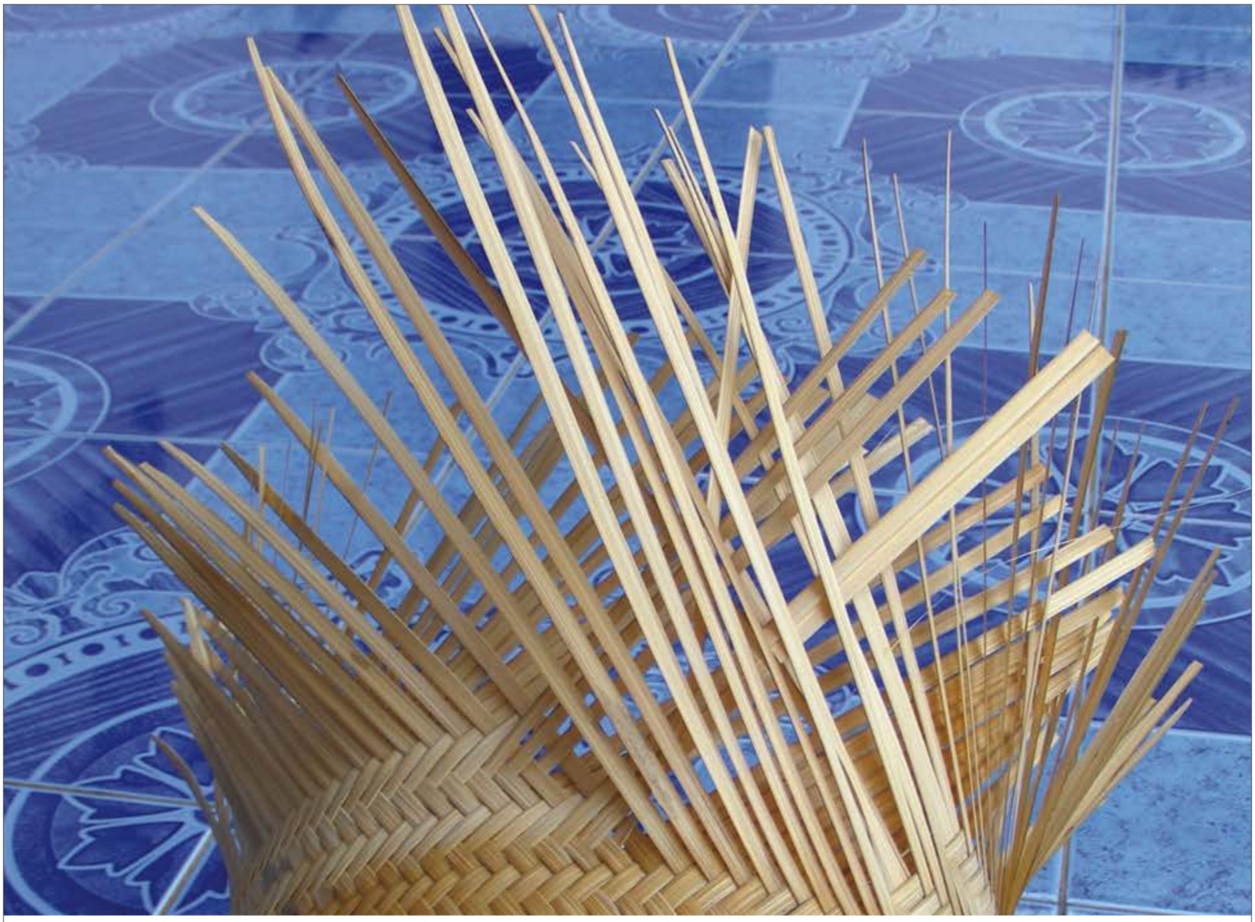

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Research Article

Modeling of the Tool Flank Wear in Turning Process

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Abstract

Tool wear modeling in machining processes is one of the important tasks in manufacturing to establish an automation based system. This will be helpful in Flexible Manufacturing Systems (FMS) and Computer Integrated Manufacturing (CIM) systems. Taking attention to this reality, a fuzzy model for predicting worn tool cutting forces in machining without the need for any worn tool calibration tests is presented in this paper. An AISI 4140 type steel was used for machining operation. Cutting times were measured during the machining in different cutting parameters including cutting speeds (V), feed rates (f) and cutting depths (d). For generalizing the model, full factorial method was applied for arranging the cutting parameters. For creating the prediction model a fuzzy logic model was developed based on the cutting parameters and machining time. The estimated tool flank wear using of the fuzzy logic model was compared with the measured values. Based on the comparison of the results, the model confirms the measured tool flank wear rates with an acceptable reliability.

