World Academy of Science, Engineering and Technology
International Journal of Materials and Metallurgical Engineering
Vol:10, No:4, 2016

Prediction of Cutting Tool Life in Drilling of Reinforced Aluminum Alloy Composite Using a Fuzzy Method

Mohammed T. Hayajneh

International Science Index, Materials and Metallurgical Engineering Vol:10, No:4, 2016 waset.org/Publication/10004238

***Abstract*—**Machining of Metal Matrix Composites (MMCs) is very significant process and has been a main problem that draws many researchers to investigate the characteristics of MMCs during different machining process. The poor machining properties of hard particles reinforced MMCs make drilling process a rather interesting task. Unlike drilling of conventional materials, many problems can be seriously encountered during drilling of MMCs, such as tool wear and cutting forces. Cutting tool wear is a very significant concern in industries. Cutting tool wear not only influences the quality of the drilled hole, but also affects the cutting tool life. Prediction the cutting tool life during drilling is essential for optimizing the cutting conditions. However, the relationship between tool life and cutting conditions, tool geometrical factors and workpiece material properties has not yet been established by any machining theory. In this research work, fuzzy subtractive clustering system has been used to model the cutting tool life in drilling of Al_2O_3 particle reinforced aluminum alloy composite to investigate of the effect of cutting conditions on cutting tool life. This investigation can help in controlling and optimizing of cutting conditions when the process parameters are adjusted. The built model for prediction the tool life is identified by using drill diameter, cutting speed, and cutting feed rate as input data. The validity of the model was confirmed by the examinations under various cutting conditions. Experimental results have shown the efficiency of the model to predict cutting tool life.

***Keywords*—**Composite, fuzzy, tool life, wear.

I. Introduction

METAL-Matrix Composites (MMCs) have been widely used in industry due to their improved properties over those of other alloys. MMCs are multiphase materials with hard reinforcing material in metallic matrices. The reinforcement in MMCs has three different forms: continuous fibers, discontinuous fibers, or particulates, with volume percentages in the range of a few percent to 60% [1].

Among the several types of MMCs, Aluminum Matrix Composites (AMCs) have been used for many advanced automotive and aerospace applications [1], [2]. AMCs become the potential engineering materials providing a good combination of properties such as strength, thermal conductivities, low thermal expansion coefficient, and enhanced wear resistance [3]-[7].

A small amount of reinforcement could be added into aluminum or its alloy to improve its modulus and strength. Many ceramic particles can be used as reinforcements including alumina (Al_2O_3) and silicon carbide (SiC). These particles are appropriate for aluminum alloy matrix due to the fact that unwanted reaction does not take place between the matrix and these particles, which may lead to degradation [8].

Although particulate composites have several advantages as shown above, they have not been utilized widely in commercial applications due to the fact that hard particles implanted in the matrix lead to severe problems in machining [6]-[8]. AMCs reinforced with (Al_2O_3) or (SiC) particles are very hard to machine because of their extreme abrasive properties [3], [4], [8]-[10].

Although significant effort has been devoted to manufacture the near-net shape parts by forging or casting, there will be always a need for machining and it cannot be eliminated completely. In addition, machining will have to be used to finish the resulting near-net-shape parts to the designed dimension and shape. Consequently, for assembly and joining, secondary machining processes are needed. One of these machining processes is drilling. These processes are normally done on the part at the last stage of the production cycle before being assembled.

Because of poor machining properties of AMCs, research has focused on improvement of the machinability of AMCs in two main directions. The first one is to discover new composites with improved machinability [11]. The second one is to investigate the influence of machining parameters on these matrixes [6]-[8], [10].

Machinability of AMCs has received significant care because of the high tool wear accompanying with machining. Cutting tool wear is an essential key issue in manufacturing industries. Cutting tool wear impacts the surface roughness of the hole. In addition, it affects the life of the cutting tool.

The reasons behind that are due to the fact that machining process is complex and necessary data is lacking. Moreover, cutting tool life depends on several variables [12].

While machining with cutting tools is one of the oldest approaches of forming parts, the most key characteristics of this process can be found out only by the experiments. Accordingly, a series of experimental studies is needed to verify further modifications of the tool, machine, and process design. Therefore, the accurate test approach and modeling along with its verification are key issues in such studies [13].

In the view of the above-mentioned machining problems, the

Mohammed Hayajneh is with the Industrial Engineering Department, Jordan University of Science and Technology, P.O. Box 3030, Irbid, 22110, Jordan (e-mail: hayajneh@just.edu.jo).

present work will investigate the influence of different cutting conditions on the cutting tool life of the drill bits during drilling of reinforced aluminum alloy composite with Al_2O_3 particles.

