters [18] taking into account the diversity of working conditions that occur during cutting process.

2. Experimental Setup and Procedure

In this study, a complex experimental setup was designed and realized to highlight the presence of cutting moments to the cutter tooth tip. Milling tests have been performed in order to assess the cutting parameters that have influence on the mechanical action, especially on the cutting moments at the tooth tip of the milling cutter.

Tests were performed on a vertical machining center with 3 axis type FIRST MCV300, which can provide 11 kW maximum spindle power and 8000 rpm spindle speed. Workpiece material is 42CrMo4 steel with dimensions 45x88mm, mounted on the dynamometer. In order to perform the moments evolution analysis at tooth tip it was used a milling cutter with one tooth. The cutting tool used is a milling cutter type R365-080Q27-S15M of 80 mm diameter, with insert that has 65° the approach angle. For measuring of the forces and moments in milling, 9257B Kistler dynamometer was used. Tests were carried out along the *X* axis and the correlation between the dynamometers framework and the machine tool framework was set. Parameters used for mechanical actions analysis were the feed f_z [mm/tooth] and the cutting speed v_c [m/min], while the depth of cut a_p [mm] was constant throughout the tests. Therefore, in order to evaluate the influence of the feed or of the cutting speed was carried out tests with different levels of feed and different levels of cutting speed, table 1.

Table 1

Feed rate and cutting speed

Exp. No.	a_p [mm]	f_z [mm/tooth]	v_c [m/min]
1	0.50	0.050	152.30
2		0.075	
3		0.100	
4		0.125	
5		0.150	
6		0.100	125.66
7			150.80
8			163.36
9			170.93
10			201.06

3. Prediction of cutting moments with artificial neural network

Cutting parameters are the most important factors influencing the process plans. The optimal selection of cutting parameters leads to a cutting actions reduction so and the power consumption reduction and thus the reduction of costs. This study proposes to realize the prediction of cutting parameters using artificial neural networks (ANN). Neural networks are a very popular tool and proved to be very good for solving optimization problems, for adaptive control of machine tools or for pattern recognition. Using artificial neural networks for fast determination of optimum cutting parameters during milling is suitable when the time is not long enough for deep analysis [18].

To use neural networks, more and more commercial software products are available. For this study was used Visual Gene Developer software 1.7 (Build 762/ 2014, freeware) developed by the Department of Chemical Engineering and Materials Science - University of California-Davis [25] and is based on a standard learning algorithm with back-propagation. The starting point for using neural networks are the numeric data collected from the experimental measurements.

Next it will be presented the ANN prediction of the moments generated in the milling process. Through this model it's achieved the cutting parameters prediction taking into account mechanical actions criterion, where in addition to the cutting forces are considered the cutting moments.

The back-propagation algorithm is used, one of the best known and with it can be approximated nonlinear functions as proved to be the cutting moments evolution in previous studies [26]. To transport the M_{xE}, M_{yE} and M_{zE} measured cutting moments at the tooth tip of the milling cutter it's requires the knowledge of the F_x, F_y and F_z cutting forces generated by the milling process. Considering that the research aims the moments analysis, the ANN responds to the three-dimensional moments prediction. The cutting moments calculated at tooth tip of the milling cutter on the three axes M_{xN}, M_{yN} and M_{zN} were predicted for different levels of feed and then of the cutting speed. To validate the ANN model, the prediction results are compared with measured experimental results.

The choice of the number of neurons, hidden layers, function activation and training algorithm are very important for satisfactory results.

The optimal number of hidden layers and neurons/hidden layer is difficult to say before [27]. In general, one hidden layer is sufficient to solve most problems. Exceptionally, it can use two, at most three hidden layers. Typically, the neurons number afferent of the input and output layers are dictated by the nature of the application. Neurons of the hidden structures have very important role to detect features, regularities contained in training patterns. Too many hidden neurons/layers can adversely affect the generalization ability of ANN.

At the same time, it leads to increase the volume of the data to be processed and therefore to the increase of the workout stage duration. A small number of neurons is not enough to create a proper internal representation of data and can lead to a big square mean error during the training epochs and thus to a big error for test data and for workout data. In conclusion, the optimal number of hidden neurons will be determined experimentally.