Key words: Cutting time, modeling, fuzzy logic, prediction

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Cutting tool condition has a strong influence on the resulting surface finish and dimensional integrity of the work piece, as well as vibrations of the machine tool. The information obtained from tool wear monitoring can be used for several purposes including; creating tool change policy, economic optimization of metal cutting operations, compensating for tool wear rate on-line and avoiding catastrophic tool failures[1]. Monitoring of a manufacturing process is essential for ensuring product quality and reducing production costs. Among the wear types, tool flank wear is so important that can be considered as tool life criterion in tool condition monitoring. Tool flank wear is found to have an adverse effects on surface finish, residual stresses and micro structural changes in the form of a white surface layer[2]. For improving the turning processes, dynamical progress of the flank wear must be modeled and predicted. There are two ways to deal with tool flank wear modeling. The first approach is based on the mathematical equations representing the corresponding physical laws[3]. The second method is based on the idea that the process is not known and there is no enough knowledge of the model structure to explain the physical behavior of the flank wear. In this method, the unknown parameters of the model are estimated using experimental data to reach to an input-output relationship. The main advantage of the second approach is that it is possible to develop a reliable empirical model without needing the physical process knowledge[4]. However, the main drawbacks of this method are the structure of the model, which is unable to give any physical meaning. In practice, combination of the two approaches is the best way, if possible, so that the most known parts can be modeled using physical knowledge and the less-known ones can be approximated through the empirical methods[5]. Some studies on tool wear have been reported which focused on estimation of tool wear by empirical modeling methods[6] including; time series methods[7], frequency domain analysis[8], pattern recognition and statistical methods[9],hidden markov model method[10], etc. These studies have gained various degrees of success in tool wear modeling although they need a lot of experimental data. However, because of the complex nature of the wear incident, its behavior is practically impossible to describe exactly by conventional modeling tools. In those cases, approaches based on artificial intelligence techniques like fuzzy logic and neural networks are the best way to cope with these problems. Monitoring and prediction of tool wear needs some accurate steps that must be taken to achieve to any phase of a reliable monitoring system. A variety of techniques have been employed to carry out each phase of tool condition monitoring. Such phases include, choice of the parameters to be captured, feature extraction, feature selection and feature classification[11].

In this study, a fuzzy logic model was developed for predicting the tool flank wear. For this, a CNC machine tool and a carbide tool were used for conducting the experiments. Full factorial method was applied to design the experiments. Cutting parameters and the time were used as input variables in designing the fuzzy logic model. For generalizing the fuzzy prediction model, many of the existing membership functions in MATLAB program were tried and the "Gaussian" method was selected. After modeling the cutting forces, the measured and estimated values of the fuzzy logic model were compared to confirm the model reliability. The comparing results show the efficiency of the fuzzy logic model.

MATERIALS AND METHODS

A Johnford TC-35 CNC machine tool was used for conducting the experiments. A Sandvik-Coromant insert (TNMG 1604-QM H13) was selected as the cutting tool. The material used for machining was SAE 4140. The cutting parameters applied in machining operation were selected based on ISO 3685 Standard (Table 1). A Dino Capture microscope was used to measure the flank wear rate of the cutting tools (Fig. 1).

Experiment design: Experimental design is an important task in empirical modeling and data based systems. It will be helpful to develop generalized models which could be applicable in the other machining conditions. To reach to this aim the full factorial method was used as the experimental

Table 1: Cutting parameters

Cutting speed (m min^{-1})	Feed rate (mm rev^{-1})	Cutting depth (mm)
110	0.17	0.75
135	0.22	1.25
160	0.27	1.75

Fig. 1: Microscope used for measuring the tool wears

design method. By applying the full factorial method, a total of 108 experiments were designed using of JMP program.

Experiment procedure: In conducting the experiments, the machining operation continued until the tool life was expired. The tool flank wear rates were measured four times (0, 0.1, 0.2 and 0.3) during the conducting of any experiment. The cutting times were estimated during the machining process for any of the measured tool flank wear. The cutting time during the experiments was estimated as:

$$t = \frac{W}{f \times N} \tag{1}$$

where, t is the cutting time, W is the work length, f is the feed rate and N is the spindle speed in rpm.