The scope of this research will introduce a new alternative technique for modeling of complex cutting processes. In recent years, fuzzy systems, which are based on fuzzy logic [17], have attracted the growing attention in different topics. The use of fuzzy techniques for modeling of these processes might be justified due to the ability of this new method to tackle uncertainty and fuzziness that are common in [8], [14]-[16].

The proposal of fuzzy set theory and the applications of considering fuzzy data to the regression models have been suggested in the literature [18].

Other researchers developed many suitable methods in fuzzy modeling [19]-[26] that added more objectivity in the process of models building. These methods are mainly based on the use of input-output data to improve human understanding. The process of building models from input-output data consists of two major steps: structure identification and parameter identification [8], [14], [16].

This research study will address studying the influence of cutting conditions on the cutting tool life in drilling of Al_2O_3 particle reinforced aluminum alloy composite. Additionally, a subtractive clustering fuzzy system will be used to model the effect of cutting conditions on the cutting tool life in the drilling processes. The input data for the cutting tool life model are: cutting speed, feed rate, and drill diameter, whereas, the output data is represented by the cutting tool life [27].

It is anticipated that the results of this research work will illustrate the capability of fuzzy modeling as prediction technique to estimate the cutting tool life in drilling of Al_2O_3 particle reinforced aluminum alloy composite.

II. Fuzzy Subtractive Clustering

The key idea of clustering is to extract accepted groupings of data from a large data set. Therefore, clustering can be an actual procedure to deal with large sets of data. In subtractive clustering technique proposed by Chiu [19], all data points are considered as nominees for cluster centers. Each data point is given a potential Pj according to its locus with respect to all other data points:

$$P_j = \sum_{k=1}^{N} \exp\left(-\alpha \left\| z_i - z_k \right\|^2\right) \tag{1}$$

where;

$$\alpha = \frac{4}{r_a^2} \tag{2}$$

N is the total number of data points, r_a is a constant called hypersphere cluster radius that defines the neighborhood. Data points outside r_a have small effect on the potential, and $\|.\|$ represents the Euclidean distance.

The data point with the highest potential, denoted by P_1^* is selected as the first cluster center $c_1 = (d_1, e_1)$. The potential of each data point is revised using the formula

$$P_{j-new} = P_{j-old} - P_1^* \exp\left(-\beta \left\| z_j - c_1 \right\|^2\right) \tag{3}$$

where

$$\beta = \frac{4}{r_b^2} \tag{4}$$

with r_b is the hypersphere penalty radius constant greater than r_a. Thus, an amount representing the potential of each data point is subtracted as a function of its distance from c_1. r_b outlines the effective subtractive range and aids in avoiding closely spaced cluster centers and is given by $r_b = \eta r_a$, where η is a positive constant greater than 1 and is called the squash factor. Again, the data point with the highest potential P_2^* is considered to be the next cluster center c_2, if $P_2^* \succ \bar{\varepsilon} P_1^*$ where $\bar{\varepsilon}$ is the accept ratio. If this is not the case but the condition ($\frac{d_{\min}}{r_a} + \frac{P_2^*}{P_1^*} \geq 1$) holds with $d_{\min}$ the minimal distance between c_2 and all previously found cluster centers, the data point is still accepted as the next cluster center c_2. Further iterations can then be executed to find new cluster centers c_1. If a possible cluster center does not fulfill the above defined conditions, it is rejected as a cluster center and its potential is set to 0. The data point with the next highest potential P_k^* is selected as the new possible cluster center and re-tested. The clustering ends if the condition ($p_k^* \succ \bar{\varepsilon} P_1^*$) is satisfied with $\underline{\varepsilon}$ the reject ratio.

After subtraction, the second cluster center is designated based on its new potential in relation to an upper acceptance threshold, $\bar{\varepsilon}$ (acceptance ratio), a lower rejection threshold $\underline{\varepsilon}$ (reject ratio), and relative distance criterion [20], [28]. Subtractive clustering has four weight parameters, the acceptance ratio $\bar{\varepsilon}$, reject ratio $\underline{\varepsilon}$, cluster radius r_a and squash factorη. The degree to which a rule i is fulfilled is defined in terms of the distance to the defined cluster centers:

$$w_i(x) = \exp\left(-\alpha \left\| x - d_i \right\|^2\right) \tag{5}$$

There are two common types of fuzzy models: Mamdani type [29] and Sugeno types [30]. In the Sugeno model the system with ''m'' inputs can be represented as a set of ''n'' rules of the following format:

$$\begin{aligned} &R_i : \text{IF } x_i = A_1^i \text{ AND } x_2 = A_2^i, \ldots\ldots \text{AND } x_m = A_m^i \text{ THEN} \\ &y_i = a_{i0} + a_{i1}x_i + \ldots\ldots + a_{im}x_m \end{aligned} \tag{6}$$

where $a_{i0}, a_{i1},........, a_{im}; i = 1,2,......, n$ are regression parameters.

