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Modeling micro-end-milling operations. Part III: influence of tool wear

W.Y. Bao, I.N. Tansel *

Mechanical Engineering Department, Florida International University, Center for Engineering and Applied Sciences, 10555 West Flagler Street, Miami, FL 33174, USA

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Abstract

The characteristics of the cutting forces were studied at different usage levels and the analytical model of the micro-end-milling operations was modified to represent the tool wear. A new expression was derived from the model to estimate the remaining tool life from experimental data. The parameters of the model are estimated by using genetic algorithms. The difference between the simulated and experimental cutting force profiles for new and worn tools was less than 8%. The remaining tool life was estimated with typically 10% error from the experimental data. Maximum error was 20%. The introduced analytical model and genetic algorithm-based parameter estimation approach is very convenient for on-line tool wear monitoring without extensive experimental study. © 2000 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Many researchers and manufacturers have studied end-milling operations to design better tools, to perform machining operations at the optimal cutting conditions, to avoid chatter, and to monitor tool condition. Depending on the objectives of the study, different approaches were used. Analytical models were developed to design cutting tools better, and to understand the characteristics of cutting forces [1,2]. To study the dynamic characteristics of the machining numerical methods were widely used [3,4]. To investigate the influence of run-out and tool flexibility, numerical methods were improved further. To detect tool breakage and estimate wear, characteristics of various signals were studied [5,6], and the effectiveness of empirical models including the time

* Corresponding author. Tel.: +1-305-348-1932; fax: +1-305-348-3304.
E-mail address: tanseli@eng.fiu.edu (I.N. Tansel).

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Nomenclature

F_x	feed direction cutting force (N)
F_y	normal direction cutting force (N)
F_u	unit force (N)
r	tool radius (inch)
Z	the number of tool teeth
β	tooth helix angle (rad)
r_o	run-out length (inch)
γ	run-out angle (rad)
n	spindle speed (rpm)
f	feed rate (ipm)
f_t	feed per tooth (inch)
a	depth of cut (inch)
b	width of cut (inch)
θ	tool cutting angle (rad)
θ_s	integrating start angle (rad)
θ_e	integrating end angle (rad)
p	proportional factor
K_m	material coefficient (N/cm^2)

series analysis and neural networks was demonstrated [7–10]. Analytical and empirical models were used with very different objectives. In this study, a recently proposed analytical model of micro-end-milling operations (MEMO) [11,12] was modified to represent tool wear at any stage of tool usage, and the application of genetic algorithms was proposed for estimation of the parameters of the model. Tool condition can be estimated from the values of these parameters. In this paper, the concept is only introduced; however, the proposed integrated method can be used for on-line monitoring of tool condition.

The increase of cutting forces with tool wear was observed in turning operations a long time ago [13]. However, estimation of the tool wear from the cutting force is not easy since the cutting forces continuously change even in typical turning operations when the cutting conditions change. If identical parts are going to be machined, commercial tool monitoring systems warn the operator if the monitored signals get out of an envelope while a part is turned. The number of parameters increase in end-milling operations and estimation of the tool condition becomes much more complicated. Training of neural networks with simulated data to evaluate the tool condition is one of the possible solutions. However, testing every possible overlap, depth of cut, and possible failure requires working with thousands of training cases generated by simulation [10].

Modification of the analytical models of the end-milling operations to represent the tool wear is straightforward. However, estimation of the parameters of these non-linear models and cutting conditions could be extremely time consuming, if the conventional optimization techniques are used. Genetic algorithms [14,15] allow the user to determine the resolution of each parameter of the non-linear objective function and estimate them quickly.

In the following sections the genetic algorithms are briefly discussed, the proposed model is introduced, and the validity of the model is demonstrated by comparing the simulations with experimental data obtained from the machining of metal (NAK-55 steel) and non-metal (EDM POCO-C3 graphite) workpieces. The tool life can be estimated by using the proposed model from the monitored cutting force data. The model can be easily simplified to represent the conventional end-milling operations (CEMO).

2. Theoretical background

In this section, the developed analytical cutting force model is outlined and genetic algorithms are briefly discussed.