Fuzzy logic: The term "fuzzy logic" was introduced with the 1965 proposal of fuzzy set theory by Zadeh[12]. Fuzzy logic has been applied to many scientific fields, from control theory to artificial intelligence. It is a form of multi valued logic that deals with approximate, rather than exact reasoning. Compared to conventional binary logic, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1 Zadeh[12]. Zadeh's principle of incompatibility says ''As the complexity of a system increases, the human ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance become almost mutually exclusive characteristics''. In other words, the closer one looks at a real world problem, the fuzzier its solution becomes[13]. Fuzzy logic is a simple way to map an input space to an output space and to model the non linear incidents. Fuzzy inference system is the process of formulating the mapping from a given input to an output variable. The process of creating the fuzzy inference involves membership functions, operators and if-then rules. A membership function is a fuzzification curve that defines how an input is mapped to a degree of membership between 0 and 1. There are two types of fuzzy inference systems in MATLAB program including Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined[14]. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. It was proposed by Mamdani and Assilian[15]. Mamdani's effort was based on Lotif Zadeh[16] paper on fuzzy algorithms for modeling the complex systems and decision processes. Mamdani method was used in this study for fuzzy modeling.

Fuzzy logic modeling: In this study, fuzzy logic tool box in MATLAB was used for establishing the cutting force modeling program. For creating the model, four inputs including cutting speed (V), cutting depth (d), feed rate (f) and cutting time (t) were regarded as the input of the fuzzy logic and the tool flank wear was selected as the output. For developing the model, the "Gaussian" type of membership function selected as appropriate membership function. By using the Mamdani's method, the model was created as (Fig. 2).

In fuzzy modeling approach, there are three cutting parameters and three respective levels are considered for each of the parameters. Therefore, three fuzzy sets were considered

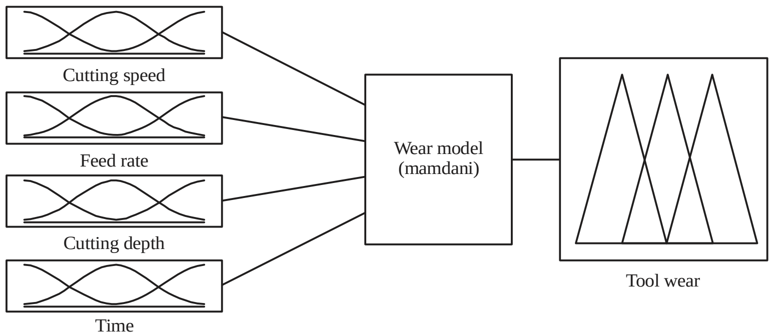


Fig. 2: Fuzzy logic model designed for tool wear estimation

for each of the cutting parameters as the inputs and a total of 108 fuzzy sets were selected for the cutting time to the 108 measured values equal to the experiment numbers. Furthermore, four fuzzy sets were assigned for the four levels of the output variable (tool flank wear), including 0, 0.1, 0.2 and 0.3 mm. After fuzzifying the data, a total of 108 rules were created for establishing the fuzzy inference system. Some of the created rules are written as:

- If cutting speed is v1, feed rate is f2, cutting depth is d1 and time is t1 then tool wear is Vb1 (1)
- If cutting speed is v1, feed rate is f2, cutting depth is d1 and time is t2 then tool wear is Vb2 (1)
- If cutting speed is v1, feed rate is f2, cutting depth is d1 and time is t3 then tool wear is Vb3 (1)
- If cutting speed is v1, feed rate is f2, cutting depth is d1 and time is t4 then tool wear is Vb4 (1)
- If cutting speed is v2, feed rate is f2, cutting depth is d1 and time is t5 then tool wear is Vb1 (1)
- If cutting speed is v2, feed rate is f2, cutting depth is d1 and time is t6 then tool wear is Vb2 (1)
- If cutting speed is v2, feed rate is f2, cutting depth is d1 and time is t7 then tool wear is Vb3 (1)
- If cutting speed is v2, feed rate is f2, cutting depth is d1 and time is t8 then tool wear is Vb4 (1)
- If cutting speed is v3, feed rate is f2, cutting depth is d1 and time is t9 then tool wear is Vb1 (1)
- If cutting speed is v3, feed rate is f2, cutting depth is d1 and time is t10 then tool wear is Vb2 (1)
- If cutting speed is v3, feed rate is f2, cutting depth is d1 and time is t11 then tool wear is Vb3 (1)
- If cutting speed is v3, feed rate is f2, cutting depth is d1 and time is t12 then tool wear is Vb4 (1)
- If cutting speed is v1, feed rate is f2, cutting depth is d1 and time is t13 then tool wear is Vb1 (1)
- If cutting speed is v1, feed rate is f1, cutting depth is d1 and time is t14 then tool wear is Vb2 (1)
- If cutting speed is v1, feed rate is f1, cutting depth is d1 and time is t15 then tool wear is Vb3 (1)
- If cutting speed is v1, feed rate is f1, cutting depth is d1 and time is t16 then tool wear is Vb4 (1)
- If cutting speed is v2, feed rate is f1, cutting depth is d1 and time is t17 then tool wear is Vb1 (1)