III. Experimental Procedures

The matrix material used in this study was aluminum alloy and Al_2O_3 particles were used in the manufacturing the cast bars studied in this investigation.

The processing of Al-10 Vol.% Al_2O_3 composite has been attained by insertion the aluminum in a crucible inside an electrical furnace. The temperature of the melt was observed by the K-type thermocouple. The furnace was switched off, and an appropriate quantity of the Al_2O_3 particles was added. Directly, the stirrer at a speed of 600 rpm was implanted inside the melt to blend the added reinforcing particles. At the end of the mixing period, the metal inside the crucible was poured into a metallic mould.

Experiments have been carried out to examine the influences of the cutting conditions on the tool life in drilling of Al_2O_3 particle reinforced aluminum alloy composite. To examine the effect of machining parameters on the tool life, three main cutting parameters were used: drill diameter (D), cutting speed (V), and cutting feed rate (f).

To construct the fuzzy model for predicting the drilling tool life, training and testing data with regard to process cutting factors and cutting tool life have been established. A number of experiments were performed on radial bench drilling machine OPTI RB 35 using high speed steel twist drills for drilling the produced composites. Standard, two-flutes, 118-degree point angle twist drills were used. The holes were drilled dry without the use of bushing. The drilling cutting factors were selected by changing the drill diameter in the range of 6–12 mm (6, 9, 12 mm), cutting speed in the range of 8–24 m/min (8, 16, 24 m/min), and cutting feed rate in the range of 0.05–0.15 mm/rev (0.05, 0.10, 0.15 mm/rev). Therefore, 27 (3(D) × 3(V) × 3(f)) drilling experiments were carried out to measure the cutting tool life, T.

Tool life is defined as the cutting time required reaching a tool life criterion. This criterion to define the effective tool life for HSS tools is recommended by the International Standards Organization (ISO) [31]. The criterion recommended by ISO to define the effective tool life for HSS tools is regularly worn average flank wear of 0.3 mm or maximum flank wear of 0.6 mm. The tool life used in this study is defined as the period of drilling time that the average flank wear land is equal to $V_B = 0.3mm$. In the experiments, the width of flank wear land was measured by using the tool makers' microscope. Tool wear was measured with a microscope after each workpiece. The drilling was ended after each workpiece, and the drill was taken out of the machine for measurement of the tool wear. The average flank wear is used as the criterion to describe the drill condition, and is attained by measuring the wear at different points on either of the cutting edges [32]. The average flank wear land V_B is calculated by averaging two positions of the flank wear land on the cutting edges. The evaluation of V_B was obtained using two measurements as shown in Fig. 1, and considering their average:

$$V_B = \frac{V_{B1} + V_{B2}}{2} \tag{7}$$

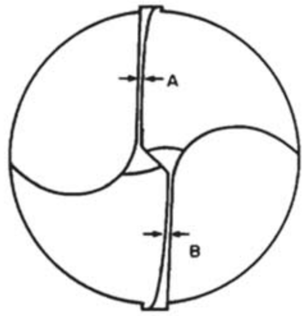

Fig. 1 Flank wear land on the drill

IV. Results and Discussion

A complete set of experiments has been performed. Three drill diameters D, (6, 9, 12 mm), three cutting speeds, V, (8, 16, 24 m/min), and three cutting feed rates (0.05, 0.10, 0.15 mm/rev) have been used.

TABLE I
EFFECT OF MACHINING PARAMETERS ON THE CUTTING TOOL LIFE (TRAINING SET)

Test No.	Drilling diameter D (mm)	Cutting Speed V (m/min)	Cutting feed rate f (mm/rev)	Tool Life T (s)
1	12	8	0.05	323
2	9	8	0.15	57
3	6	8	0.05	502
5	9	24	0.05	179
4	6	8	0.15	45
6	12	8	0.15	46
7	9	8	0.05	893
8	12	24	0.05	162
9	9	16	0.05	268
10	12	16	0.05	269
11	6	24	0.10	38
12	9	16	0.15	56
13	6	16	0.05	215
14	9	24	0.10	60
15	6	8	0.10	49
16	12	8	0.10	129
17	6	24	0.05	167
18	9	16	0.10	71
19	12	24	0.10	57
20	6	24	0.15	29
21	12	16	0.15	41

In this work, flank wear value $V_B = 0.3mm$ was used as a tool life criterion. The number of possible combinations is 3 Drill diameters × 3 Cutting speeds × 3 Cutting feed rates. The tool life database was collected randomly for each of the 27 drilling experiments defined by the levels of independent variables. The original 27 databases were arbitrarily separated into two data sets, training set and a testing set. The training set involved 21 records, which were used to construct the fuzzy model, and the testing set encompassed six records, which were used to test the validity of the fuzzy model as shown in Tables I and II, respectively.