The input parameters in the model are: the feed and cutting speed while the cutting moments on the three directions are output variables. The training mode as well as the routes used in the prediction process is shown in the Fig. 1.

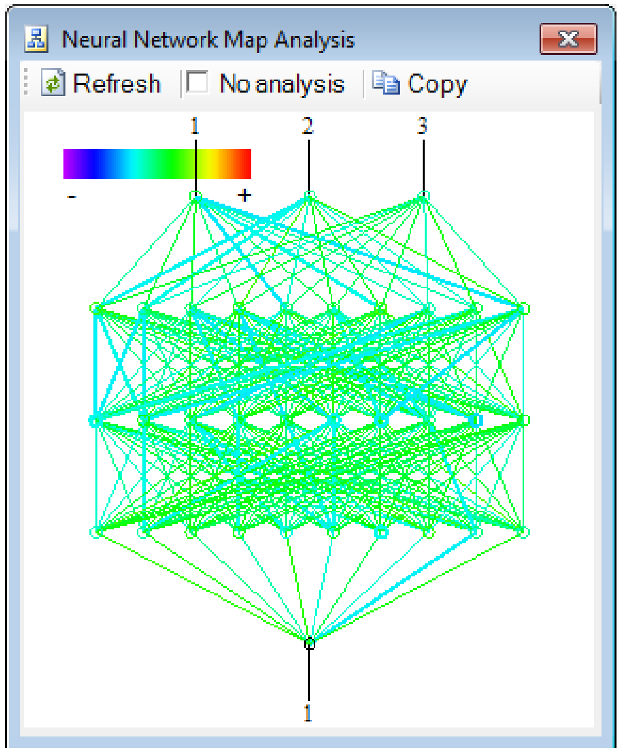

Fig. 1. Neural network map analysis

Links between levels of the hidden layers nodes through which information flows are represented by lines that can have a palette of colors from violet (corresponding to the negative numbers (-1)) to red (corresponding to the positive numbers (+1)). It notes that in the Fig. 1 predominate the bright green and turquoise colors, so information flows are concentrated around zero. The width of the line is proportional to the weight factor in absolute value or the threshold value.

For the purpose of applying the model are used experimental data presented by the series of real numbers (for one revolution when the milling cutter is totally engaged in the workpiece), table 2.

Table 2

Input and Output data

Exp No.	f [mm/rev]	v_c [m/min]	F_x [N]	F_y [N]	F_z [N]	M_{xE} [Nm]	M_{yE} [Nm]	M_{zE} [Nm]
1	0.050	152.30	188.812	175.903	112.580	15.100	19.337	6.683
2	0.075		278.931	248.963	133.331	26.121	25.685	12.328
3	0.100		306.457	251.862	172.546	28.232	28.446	11.484
4	0.125		278.901	261.260	128.509	26.620	22.631	9.993
5	0.150		263.153	337.677	149.017	35.979	25.283	14.692
6	0.100	125.66	540.649	377.868	185.791	40.118	43.531	18.022
7		150.80	343.323	296.494	136.001	33.058	32.254	14.380
8		163.36	590.759	472.839	224.243	47.920	42.441	26.529
9		170.93	342.728	281.571	129.913	36.378	36.338	11.801
10		201.06	343.415	354.950	157.791	36.306	26.928	21.628

Because the Visual Developer Gene software (VGD) works with numbers series contained in the closed interval [-1, 1] the data will be divided so that to fit in this interval. In this study, it has been considered the following configuration of neural networks:

1 input variable (feed rate f; cutting speed v_c)

3 output variables (cutting moments M_{xN}, M_{yN}, M_{zN})

3 hidden layers; 10 neurons on the hidden layer; learning rate - 0.01; transfer function - hyperbolic tangent;

After setting the neural network configuration, the experimental data were introduced. The training data set and, then, the data for the prediction have been loaded.

4. Results and Discussion

To study the evolution and prediction of the cutting moments is chosen the zone when the milling cutter is totally engaged in the workpiece so as to eliminate transient effects generated during the milling process. The predictive analysis of the cutting moments takes into account the qualitative characteristic of the moment's evolution in the cutting process.