RESULTS AND DISCUSSION

To design a reliable model, all of the effective parameters on the model variable must be specified. In this evaluating process the ineffective parameters are eliminated from modeling requirements. Therefore, before developing the fuzzy model, the ANOVA test was conducted to extract the meaningfully of the parameters. The results of effect tests are presented in Table 2. Based on the result of p-values which are under 0.05, all of the input variables have a meaningful affection on the tool flank wear. Also, among the cutting parameters; cutting speed, feed rate and cutting depth were respectively the most effective parameters on the tool flank wear. Because the F ratios for the cutting parameters are; 195 for cutting speed, 116 for feed rate and 29 for cutting depth.

The tool wear is a dynamical process that is changed based on the cutting time. Moreover, the cutting parameters are affecting the tool flank wear. The three dimensional graphic of the input parameters and the tool wear has been given in Fig. 3, as a result of the fuzzy logic modeling. As is obvious in the figure, tool flank wear rate is increasing during the cutting time, however the relationship between time and the tool wear is non linear. Also, the cutting speed has a direct affection on the tool flank wear during the time.

The affection of the feed rate is shown in Fig. 4. In constant values of the cutting speed and cutting depth, the tool flank wear is increasing by any increase in the feed rates. However, the slope of this increase is changing based on the cutting parameters.

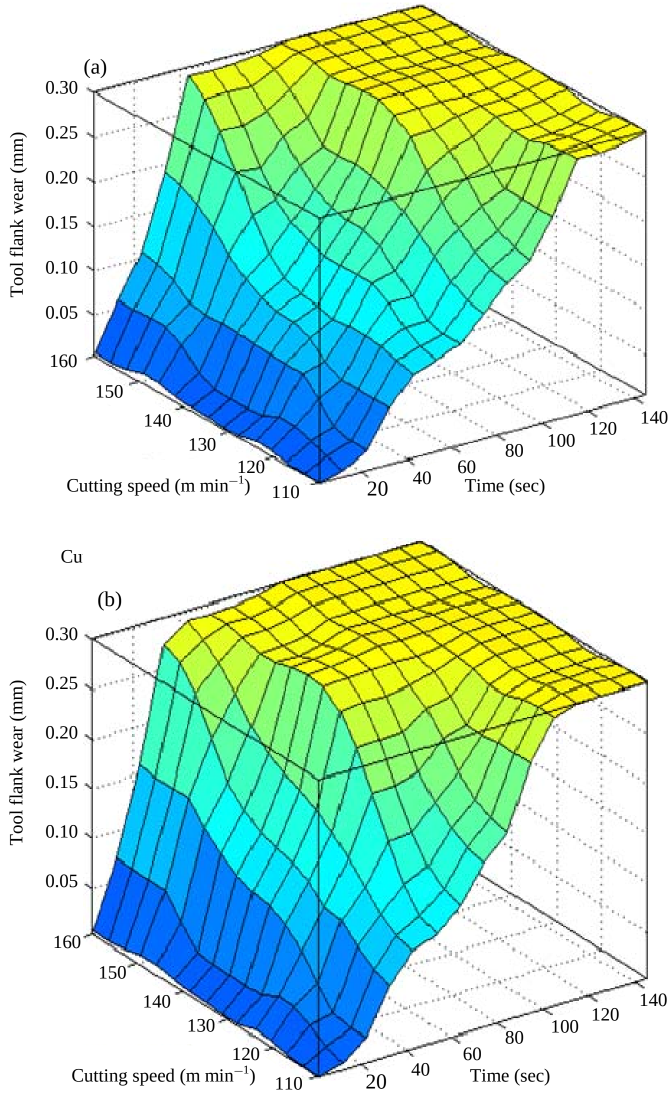


Fig. 3(a-b): Effect of cutting speed on the tool wear during the cutting time (a) V = 110 m min^{-1}, d = 1.25 mm and (b) V = 160 m min^{-1}, d = 1.75 mm