The model for the output (i.e. the cutting tool life) was identified by using the input parameters. Fuzzy logic toolbox was used to construct the fuzzy model.

TABLE II
EFFECT OF MACHINING PARAMETERS ON THE CUTTING TOOL LIFE (TESTING SET)

Test No.	Drilling diameter D (mm)	Cutting Speed V (m/min)	Cutting feed rate f (mm/rev)	Tool Life T (s)
1	12	16	0.10	172
2	9	8	0.10	275
3	6	16	0.15	219
4	12	24	0.15	214
5	6	16	0.10	21
6	9	24	0.15	388

The process of constructing the fuzzy model was performed by creating of clusters in the data space. The clusters were projected into each dimension in the input space, and each projection outlines an antecedent of a rule. The identified first order Sugeno fuzzy model [22] is as follows:

$$R_1 : \text{IF } x_1 = A_1^1 \text{ and } x_2 = A_2^1 \text{ and } x_3 = A_3^1$$
$$\text{THEN}$$
$$y_i = a_{10} + a_{11}x_1 + a_{12}x_2 + a_{13}x_3 \tag{8}$$
.
.
$$R_k : \text{IF } x_1 = A_1^k \text{ and } x_2 = A_2^k \text{ and } x_3 = A_3^k$$
$$\text{THEN}$$
$$y_k = a_{k0} + a_{k1}x_1 + a_{k2}x_2 + a_{k3}x_3$$

where the three input variables x_1, x_2 and x_3, are the drill diameters, cutting speed and cutting feed rate, respectively. While the output variable y_k for $k = 1,2, \ldots.., k$ is the cutting tool life for rule k, and a_{k0}, a_{k1}, a_{k2}, and a_{k3} were the regression parameters [33].

The optimization of the system modeling, however, can be determined by finding the optimum range of the clustering parameters. Therefore, several searches were carried out on parameters such as the squash factor (η), cluster radius (r_a), acceptance ratio ($\bar{\varepsilon}$) and reject ratio (ε) as. Backpropagation optimization method was used to train the FIS [26].

Fig. 2 shows the backpropagation error versus the number of rules. Fig. 2 displays that the value of error is nearly fixed after the number of rules equal 9. Numerous searches are carried out on parameters such as the cluster radius, reject ratio, acceptance ratio and squash factor to optimize the system modeling.

The found fuzzy model is able of predicting the tool life for a given set of inputs. Therefore, the operator can predict the cutting tool life for a certain set of cutting parameters as seen in Fig. 3.

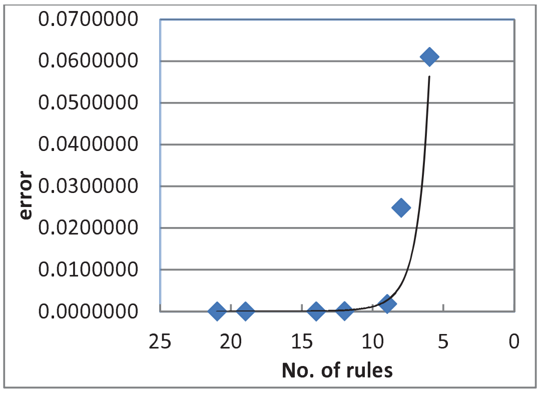

Fig. 2 Number of rules versus backpropagation error

The model is verified by comparing the fuzzy output with testing set and with the training set used to construct the fuzzy model. The results of these tests are in good agreement with those forecasted using the fuzzy model as shown in Figs. 4 and 5. Fig. 4 shows a comparison of the fuzzy model output with the training data, while Fig. 5 compares the fuzzy model output with the testing data for the tool life. As it can be seen in Figs. 4 and 5, the average training error is about 0.0018416 s, while the average testing error is about 5.9696 s, respectively.

V. CONCLUSIONS

In the present study, a subtractive clustering fuzzy identification method and a Sugeno-type fuzzy inference system were used to model and predict the tool life in drilling of reinforced aluminum alloy composite. The following conclusions can be drawn from the present investigation:

1. This study establishes relationship between the input and output parameters in drilling of Al_2O_3 particle reinforced aluminum alloy composite.
2. A subtractive clustering based fuzzy identification method and a sugeno type fuzzy inference system are used for modeling and predicting the cutting tool life. The model for the cutting tool is identified by using the drill diameter, cutting speed and cutting feed rate as input data and cutting tool life as the output data.
3. The results of this research work illustrated the capability of fuzzy modeling as prediction technique to estimate the cutting tool life in drilling of Al_2O_3 particle reinforced aluminum alloy composite. The ability to forecast the cutting tool life during drilling is essential for the optimizing of cutting conditions. Fuzzy modeling of the cutting tool life will introduce a better knowledge of the influence of process parameters on cutting tool life. This knowledge can help in optimizing of cutting conditions and controlling tool change strategies when the process parameters are adjusted.

