IACSIT International Journal of Engineering and Technology, Vol.3, No.1, February 2011
ISSN: 1793-8236

Tool Life Prediction in Face Milling Machining of 7075 Al by Using Artificial Neural Networks (ANN) and Taguchi Design of Experiment (DOE)

Amir Mahyar Khorasani[1], Mohammad Reza Soleymani Yazdi[2] and Mir Saeed Safizadeh[3]

Abstract—**Tool life is an important indicator of the milling operation in manufacturing process. Studies and analyses of milling process are usually based on three main parameters composed of cutting speed, feed rate and depth of cut. The aim of this study is to discover the role of these parameters in tool life prediction in milling operations by using artificial neural networks and Taguchi design of experiment. Machining experiments were performed under various cutting conditions by using sample specimens. A very good agreement between predicted model and experimental results was obtained. The correlation between the estimated and experimental data was 0.96966 for train and 0.94966 for test.**

Index Terms—**Artificial neural networks, Face milling, Taguchi Design of Experiment, Tool life prediction.**

I. Introduction

Milling process is the second most common method (after turning) for metal cutting and especially for the finishing of machined parts. In modern industry the goal is to manufacture low cost, high quality products in short time.

Predictive models of machining processes and tool life can be applied to help businesses gain a competitive edge. In this time of expanding global markets, it has become essential for manufacturers to improve process efficiencies, maintain stricter part tolerances, and enhance part quality. Furthermore, the motivation for using analytical tools for process optimization, rather than costly trial and error, has perhaps never been greater. Dynamic models of milling processes provide the ability to predict stable cutting condition and increases tool life for a large combination of process. The application of the Artificial Neural Networks (ANN) model for the modeling purpose in various different areas including machining is used very widely by researchers.

A good review on cutting force control and tool wear monitoring in end milling can be found in [1]–[7]. Soichi and Takuya studied on a long-term control scheme of cutting forces to regulate tool life in end milling processes [8]. Indices based on milling force for tool wear in milling have been investigated by Yan et.al [9]. Bhattacharyya et.al [10] investigated on cutting force-based real-time estimation of tool wear in face milling using a combination of signal processing techniques while tool wear in high speed milling using detection process approach has been done by Kious et.al [11]. Estimation of tool wear during CNC milling using neural network-based sensor fusion was implemented by Ghosh et.al [12]. On-line metal cutting tool condition monitoring using multi-layer perceptron neural networks was studied by Lister and Dimla [13]. Tool condition monitoring using artificial intelligence methods has been carried out by Balazinski et.al [14]. Cho and Ko estimated tool wear length in finish milling using a fuzzy inference algorithm [15]. Intelligent process supervision for predicting tool wear in machining processes was done Alique by and Haber [16]. Ning and Veldhuis[17] analyzed mechanistic modeling of ball end milling including tool wear. Prediction of flank wear by using back propagation neural network modeling when cutting hardened H-13 steel with chamfered and honed CBN tools is used by Ozel and Nadgir [18] Also tool cutting force modeling in ball-end milling using multilevel perceptron was implemented by Zuperl and Cus [19]. Rivero et.al [20] worked on tool wear detection in dry high-speed milling based upon the analysis of machine internal signals and Orhan et.al [21] evaluated tool wear by vibration analysis during end milling of AISI D3 cold work tool steel with 35 HRC hardness. Furthermore Tool wear perdition from acoustic emission and surface characteristic via an artificial neural network has been carried out by Wilkinson and Reuben [22].

By considering the abilities and limitations of above approaches for the tool life and tool wear monitoring, the focus of this study is finding the relation of cutting parameters (feed rate, depth of cut and spindle speed) on tool life and illustrate the capability of (ANN) to predict and modeling tool life.

II. Experimental Setup

A. Milling machine

Experiments were carried out at the university of Applied Science and Technology on a milling machine as shown in Fig 1. The experiments were conducted in a ZXX6350ZA vertical axis milling machine using tool life 20mm diameter cutter mill with 4 cutter inserts (Fig 2). The cutter mill was made by high speed steel-E (HSS-E). Work-pieces used for this experiment was Al 7075.