Table 2: ANOVA effect tests

Parameters	Degree of freedom	Sum of squares	F ratio	Prob>F
Cutting speed (m min^{-1})	1	0.3182801	195.5936	<0.0001
Feed rate (mm rev^{-1})	1	0.1895333	116.4744	<0.0001
Cutting depth (mm)	1	0.0474961	29.1879	<0.0001
Time (sec)	1	1.0707666	658.0213	<0.0001

The effect of the cutting depth along with the cutting time on the tool wear is given in Fig. 5. As is obvious in the figure, the slope of the cutting depth is lower than the other cutting parameters. In the developed tool wear monitoring system when the tool wear reaches to 0.3 mm, it implies that the cutting tool must be changed with a new one. Based on the ISO Standard the 0.3 mm of flank wear is the tool life finish criterion.

After developing the model all of the used 108 experiment results were compared with the fuzzy model prediction results to obtain the R^2 value of the experiments. Based on the comparison result, the obtained R^2 value for this model is 0.8682 and it implies that the reliability of the fuzzy model for prediction of the tool wear is acceptable (Fig. 6).

In comparison with the previous studies, this research can be used not only in automation based manufacturing systems

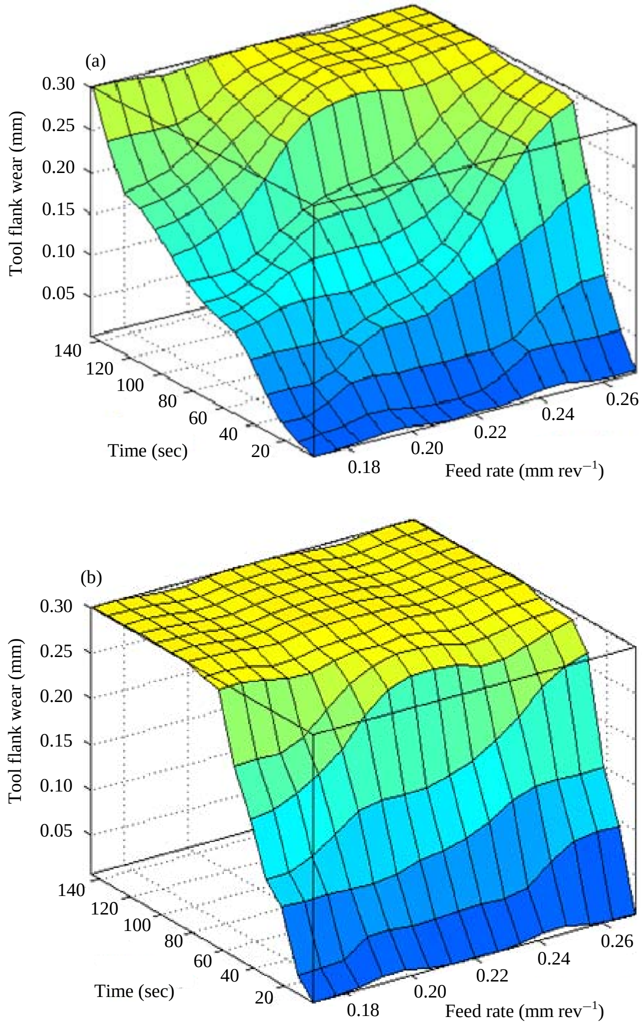


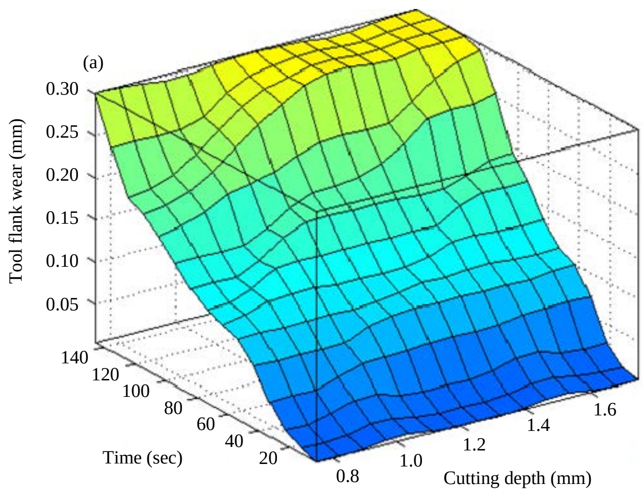
Fig. 4(a-b): Effect of feed rates on the tool wear during the cutting time (a) f = 0.17 mm rev^{-1}, d = 0.75 mm and (b) f = 0.17 mm rev^{-1}, d = 0.75 mm

but also in a small work shop and single manufacturing systems. Also, this method can be used with a small size of experiments while in the other modeling methods, a lot of experiments must be conducted to reach to a reliable prediction model.