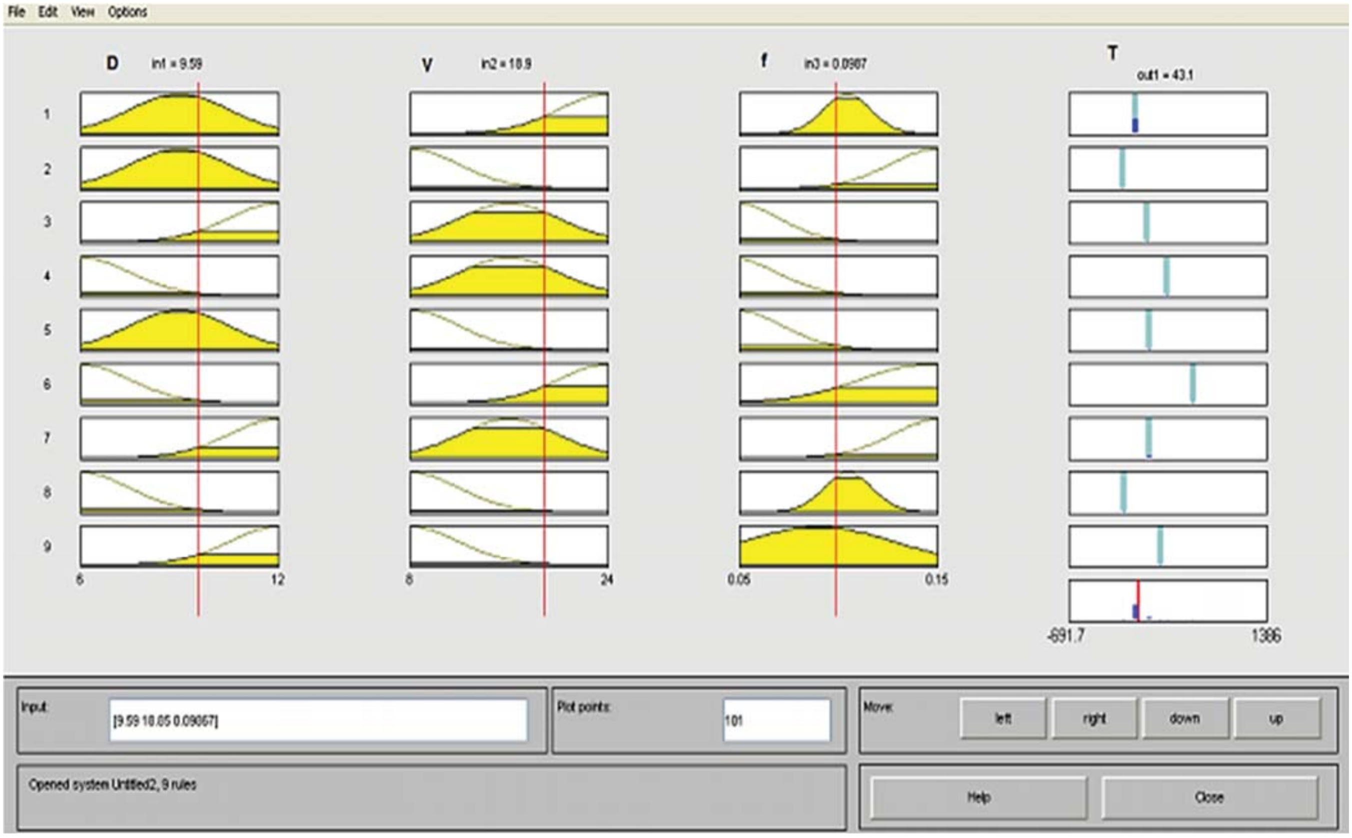

Fig. 3 Rule viewer of Fuzzy toolbox of Matlab 7.0 of modeling the cutting tool life with 9 rules