2.1. Cutting force model of micro-end-milling operations

According to the developed analytical model [11,12] the cutting forces of MEMO can be calculated by using the following expressions:

$$F_x=F_u\left[C_3\frac{f_t}{r}\sin^3\theta+C_4\frac{f_t}{r}\cos^3\theta-(1+C_5)\sin^2\theta+\frac{1}{2}p(1+C_5)\sin 2\theta+\left(C_6-\frac{f_t}{r}\right)\sin\theta -pC_6\cos\theta-p(1+C_5)\theta\right]\Bigg|_{\theta_s}^{\theta_e} \quad (1)$$

$$F_y=F_u\left[C_4\frac{f_t}{r}\sin^3\theta-C_3\frac{f_t}{r}\cos^3\theta-p(1+C_5)\sin^2\theta-\frac{1}{2}(1+C_5)\sin 2\theta+p\left(C_6-\frac{f_t}{r}\right)\sin\theta +C_6\cos\theta+(1+C_5)\theta\right]\Bigg|_{\theta_s}^{\theta_e} \quad (2)$$

where:

$$F_u=\frac{K_m r f_t}{2\tan\beta} \quad (3)$$

$$f_t=\frac{f}{nZ}$$

$$C_3=\frac{1}{3}\left(1+p\frac{2}{\pi}\right)$$

$$C_4=\frac{1}{3}\left(p-\frac{2}{\pi}\right)$$

$$C_5=\pm\frac{2r_o}{\pi r}\sin\gamma,\ \pm \text{ for each cutting edge, respectively}$$

$$C_6=\pm\frac{4r_o}{f_t}\cos\gamma,\ \pm \text{ for each cutting edge, respectively}$$

2.2. Genetic algorithms

Genetic algorithms are a class of dynamic computational models that mimic natural selection and biological evolution to solve problems. Based on biological theories, the deoxyribonucleic acid (DNA) molecule — a tiny corkscrew built from simple chemicals and including a large number of genes that define individual parts of an organism's blueprint — is the most fundamental piece of life's mystery. The offspring inherit the characteristics from their parents through the genes. The survivors, who are dependent on natural selection and "survival of the fittest", determine the characteristics of the next generation, and therefore the evolution of the species[14,15].

The first application to solve problems by using biological evolution was proposed in 1975 by John Holland [16]. Based on the biological DNA theory, a binary number was designated as an individual chromosome to carry information of the data set, in which each bit represents a gene (see Fig. 1). The individuals followed the biological DNA hereditary processes to mate with each other and inherit a new generation through gene crossover and mutation. Natural selection as a rule determined the survivals of the next generation. The evolution would continue until one individual of the generation fitted the requested fitness level (see Fig. 2).

In the view of the optimization, the genetic algorithm is a powerful tool to find the optimal solution of the problems with large data sets by using random search techniques. The natural selection rule is the key to finding the optimal solution from the genetic evolution. The crossover operation keeps the better information from the last generation and the mutation operation helps to search the domain completely to avoid the search being trapped in a local maximum or mini-

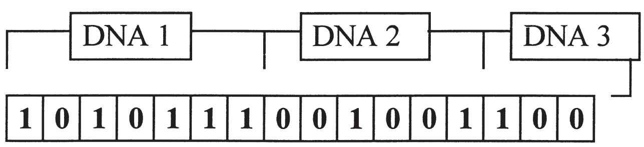

Fig. 1. A data chromosome with 20 genes presenting 3 DNA.

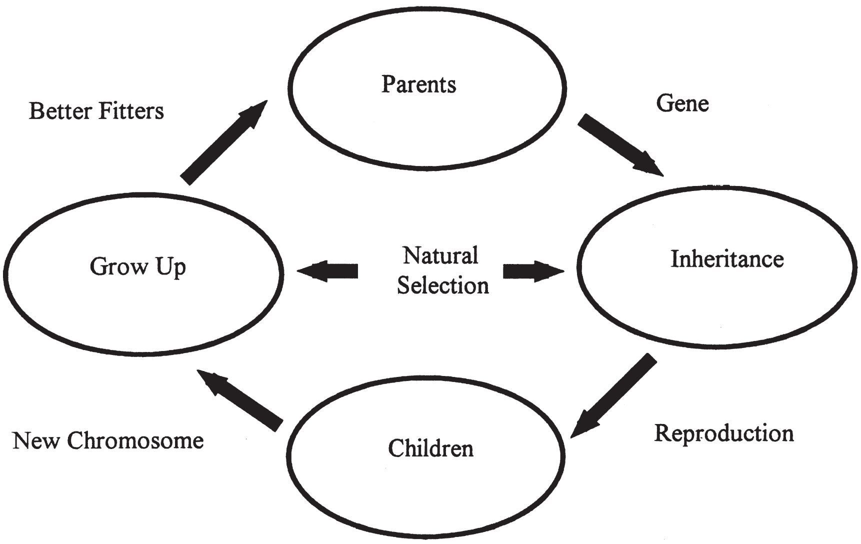

Fig. 2. Biological evolution cycle of species.

mum. The population size, mating pool size and the numbers of the children from each couple are decided by the problem study.