To prove the accuracy of the developed model, the results were compared with some studies in literature. In a study Deiab *et al.*[17], a tool wear model was developed using of 5 different cutting speed, three different feed rates and one cutting depth. The graphical results of the developed model in the literature and the present model are given in Fig. 7. Based on the figures, the time-tool wear graphic of the literature model (Fig. 7b) confirms the result of the developed model in this study. So, both results represent the same behavior. Also, the prediction accuracy in both models is almost equal to 86%.

In another study Sharma *et al.*[14] a model was developed to predict the tool flank wear during the time. The graphical results are given in Fig. 8. As is seen in the figure, the tool flank wear is increasing during the machining time in the developed diagram in the literature (Fig. 8b) and in this study (Fig. 8a).

In a developed model in the other study[18], the results of the prediction model was given as a time-tool flank wear diagram. As shown in Fig. 9, the diagram extracted from the model confirms the results of the present study and both models follow the same behavior. However, the values of the flank wear and time are different, because the used parameters and materials are very different with each other. In other words, in the introduced studies, the values are different; however all of the diagrams follow the same attitude.



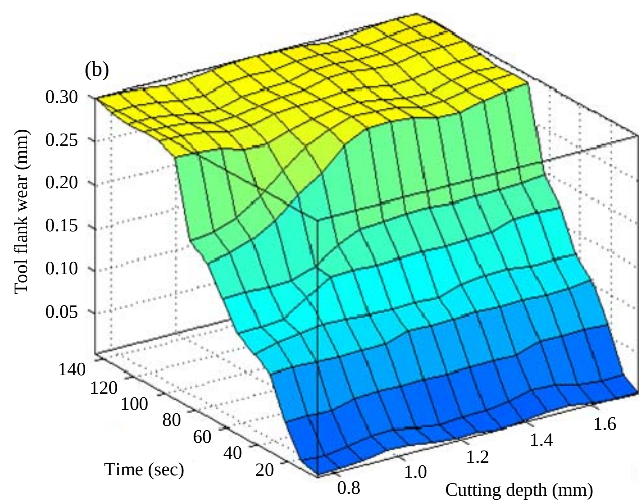


Fig. 5(a-b): Effect of cutting depth on the tool wear during the cutting time (a) V = 110 m min^{-1}, d = 0.17 mm and (b) V = 110 m min^{-1}, d = 0.22 mm