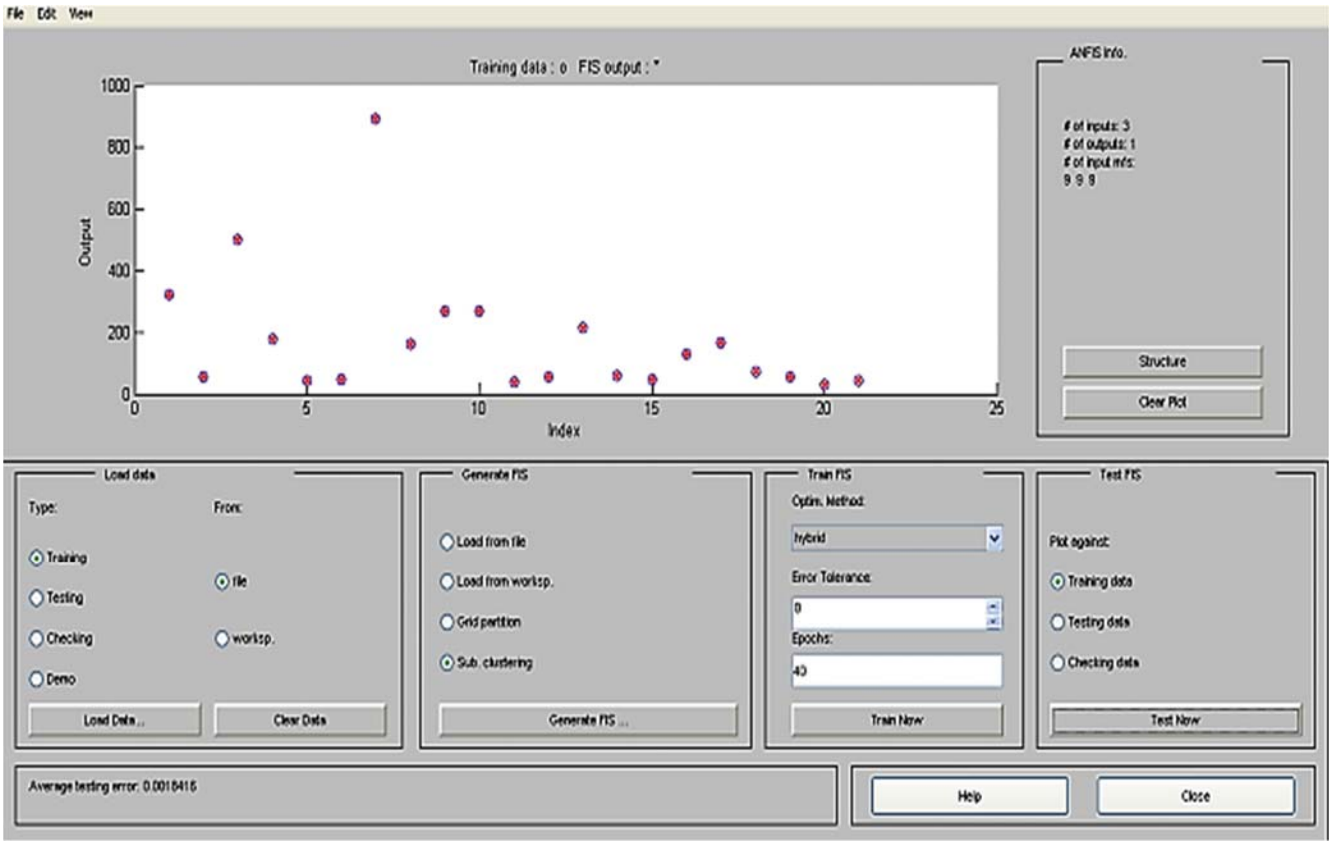

Fig. 4 Comparison of fuzzy model output with training data for the cutting tool life