After running the data shown in table 3 has been obtained:

Table 3

Prediction of cutting moments M_{xN}, M_{yN} and M_{zN} by using ANN

Exp. No.	Measured			Predicted			Error %		
	M_{xE} [Nm]	M_{yE} [Nm]	M_{zE} [Nm]	M_{xN} [Nm]	M_{yN} [Nm]	M_{zN} [Nm]			
1	15.100	19.337	6.683	17.190	21.268	7.703	13.85	9.98	15.25
2	26.121	25.685	12.328	25.960	26.912	14.537	0.62	4.78	17.92
3	28.232	28.446	11.484	27.652	28.606	11.804	2.05	0.56	2.78
4	26.620	22.631	9.993	26.677	24.469	11.507	0.22	8.12	15.10
5	35.979	25.283	14.692	34.217	27.110	15.048	4.90	7.23	2.42
6	40.118	43.531	18.022	40.118	42.292	16.436	0.002	2.84	8.80

7	33.058	32.254	14.380	38.283	36.789	16.945	15.80	14.06	17.83
8	47.920	42.441	26.529	43.445	38.863	22.449	9.33	8.43	15.37
9	36.378	36.338	11.801	39.343	36.614	12.996	8.15	0.75	10.12
10	36.306	26.928	21.628	38.145	31.708	18.222	5.06	17.74	15.74

It is observed that, for feed, the maximum prediction error is 17.92%, which means that the difference between measured and predicted moments is around 2.2 Nm. For cutting speed the maximum prediction error is 17.83%, which means that the difference between measured and predicted moments is around 2.5 Nm.

In the figures below it is presented the cutting moments evolution according to the feed rate; the measured values was compared with the prediction of ANN.

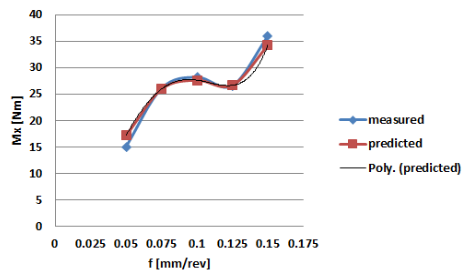

Fig. 2. Moments at the tooth tip of milling cutter M_{xE} and M_{xN} according to feed f

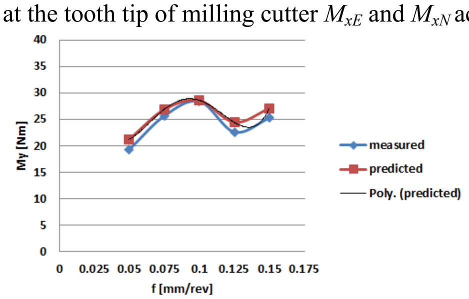

Fig. 3. Moments at the tooth tip of milling cutter M_{yE} and M_{yN} according to feed f

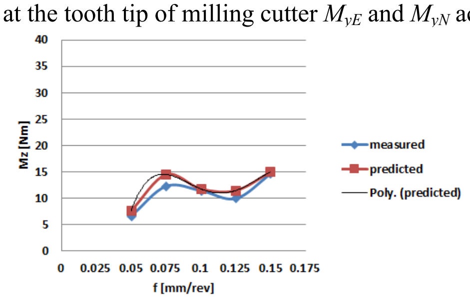

Fig. 4. Moments at the tooth tip of milling cutter M_{zE} and M_{zN} according to feed f

It is presented the cutting moments evolution according to the cutting speed; the measured values was compared with the prediction of ANN.

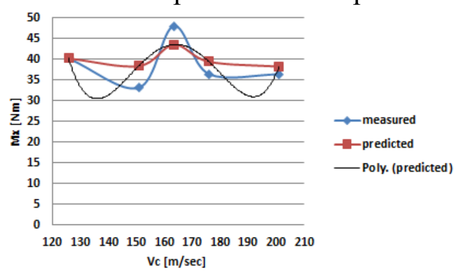

Fig. 5. Moments at the tooth tip of milling cutter M_{xE} and M_{xN} according to cutting speed v_c