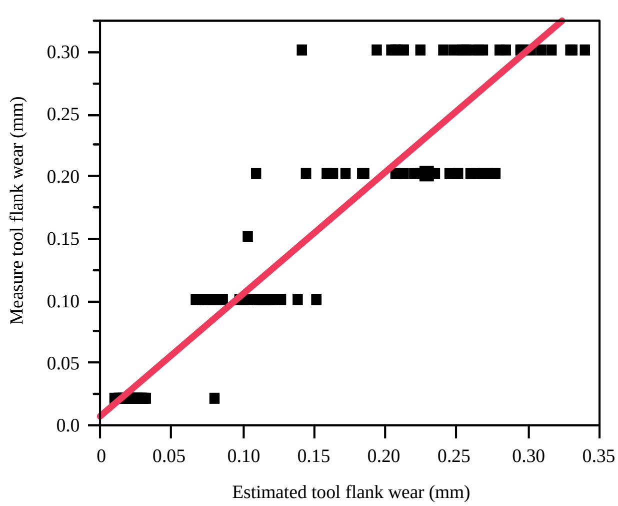


Fig. 6: Comparing the measured and estimated tool flank wear, R^2 = 0.8682

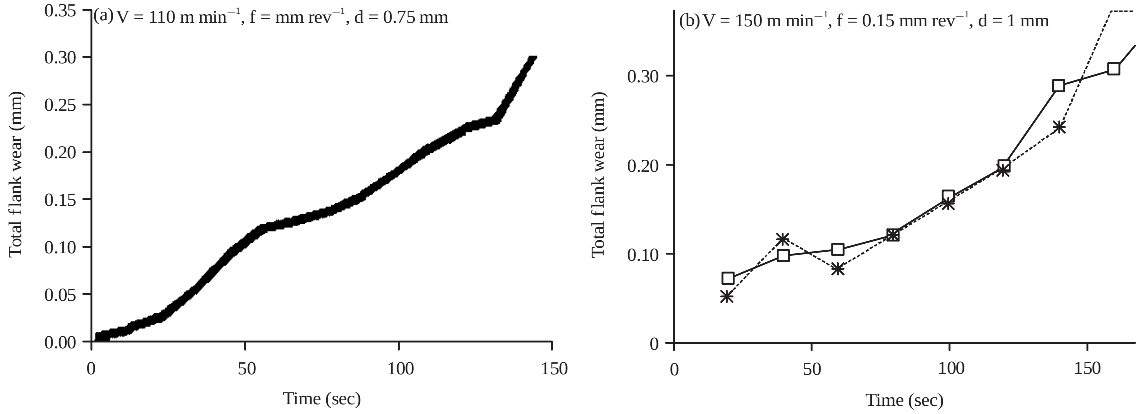


Fig. 7(a-b): Comparing the results of the developed model in this study with the literature (a) Present model, R^2 = 0.86 and (b) Literature model, prediction accuracy = 84%

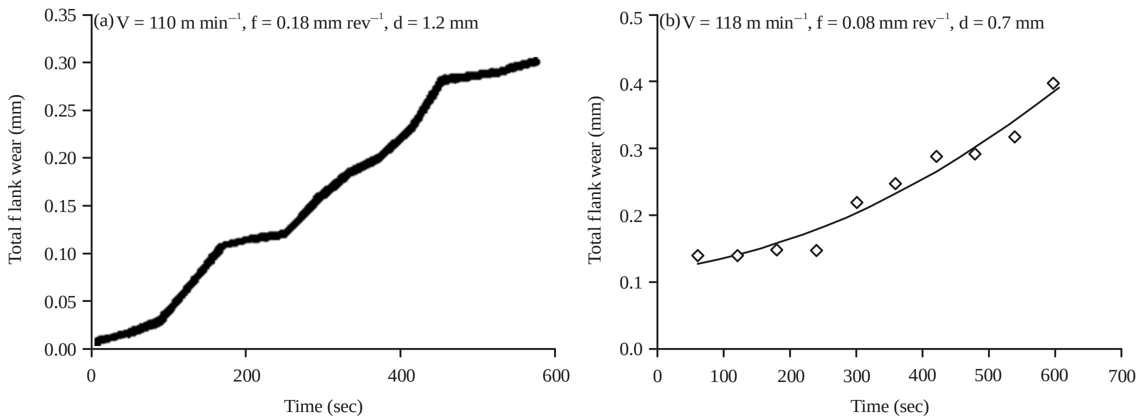


Fig. 8(a-b): Comparing the results of the developed model in this study with the literature (a) Present model and (b) Literature model

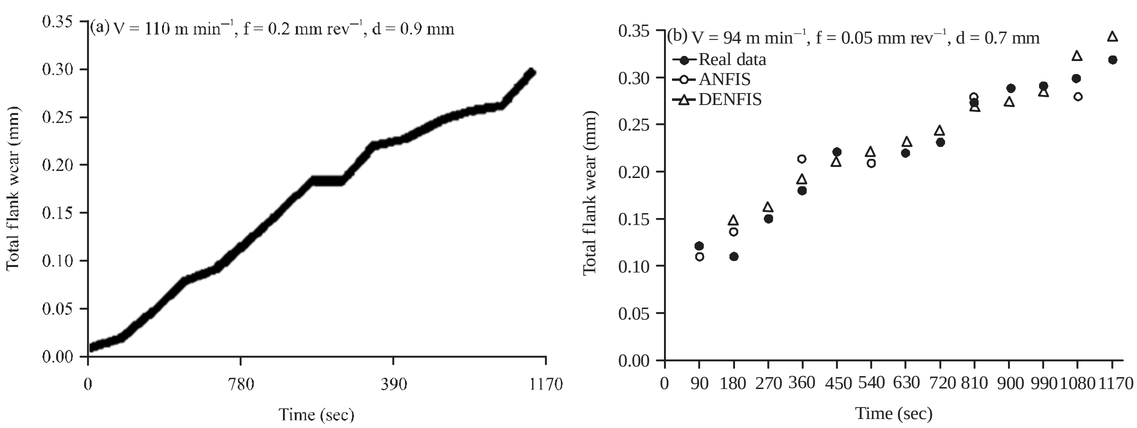


Fig. 9(a-b): Comparing the results of the developed model in this study with the literature (a) Present model and (b) Literature model

In all of the introduced models in the literature, there is a problem with the online tool wear predicting. However, the developed model in this present study overcome this problem and give a simple online tool wear prediction system which can be used not only in an automation system but also in a small workshop. Using of fuzzy logic capabilities in MATLAB program is the other specifications of the present study which can be used easily in machining plants.