[1] MSC Student, Faculty of Hi-tech and Eng., IUIM, Tehran – Iran- khorasanimahyar@hitech.iuim.ac.ir - (corresponding author)
[2] Assistant Professor, Mech. Eng. Dept., IH University, Tehran – Iran- soleymani@iuim.ac.ir
[3] Faculty of Mechanics, Iran University of Science and Technology, Hengham street, Resalat square Tehran, Iran. safizadeh@iust.ac.ir

Fig 1. Milling machine

The yield strength is 145 MPa, ultimate tensile strength 275 MPa and the amount of elongation is 10, whih illustrates in Fig 2.

Fig 2. End mill

B. The Taguchi design of experiments method

The most efficient method of experimental planning is Design of Experiments (DOE) using the Taguchi approach, which was adopted in this paper. (DOE) incorporates the orthogonal arrays, developed by Taguchi, to successfully design and conduct fractional factorial experiments that can collect all the statistically significant data with the minimum possible number of repetitions. Full factorial experiments are conducted or one factor at a time strategies are followed. The former cannot be implemented when there are too many factors under consideration because the number of repetitions required would be prohibitive, from a time and cost viewpoint. In this experiment each parameter has 5 levels which are so degree of freedom (DOF) for each parameter is 4. The total calculated (DOF) is 4×4×4×4×4=1024.

After determining the number of (DOF), the next step is to choose suitable orthogonal array. In Taguchi (DOE), orthogonal array must be more than or equal to the (DOF) of design parameters. So the best orthogonal array by using Taguchi DOE is L25 (5∗∗5). This array contains 25 repetitions (Table 1).

TABLE I TAGUCHI (DOE) IN THIS WORK

No	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Tool life measured during process (min)
1	95	22	0.2	264
2	95	98	0.4	27
3	95	132	0.6	23
4	95	200	0.8	18
5	95	360	1	12
6	360	22	0.4	554
7	360	98	0.6	455
8	360	132	0.8	398
9	360	200	1	316
10	360	360	0.2	303
11	565	22	0.6	612
12	565	98	0.8	462
13	565	132	1	402
14	565	200	0.2	387
15	565	360	0.4	276
16	950	22	0.8	180
17	950	98	1	157
18	950	132	0.2	350
19	950	200	0.4	367
20	950	360	0.6	153
21	1500	22	1	160
22	1500	98	0.2	163
23	1500	132	0.4	140
24	1500	200	0.6	113
25	1500	360	0.8	46

III. MODELING OF THE TOOL LIFE BY ARTIFICIAL NEURAL NETWORKS

In this section, based on the experimental data, the tool life modeling and prediction is carried out by using multi layer perceptron (MLP) neural networks. MLP neural network is one of the most popular supervised (ANN) which has the ability to solve nonlinear problems.

25 examples have been used for the off-line training and performance checking of the proposed model.

As shown in Fig 3, a four-layer (MLP) is used, including 3 inputs (i.e. cutting speed, feed rate and depth of cut), 2 hidden layers containing 5 neurons, and an output layer with a single neuron (i.e. tool life), 3×3×2×1.

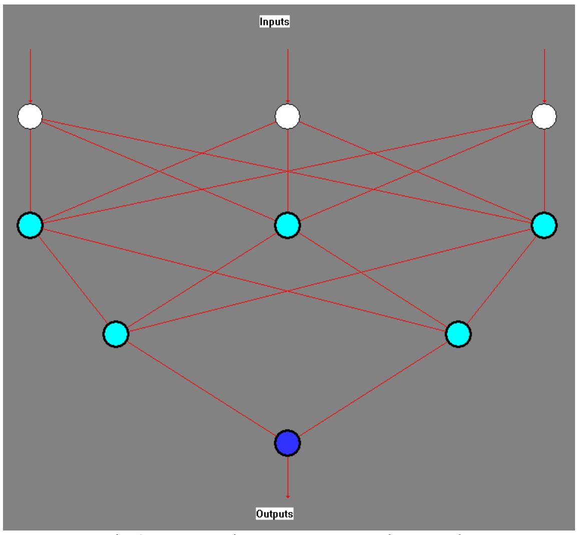

Fig 3. Proposed perceptron neural networks

Hidden layers must have equitable covering rate on learning data therefore, the best architecture and parameters of the (MLP) model are chosen through several tests which are not presented in this paper. Sigmoid, Gaussian and Hyperbolic Scant transfer functions have been applied for neurons of hidden and output layers, respectively.