The architecture of the genetic algorithms can be developed by using the following steps:

- Selection of mating couples (parents) from the population pool.
- Selection of hereditary chromosomes of the next generation from their parents.
- Gene crossover.
- Gene mutation.
- Creation of the next generation (children).
- Evolution.

The first generation can be randomly created, and repeating the above steps can evolve each following generation. The evolution continues until the fitness is in a requested fitness level.

3. Cutting force modeling of micro-end-milling operations with tool wear

In this section, the analytical model of MEMO with tool wear representation capability is introduced. Identification of the parameters of the proposed model by using the genetic algorithms is presented. Tool life estimation is discussed.

3.1. Analytical cutting force model with tool wear representation

From the previous experimental study of tool wear of the MEMO, the following conclusions can be drawn [17,18]:

- Both feed- and normal-direction cutting forces increase with tool wear.
- The ratio of both feed- and normal-direction cutting forces between a new and a used tool remains the same in the entire tool rotation. The cutting force characteristics of both directions have similar performance.

Progress of tool wear can be studied in two stages. In the first stage, the tool wears gradually and cutting force increases slightly. The second stage starts when the tool has been used for a certain time and the cutting edges of the tool cannot perform their tasks effectively since they get dull, or are damaged, or are covered with tiny chips. Cutting forces increase much faster in the second stage than in the first stage and the tool breaks in a short time. Depending on the characteristics of the tool, workpiece and cutting conditions, the first stage may last between a few seconds to a few days. To represent the characteristics of the cutting force at different usage levels the following wear coefficient is proposed:

$$K_W=1+(C_1L)^{C_2} \tag{4}$$

where: L is the tool life (inch), C_1 (1/inch) and C_2 are parameters.

The parameter C_1 is the tool wear gradient. It depends on the tool, workpiece and cutting conditions. If the tool wear gradient is small, the progress of the tool wear will take a long time. It presents the cutting force linear growth with the tool wear. The parameter C_2 shows the exponential growth tendency of the cutting force; its influence is minimal for a new tool. However, when the tool wear becomes significant, the parameter C_2 presents how quickly the tool will fail. This is related to the hardness of the workpiece material.

The new model uses the same expressions as the analytical model (Expression Eq. (1) and Eq. (2)). However, the following term (Expression Eq. (3)) is modified to represent the effect of tool wear to the characteristics of the cutting force:

$$F_{\mathrm{u}}=\frac{K_{\mathrm{w}}K_{\mathrm{m}}rf_{\mathrm{t}}}{2\tan\beta} \tag{5}$$

For a new tool, K_{w} is equal to 1. Theoretically, K_{w} is always bigger than 1 for a used tool and equal to 0 when the corresponding edge of the tool is broken.

3.2. Determination of parameters of the proposed wear model

The wear parameters of the model are obtained from the experimental data by using a genetic algorithms software called GATool (Genetic Algorithms Research Tool) that was developed in 1998 [19]. The objective function of the optimization program was the difference between the experimental and simulated maximum cutting force in feed or normal direction. The objective function is expressed as the following equation:

$$\mathrm{Min}(E)=\frac{1}{N}\sum_{i=1}^{N}|F_{\mathrm{max}}^{\mathrm{estimated}}(i)-F_{\mathrm{max}}^{\mathrm{actual}}(i)| \tag{6}$$

where: E is the average absolute error, N is the number of the experimental data, $F_{\mathrm{max}}^{\mathrm{actual}}(i)$ is the experimental maximum cutting force in feed or normal direction at the ith tool life, $F_{max}^{estimated}(i)$ is the estimated maximum cutting force in feed or normal direction at the ith tool life.

In the genetic evolution procedures, 20-bit binary coding was used for two coefficients by assigning 10 bits for each one. The population size was five. Mating pool size was two versus two and one child from each couple. The uniform crossover (with 0.5 probability), jumping mutation (with 0.1 probability), creeping mutation (with 0.05 probability) and elitism were chosen.