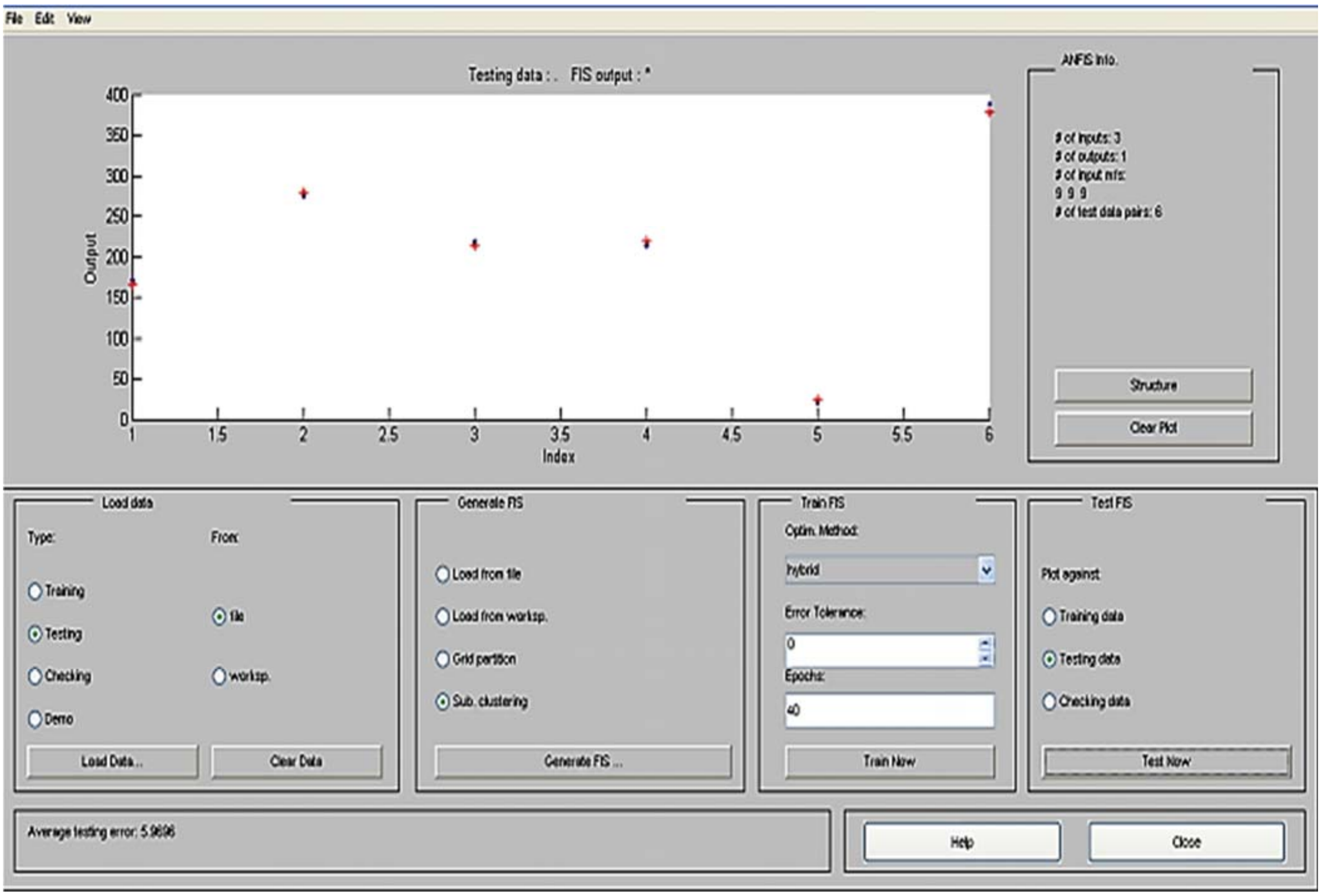

Fig. 5 Comparison of fuzzy model output with testing data for the cutting tool life

REFERENCES

[1] J.M. Kunz, C.C. Bampton, "Challenges to developing and producing MMCs for space applications," Journal of Materials Vol. 53, No. 4, pp. 22–25, 2001.

[2] Rohatgi PK.," Cast aluminum matrix composites for automotive applications," JOM, pp. 10–5. 1991.

[3] Adel Mahmood Hassan, Ahmad Turki Mayyas, Mohammed T. Hayajneh, and Abdalla Alrashdan," Wear behavior of Al-Mg-Cu composites containing SiC particles," Tribology International, Vol. 42, pp. 1230–1238, 2009.

[4] Mohammed T. Hayajneh, Adel Mahammoud Hassan, Abdalla Alrashdan, and Ahmad Turki Mayyas " Prediction of Tribological Behaviour of Aluminum-Copper Based Composite Using Artificial Neural Network", Journal of Alloys and Compounds, Vol. 470, pp. 584-588, 2009.

[5] Adel Mahammoud Hassan, Abdalla Alrashdan, Mohammed T. Hayajneh and Ahmad Turki Mayyas, "Prediction of density, porosity and hardness in aluminum–copper-based composite materials using artificial neural network", Journal of Materials Processing Technology, Vol. 209, pp. 894–899, 2009.

[6] Mohammed T. Hayajneh, Adel Mahammoud Hassan and Ahmad Turki Mayyas," Artificial neural network modeling of the drilling process of self-lubricated aluminum/alumina/graphite hybrid composites synthesized by powder metallurgy technique," Journal of Alloys and Compounds, Vol. 478, pp. 559–565, 2009.

[7] Mohammed T. Hayajneh, Adel Mahammoud Hassan and Mohammad Abdul-Hameed Al-Omari, "The Effect of Graphite Particles Addition on the Surface Finish of Machined Al-4wt% Mg Alloys", Journal of Materials Engineering and Performance, Vol. 10, No. 5, pp. 521-525, 2001.

[8] Mohammed T. Hayajneh, Adel Mahammoud Hassan," Modeling The Machinability of Self-Lubricated Aluminum/Alumina/Graphite Hybrid Composites Using A Fuzzy Subtractive Clustering-Based Sys.tem Identification Method," International Journal of Machining and Machinability of Materials (IJMMM), Vol. 3, Nos. 3/4, pp. 252-271, 2008.

[9] Sahin, Y., Kok, M., Celik, H., "Tool wear and surface roughness of Al2O3 particle-reinforced aluminium alloy composites". Journal Material Process Technology 128, 280-291, 2002

[10] A.M. Hassan, M.T. Hayajneh and M.K. Al-Mahasneh," Machinability of Al-4%wt Mg-Al2O3-Graphite Composites Produced by Compo-Casting," Materials Science Forum, Trans Tech Publications, Switzerland, Vols. 636-637 pp. 171-176, Doi:10.4028/www.scientific.net/MSF.636-637.171, 2010.