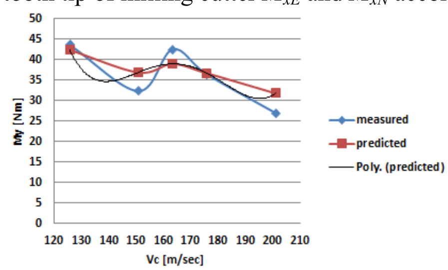

Fig. 6. Moments at the tooth tip of milling cutter M_{yE} and M_{yN} according to cutting speed v_c

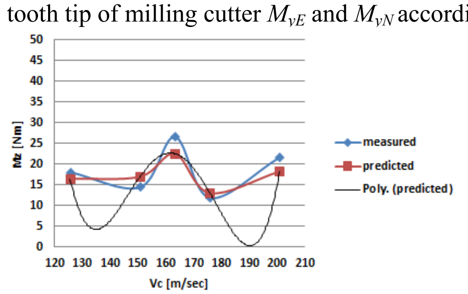

Fig. 7. Moments at the tooth tip of milling cutter M_{zE} and M_{zN} according to cutting speed v_c

Mathematical description of the result moments is represented by a 4th order polynomial function. The cutting moment's evolution is variable depending of the cutting parameters and it is influenced by dynamic characteristic of the tool /chip/workpiece contact.

5. Conclusions

This study presented an approach for the prediction of cutting parameters during milling using ANN. The tool used for predicting the cutting parameters with neural network was Visual Gene Developer software. The model which gave the satisfactory results is a model consists of 1 input layer, 3 hidden layers with 10 neurons and 3 outputs layers. It was used back-propagation learning algorithm.

The error values for the cutting moments at the feed variation were maximum 17.92% and at the cutting speed variation were maximum 17.83%. The obtained results show that ANN can easily be used to predict the effects of cutting parameters on the milling moments. The moments have influence both on the power consumption and the processing quality, being absolutely necessary to integrate them in predictive models. By moments prediction it can by predicted the energy consumed by the process, without having to accomplish measurements which need time and the process quality is not influenced. Through the operating algorithm improvement of the neural network it can be obtained much smaller errors. In perspective, to obtain the most accurate results - the lowest possible errors, will be essential conducting a campaign of experimental tests with varying cutting parameters according to an experiences plan that take into account ANN analysis. For the proposed model it is required determination of the error coefficients of the model obtained from combining several experimental tests.

Acknowledgements

This paper has been financially supported within the project entitled "Horizon 2020 - Doctoral and Postdoctoral Studies: Promoting the National Interest through Excellence, Competitiveness and Responsibility in the Field of Romanian Fundamental and Applied Economic Research", contract number POSDRU/159/1.5/S/140106. This project is co-financed by European Social Fund through Sectoral Operational Programme for Human Resources Development 2007-2013. Investing in people!

R E F E R E N C E S

[1]. *D. Toulouse, Y. Couétard, O. Cahuc, A. Gérard*, An experimental method for the cutting process in three dimensions, Journal de Physique IV 7, C3, p. 21-26, 1997.

[2]. *P. Darnis, O. Cahuc, Y. Couétard*, Energy balance with mechanical actions measurement during a turning process, Int. Seminar on Improv. MachineTool Performance - CIRP, 2000.

[3]. *O. Cahuc, P. Darnis, A. Gérard, J.-L. Battaglia*, Experimental and analytical balance sheet in turning applications, Int. J. Adv. Manuf. Technol.18, 9, p. 648-656, 2001.

[4]. *O. Cahuc, A. Gerard*, Metrology influence on the cutting modelisation, 15th International Conference on Manufacturing Systems, Bucarest, Romania 2006.

[5]. *G. Albert, O. Cahuc, R. Laheurte, P. Darnis, JY. K'nevez*, Approche énergétique de la coupe en fraisage. In: 5eme Assises machine et usinage à grande vitesse. Nantes, France, 2008.

[6]. *G. Albert*, Identification et modélisation du torseur des actions de coupe en fraisage, These de doctorat, Université Bordeaux 1, n° 4152, 2010.

[7]. *O. Tuysuz, Y. Altintas, H.-Y. Feng*, Prediction of cutting forces in three and five-axis ballend milling with tool indentation effect, Int. J of Machine Tools and Manufacture, vol. 66, 2013.

[8]. *S. Aykut, M. Gölcü, S. Semiz, H.S. Ergür*, Modeling of cutting forces as function of cutting parameters for face milling of satellite 6 using an artificial neural network, Journal of Materials Processing Technology 190, pp. 199–203, 2007.