The proposed method of the optimization of the wear parameters is presented in Fig. 3.

3.3. Estimation of the remaining tool life

The expression to calculate the remaining tool life can be derived from the presented equations in the previous section. If it is assumed that a tool would be broken when the force reached a critical cutting force such as F_c, which can be obtained theoretically from the stress analysis or experimentally by breaking the tool, the remaining tool life can be estimated by using the following expression:

$$L_t = \frac{1}{C_1}\left(C_2\sqrt{\frac{F_c}{F_{max}^{new}} - 1} - c_2\sqrt{\frac{F_{max}^{current}}{F_{max}^{new}} - 1} \right) \tag{7}$$

where: L_t is the remaining tool life, F_c is the critical cutting force in feed or normal direction, F_{max}^{new} is the maximum cutting force in feed or normal direction of a new tool estimated by the

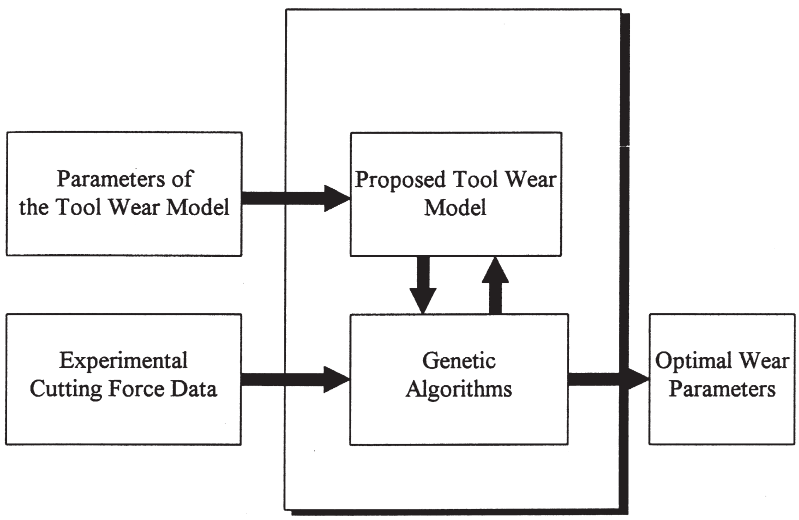

Fig. 3. Optimization of the wear parameters of the proposed model for micro-end-milling operations.

analytical model, $F_{\max}^{\text{current}}$ is the maximum cutting force in feed or normal direction of the tool at the certain usage level.

Theoretically, the maximum cutting force is smaller than the critical cutting force during the machining so that the tool will be broken at any time if the maximum cutting force exceeds the critical cutting force.

4. Experimental setup

The experiments of MEMO were performed at Florida International University and the Engineering Prototype Center of Radio Technology Division of Motorola Inc. Three different Fadal CNC machines were used in the experiments. The test workpiece was attached to a Kistler 9257B 3-component piezoelectric dynamometer that was installed on the table of the machine tool. Two components of the cutting force were collected by using Nicolet 310 and Nicolet Integra model 10 digital oscilloscopes through a Kistler 3-channel charge amplifier. The typical experimental setup, equipment and contents were presented [11].

In the tool wear test of steel workpieces, the cutting force data were directly collected by using the dynamometer and digital oscilloscope when the tool was machining the workpiece. Because the cutting forces were almost at the same level with the experimental noise during the machining of EDM POCO-C3 graphite workpieces, an aluminum test piece was attached to the top of the EDM POCO-C3 workpiece and machined periodically. The cutting force data were collected when the tool was cutting the aluminum test piece in order to have high signal-to-noise ratio (S/N).

5. Results and discussion

In this section, the relationship between the tool wear and cutting force is discussed. The cutting force (including new and worn tools) and remaining tool life estimation accuracy of the proposed model are presented.

5.1. Relationship between the tool wear and cutting force

The typical tool wear and increasing cutting force relationship has been known for a long time. In this study this relationship was investigated by monitoring the cutting force characteristics of carbide micro-end-mills while they were worn by cutting very hard metal (steel) and very soft non-metal (graphite) workpieces.