[11] I. Bell, T.F. Stephenson, A. Warner, V. Songmene, SAE International Congress & Exposition, Detroit, MI, , pp. 24–27, 1997

[12] J.A. Arsecularatne, L.C. Zhang, C. Montross, "Wear and tool life of tungsten carbide, PCBN and PCD cutting tools," International Journal of Machine Tools & Manufacture 46, 482–491. 2006

[13] Viktor P. Astakhov, Vasily V. Galitsky, "Tool life testing in gundrilling: an application of the group method of data handling (GMDH)," International Journal of Machine Tools & Manufacture 45, 509–517, 2005

[14] Mohammed T. Hayajneh and Saleh Radaideh, "Monitoring Hole Quality in Drilling Process Using Fuzzy Subtractive Clustering Based System Identification Method," Journal of Testing and Evaluation, Vol. 35, No. 3, pp. 297-302, 2007.

[15] Mohammed T. Hayajneh, "Fuzzy Clustering Model for Surface Finish Prediction in Fine Turning Process," International Journal of Machining Science and Technology, Vol. 9, pp. 437-451, 2005.

[16] Mohammed T. Hayajneh and Saleh M. Radaideh, "Modeling Surface Finish in End Milling Process Using Fuzzy Subtractive Clustering Based System Identification Method," Materials and Manufacturing Processes, Vol. 18, No. 4, 2003.

[17] Zadeh, L.A." Outline of a new approach to the analysis of complex systems and decision processes", IEEE Transaction on Systems, Man, and Cybernetics, Vol. 3, pp. 28–44, 1973

[18] Yen, J. and Langari, R., "Fuzzy Logic Intelligence, Control and Information," Prentice-hall Inc, New Jersey, 1999.

[19] Chiu, S., "Fuzzy model identification based on cluster estimation', Journal of Intelligent and Fuzzy Systems, Vol. 2, pp.267–278, 1994.
[20] Demirli, K. and Muthukumaran, P., "Fuzzy system identification with higher order clustering", Journal of Intelligent and Fuzzy Systems, Vol. 9, No. 3, pp.129–158, 2000.
[21] Demirli, K., Cheng, S. and Muthukumaran, P.,"Subtractive clustering based modeling of job sequencing with parametric search", Fuzzy Sets and Systems, Vol. 137, pp.235–270, 2003.
[22] Jang, J., " ANFIS: Adaptive-network-based fuzzy inference system", IEEE Transactions on Systems Man and Cybernetics, Vol. 23, No. 3, pp.665–685, 1993.
[23] Takagi, T. and Sugeno, M., "Fuzzy identification of systems and its applications to modeling and control", IEEE Transactions on Systems Man and Cybernetics, Vol. 15, pp.116–132, 1985.
[24] Sugeno, M., Kang, G.T., "Structure identification of fuzzy model", Fuzzy Sets and Systems, Vol. 28, pp. 15–33. 1988.
[25] Tsai, P., Jang, S. and Shieh, S., "Predictive control of batch processes using principal surface/space analysis and fuzzy clustering empirical models", Proceedings of the American Control Conference, Vol. 2, pp.1005–1009, 2001.
[26] Mohammed T. Hayajneh, Adel Mahmood Hassan and Fatma Al-Wedyan," Monitoring defects of ceramic tiles using fuzzy subtractive clustering-based system identification method," Soft Comput, Vol.14, pp. 615–626, 2010.
[27] Jalali S. A., Kolarik W. J., "Tool life and machinability models for Drilling steels," International Journal of machine Manufacture, Vol. 31, No. 3, pp. 273-282, 1991.
[28] Alata, M., Al-Nimr, M.A. & Qaroush, Y., "Developing a multipurpose sun tracking system using fuzzy control. Energy Conversion and Management," Vol. 46, pp. 1229–1245, 2005.
[29] Mamdani, H.; Assilian, S., " An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller," International Journal of Man-Machine studies, Vol. 7, pp.1–13. 1975.
[30] Jang, J.S.R.; Chuen-Tsai, S.; Mizutani, E. Neuro Fuzzy Modeling and Soft Computing; Prentice Hall International Inc., 1997.
[31] ISO (International Organization for Standardization) (ed.), "Tool-life Testing with Single-Point Turning Tools (ISO 3685)," 2nd edition, Reference Number ISO 3685, 1993).
[32] S.C. Lin, C.J. Ting, "Tool wear monitoring in drilling using force signals, Journal of Wear, Vol. 180, pp.53-60., 1995.
[33] Bai G, Liang Z., "The application of fuzzy clustering analysis in the choice of fabric. Journal-Northwest Institute of Textile Science and Technology," Vol. 14, No. 2, pp.128-132, 2000.