The obtained Root Mean Squared (RMS) error and correlation between the estimated and experimental data were 0.005575 and 0.96966, respectively (cf. Figures 4, 5 and 6).

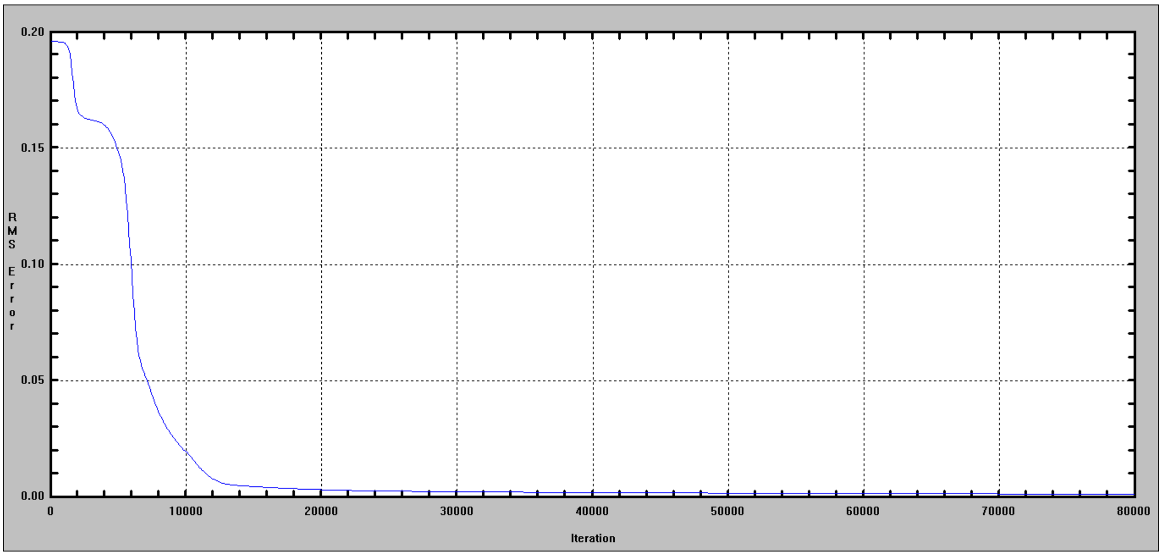

Fig 4. RMS error

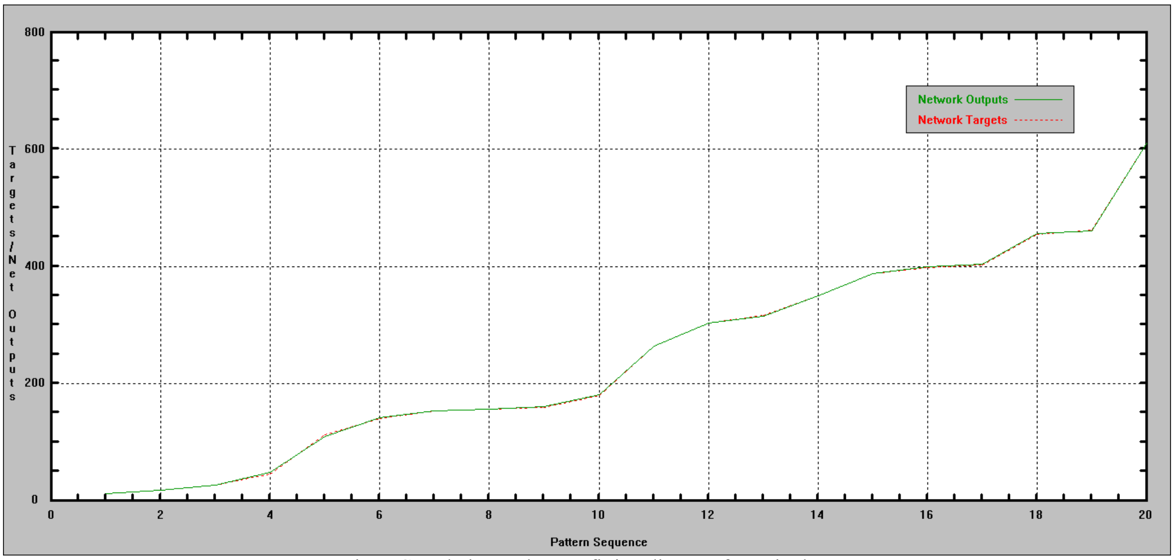

Fig 5. Correlation and curve fitting diagram for train data

Figure 7 illustrates correction coefficient versus iteration and after 10000 iteration correction coefficient reach to peak.

As shown in Figures 4 to 7, the proposed (MLP) neural network has provided proper modeling results. Indeed, this method can be reliably and successfully used for modeling of the tool life modeling.