[9]. *T. Irgolic, F. Cus, M. Paulic, J. Balic*, Prediction of Cutting Forces with Neural Network by Milling Functionally Graded Material, Procedia Engineering 69, pp.804 – 813, 2014.

[10]. *G. Albert, R. Laheurt, J.-Y. K'Nevez, Ph. Darnis, O. Cahuc*, Experimental milling moment model in orthogonal cutting condition: to an accurate energy balance, Int J Adv Manuf Technol 55, pp.843–854, 2011.

[11]. *G. Albert, Ph. Darnis, R. Laheurte, O. Cahuc*, Milling experimental model: adding the component of moment, Proceedings of IDMME - Virtual Concept, Bordeaux, France, 2010.

[12]. *Y. Couétard, O. Cahuc., P. Darnis*, Mesure des 6 actions de coupe en fraisage grande vitesse, Third International Conference on Metal Cutting and high speed machining, p. 37-42, 2001.

[13]. *R. Laheurte, O. Cahuc, P. Darnis and A. Gerard*, Behaviour law for cutting process, International Journal of Advanced Manufacturing Technology, Vol. 29, pp 17–23, 2006.

[14]. *O. Cahuc, D. Toulouse, Y. Couétard et A. Gerard*, Un nouveau modele de la zone de contact outil copeau, Comptes Rendu Academie des Sciences Paris, France, IIb 328, pp. 1–4, 2000.

[15]. *R. Laheurte*, Application de la theorie du second gradient a la coupe des materiaux, Thèse de Doctorat, Université Bordeaux 1, France, n° 2935, 2004.

[16]. *C. Ispas, O. Cahuc, C. F. Bisu, A. Gerard*, A force torsor analysis for a turning process in the presence of self-excited vibrations, ICSAAMM, Tarbes, France, 2009.

[17]. *S. Laporte*, Comportement et endommagement de l'outil en perçage à sec: applications aux assemblages aéronautiques, Thèse de doctorat, Université de Bordeaux 1, n° 3088, 2005.

[18]. *F. Cus, U. Zuperl*, Approach to optimization of cutting conditions by using artificial neural networks, Journal of Materials Processing Technology 173, pp. 281–290, 2006.

[19]. *M. Nalbanta, H. Gökkayab, I. Toktas, G. Sur*, The experimental investigation of the effects of uncoated,PVD-and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks, Robotics and Computer-Integrated Manufacturing 25, pp. 211–223, 2009.

[20]. *A. M. Zain, H. Haron, S. Sharif*, Prediction of surface roughness in the end milling machining using Artificial Neural Network, Expert Systems with Applications 37, p. 1755–1768, 2010.

[21]. *R. A. Mahdavinejad, N. Khani and M. M. S.d Fakhrabadi*, Optimization of milling parameters using artificial neural network and artificial immune system, Journal of Mechanical Science and Technology 26 (12), pp. 4097~4104, 2012.

[22]. *A. K. S. Meenu*, Optimized Prediction and Modeling Under End Milling Machining By ANOVA And Artificial Neural Network, IJERT, Vol. 2 Issue 3, ISSN: 2278-0181, 2013.

[23]. *D.M. D'Addona, R. Teti*, Image data processing via neural networks for tool wear prediction, Procedia CIRP 12, pp. 252 – 257, 2013.

[24]. *D Bajić, L. Celent, S. Jozić*, Modeling of the Influence of Cutting Parameters on the Surface Roughness, Tool Wear and Cutting Force in Face Milling in Off-Line Process Control, Journal of Mechanical Engineering 58 11, pp. 673-682, 2012.

[25]. ***http://visualgenedeveloper.net/

[26]. *G. Albert, O. Cahuc, R. Laheurte, P. Darnis*, Étude experimentale de la coupe en fraisage, 18ème Congrès Français de Mécanique Grenoble, 2007.

[27] *V. Tiponuţ, C. D. Căleanu*, Reţelele neuronale - Arhitecturi şi algoritmi (Neural networks - architecture and algorithms), Ed. Politehnică Timisoara, ISBN 973-9389-66-X, 2002.