CONCLUSION

It is concluded by this study that establishing a fuzzy logic based model for simulating the cutting process and tool wear progress is possible due to strong capabilities of fuzzy method. Based on the study results, the conclusions of the study can be summarized as:

- Based on the R^2 (0.8682) value of the comparisons of the measured and estimated tool flank wear rates, the fuzzy logic method can be used for tool wear monitoring with an acceptable accuracy
- In presence of the time in the model, the cutting speed was the most effective parameter on the tool flank wear
- Cutting depth, as an input parameter of the wear-time prediction model, made the smallest affection on the tool flank wear
- Using of fuzzy logic model can be used as an efficient online monitoring method in automation and flexible manufacturing systems. Furthermore, it can be applied in controlling the wear rate as Adaptive Control (AC) system in CNC machine tools

Using of the results of this study to establish an adaptive control to compensate the wear rate in turning process will be the subject of future study by the researcher.

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REFERENCES

1. El Gomayel, J.I. and K.D. Bregger, 1986. On-line tool wear sensing for turning operations. J. Eng. Ind., 108: 44-47.
2. Huang, Y., Y.K. Chou and S.Y. Liang, 2007. CBN tool wear in hard turning: A survey on research progresses. Int. J. Adv. Manuf. Technol., 35: 443-453.
3. Ljung, L., 1987. System Identification: Theory for the User. Prentice-Hall, Englewood Cliffs, NJ., USA., ISBN-13: 9780138816407, Pages: 519.
4. Sjoberg, J., Q. Zhang, L. Ljung, A. Benveniste and B. Delyon *et al*., 1995. Nonlinear black-box modeling in system identification: A unified overview. Automatica, 31: 1691-1724.
5. Bohlin, T., 1994. A case study of grey box identification. Automatica, 30: 307-318.
6. Born, D.K. and W.A. Goodman, 2001. An empirical survey on the influence of machining parameters on tool wear in diamond turning of large single-crystal silicon optics. Precision Eng., 25: 247-257.
7. Liang, S.Y. and D.A. Dornfeld, 1989. Tool wear detection using time series analysis of acoustic emission. J. Eng. Ind., 111: 199-205.
8. El-Wardany, T.I., D. Gao and M.A. Elbestawi, 1996. Tool condition monitoring in drilling using vibration signature analysis. Int. J. Mach. Tools Manuf., 36: 687-711.
9. Cheung, C.F., W.B. Lee and W.M. Chiu, 2000. Effect of tool wear on force and quality in dam-bar cutting of integrated circuit packages. J. Electron. Packag., 123: 34-41.
10. Wang, L., M.G. Mehrabi and J.E. Kannatey-Asibu, 2002. Hidden markov model-based tool wear monitoring in turning. J. Manuf. Sci. Eng., 124: 651-658.
11. Elangovan, M., S.B. Devasenapati, N.R. Sakthivel and K.I. Ramachandran, 2011. Evaluation of expert system for condition monitoring of a single point cutting tool using principle component analysis and decision tree algorithm. Expert Syst. Applic., 38: 4450-4459.
12. Zadeh, L.A., 1965. Fuzzy sets. Inform. Control, 8: 338-353.
13. Yaldiz, S., F. Unsacar and H. Saglam, 2006. Comparison of experimental results obtained by designed dynamometer to fuzzy model for predicting cutting forces in turning. Mater. Des., 27: 1139-1147.
14. Sharma, V.S., S.K. Sharma and A.K. Sharma, 2008. Cutting tool wear estimation for turning. J. Intell. Manuf., 19: 99-108.
15. Mamdani, E.H. and S. Assilian, 1975. An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man-Mach. Stud., 7: 1-13.
16. Zadeh, L.A., 1973. Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans. Syst. Man Cybernet., 3: 28-44.
17. Deiab, I., K. Assaleh and F. Hammad, 2009. On modeling of tool wear using sensor fusion and polynomial classifiers. Mech. Syst. Signal Process., 23: 1719-1729.
18. Gajate, A., R. Haber, R. del Toro, P. Vega and A. Bustillo, 2012. Tool wear monitoring using neuro-fuzzy techniques: A comparative study in a turning process. J. Intell. Manuf., 23: 869-882.