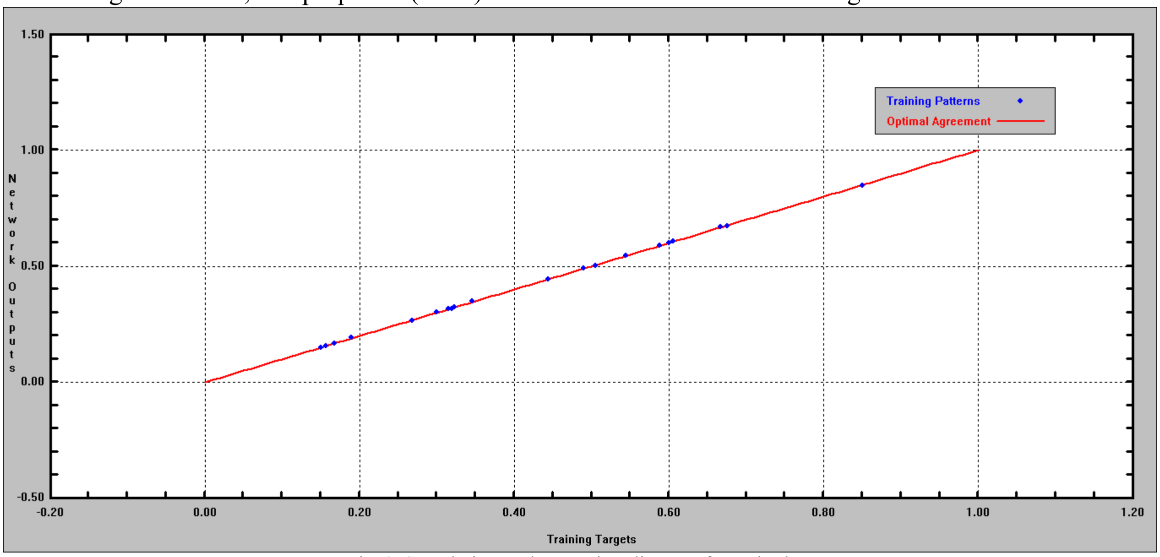

Fig 6. Correlation and scattering diagram for train data

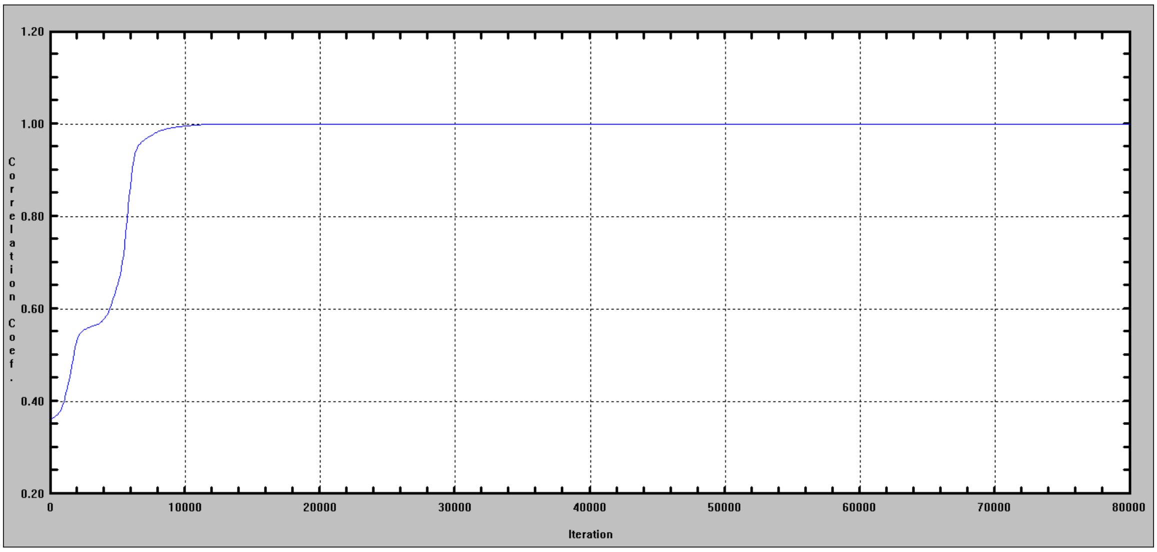

Fig 7. Correction coefficient versus iteration

IV. Results and Experimental Validation

To verify the accuracy of the obtained results, several experimental tests have been implemented. Table 2, illustrates good performance of (ANN) to predicting tool life in milling process. The obtained correlation between the estimated and experimental data was 0.94966. (cf. Figures 8 and 9).

TABLE II RESULTS OF (ANN) PREDICTION AND EXPERIMENTAL MEASUREMENT

No	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Tool life measured during process (min)	Tool life predicted by ANN (min)	Error %
1	95	132	0.6	23	26.43797	-0.14948
2	360	22	0.4	554	582.8904	-0.05215
3	565	360	0.4	276	276.3392	-0.00123
4	950	200	0.4	367	371.4312	-0.01207
5	1500	98	0.2	163	165.5439	-0.01561

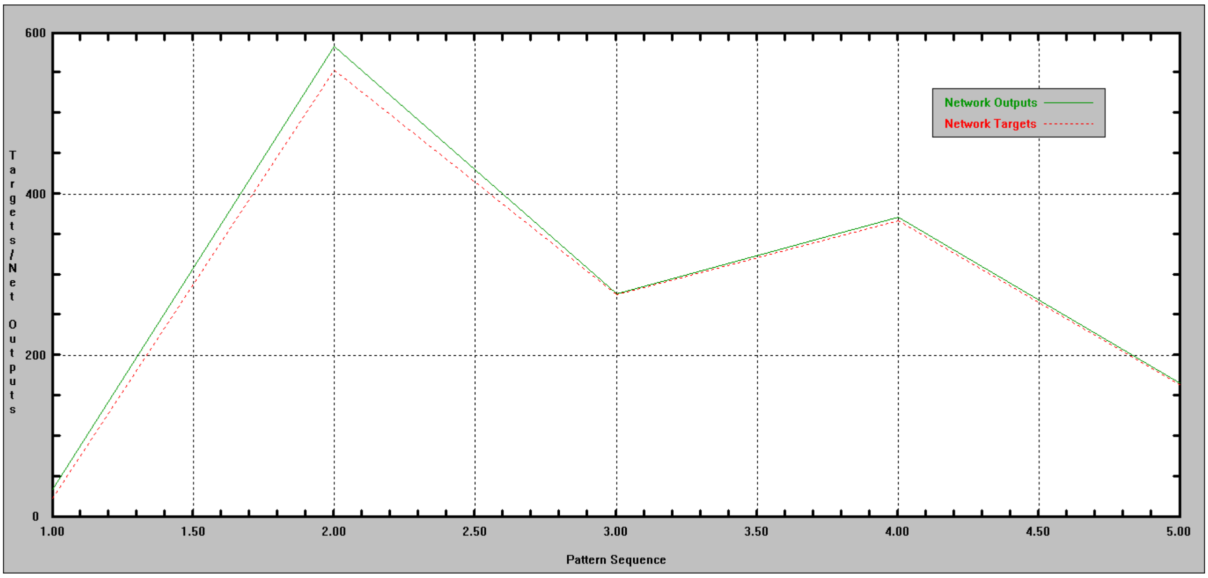

Fig 8. Correlation and curve fitting diagram for test data

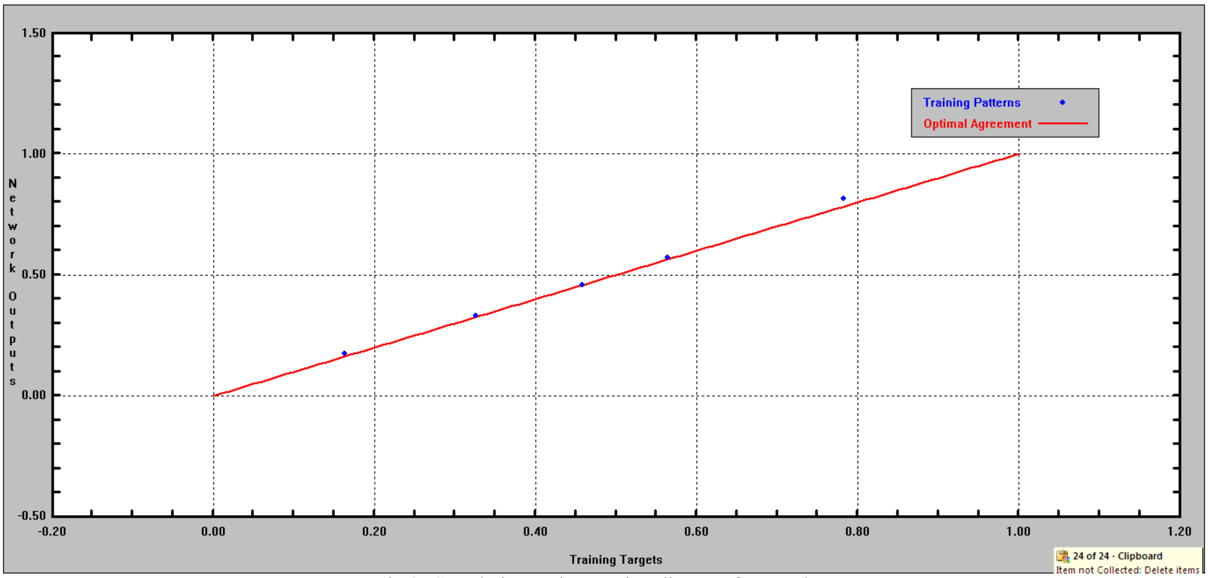

Fig 9. Correlation and scattering diagram for test data

V. Conclusion

In this study, (ANN) for modeling and predicting tool life in milling parts made of Aluminum (7075) material was developed. Given the accuracy that was achieved it is safe to conclude that all the significant factors were included in the (DOE) process. The research in the present paper can be extended towards three different steps. The first step is using Taguchi (DOE) and different combinations of cutting parameters for building database. The second step is modeling tool life by using (ANN). Third step is validation by carrying out the experimental tests.

In generating the (ANN) model statistical (RMS) was utilized. The accuracy error was found to be insignificant (3.034%). It was found that (ANN) prediction correlates very well with the experimental results. Finally the correlation for training and test was obtained 0.96966 and 0.94966 respectively and mean square error was calculated 3.1908% for test data.

REFERENCES

[1] SY. Liang, RL. Hecker, RG. Landers "Machining process monitoring and control: the state-of-the-art," Trans ASME Journal of Manufacturing Science Engineering, 126–2, 2004, pp. 297–310.

[2] AG. Ulsoy, Y. Koren "Control of machining processes," ASME Journal Dynamic System Measurement Control, 115, 1993, 301–8.

[3] Altintas Y. "Manufacturing automation: metal cutting mechanics," machine tool vibrations, and CNC design, Cambridge University Press; 2000, pp 100-103.

[4] A. Matsubara, S. Ibaraki "Monitoring and control of cutting forces in machining processes: a review," International Journal of Automation Technology 2009, pp 445–456.

[5] A. Matsubara, "Current status and trends of monitoring and control technology in machining process," Journal Society Instrument Control Engineering, Vol 41 2002, pp 781–786.

[6] E. Dimla, S. Dimla, "Sensor signals for tool-wear monitoring in metal cutting operations—a review of methods," International Journal of Machine Tools & Manufacture, Vol 40, 2000, pp 1073–1098.

[7] P.W. Prickett, C. Johns, "An overview of approaches to end milling tool monitoring," International Journal of Machine Tools & Manufacture, Vol 39, 1999, pp 105–122.

[8] S. Ibaraki, T. Shimizu, " A long-term control scheme of cutting forces to regulate tool life in end milling processes," Precision Engineering, Vol 34 2010, pp 675–682.

[9] W. Yan, Y.S. Wong, K.S. Lee, T. Ning, "An investigation of indices based on milling force for tool wear in milling," Journal of Materials Processing Technology, Vol 89, 1999, pp, 245–253.

[10] P. Bhattacharyya, D. Sengupta, S. Mukhopadhyay, "Cutting force-based real-time estimation of tool wear in face milling using a combination of signal processing techniques," Mechanical Systems and Signal Processing, Vol 21, 2007, pp 2665–2683.

[11] M. Kious, A. Ouahabi, M. Boudraa, R. Serra, A. Cheknane, "Detection process approach of tool wear in high speed milling," Measurement, Vol 43, 2010, pp 1439–1446.

[12] N. Ghosh, Y.B. Ravi, A. Patra, S. Mukhopadhyay, S. Paul, A.R. Mohanty, A.B. Chattopadhya, "Estimation of tool wear during CNC milling using neural network-based sensor fusion," Mechanical Systems and Signal Processing, Vol 21, 2007, pp 466–479.

[13] D.E. Dimla Sr. a, P.M. Lister, "On-line metal cutting tool condition monitoring.II: tool-state classification using multi-layer perceptron neural networks," International Journal of Machine Tools & Manufacture, Vol 40, 2000, pp 769–781.

[14] M. Balazinski, E. Czogala, K. Jemielniak, J. Leski, "Tool condition monitoring using artificial intelligence methods," Engineering Applications of Artificial Intelligence, Vol 15 , 2002, pp 73–80.

[15] T. J. Ko, D. W. Cho, "Estimation of tool wear length in finish milling using a fuzzy inference algorithm," Wear, Vol 169, 1993, pp 97-106.

[16] R. E. Haber, A. Alique, "Intelligent process supervision for predicting tool wear in machining processes," Mechatronics, Vol 13, 2003, pp 825–849.

[17] L. Ning, St. C. Veldhuis, "Mechanistic Modeling of Ball End Milling Including Tool Wear," Journal of Manufacturing Processes, Vol. 8, 2006, pp 21-28.

[18] T. Ozel, A. Nadgir, "Prediction of flank wear by using back propagation neural network modeling when cutting hardened H-13 steel with chamfered and honed CBN tools," International Journal of Machine Tools & Manufacture, Vol 42, 2002, pp 287–297.

[19] U. Zuperl, F. Cus, "Tool cutting force modeling in ball-end milling using multilevel perceptron," Journal of Materials Processing Technology, Vol 153–154, 2004, pp 268–275.

[20] A. Rivero, L.N. López de Lacalle, M. L. Penalv, "Tool wear detection in dry high-speed milling based upon the analysis of machine internal signals," Mechatronics, Vol 18, 2008, pp 627–633.

[21] S. Orhan, A. Osman Er, N. Camus-cu, E. Aslan, "Tool wear evaluation by vibration analysis during end milling of AISI D3 cold work tool steel with 35 HRC hardness," NDT&E International, Vol 40, 2007, pp 121–126.

[22] P. Wilkinson, R. L. Reuben, "Tool wear perdition from acoustic emission and surface characteristic via an artificial neural network," Mechanical Systems and Signal Processing, 13(6), 1999, pp 955-966.