Characteristics of the normal direction cutting force at different stages of tool life are presented in Fig. 4 and Fig. 5 when two identical tools were used to machine NAK-55 steel workpieces. Two-flute carbide end-mills with 0.030″ diameter were used in the experiments. In test 1, the cutting conditions were 30,000 rpm spindle speed, 2.5 ipm feed rate, 0.015″ width of cut and 0.015″ depth of cut. Fourteen sets of cutting force profiles were recorded at the different stages of tool life and 42″ tool life was observed. The cutting conditions of test 2 were 20,000 rpm spindle speed, 1.25 ipm feed rate, 0.0225″ width of cut and 0.015″ depth of cut. Ten sets of cutting force data were collected at the different tool usage levels and the tool had 33″ of tool life.

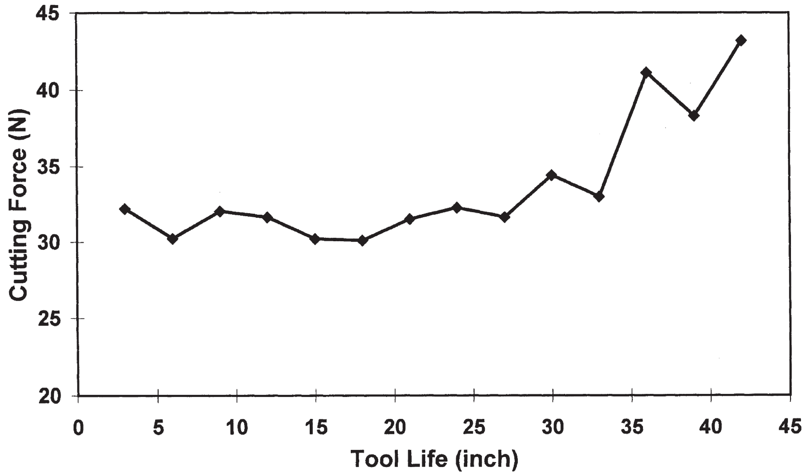

Fig. 4. Relationship of maximum cutting force and tool usage for machining of a steel workpiece with a carbide tool in test 1.

Fig. 5. Relationship of maximum cutting force and tool usage for machining of a steel workpiece with a carbide tool in test 2.

Cutting edges wear out very slowly when soft materials are cut. To evaluate the cutting force characteristics when the soft materials are cut, the tool was worn by machining EDM POCO-C3 graphite workpieces and the cutting force data were collected periodically by cutting a slot on an aluminum test piece. The cutting conditions for machining the POCO-C3 workpiece were 15,000 rpm spindle speed, 20 ipm feed rate, 0.030″ width of cut and 1/32″ depth of cut. The aluminum test piece was cut at 15,000 rpm spindle speed, 5 ipm feed rate, 0.015″ width of cut and 1/32″ depth of cut. A two-flute carbide tool with 1/16″ tool diameter was used in the tests. Nine data

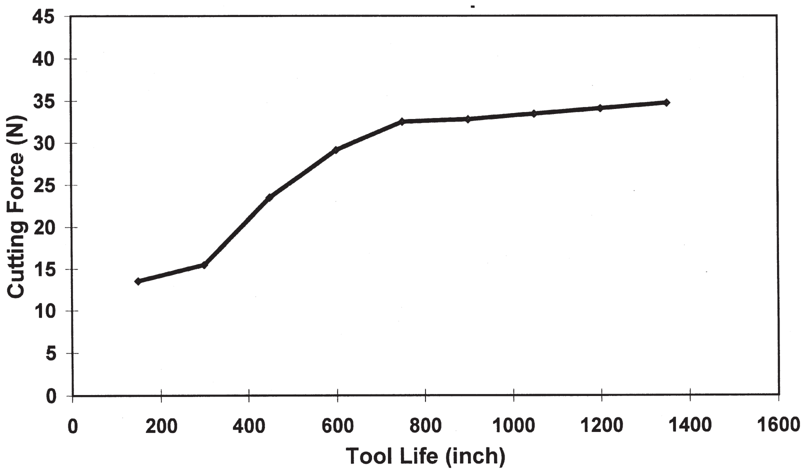

Fig. 6. Relationship of maximum cutting force and tool usage for machining of a graphite workpiece with a carbide tool.

sets of the cutting force were collected at different tool usage levels. The tool had 1350″ of tool life and did not break. Experimental data are presented in Fig. 6.

The characteristics of the cutting forces were studied during the one full rotation of the tool. The new and the worn tools had exactly the same characteristics when the profile was normalized at the identical cutting condition. However, the magnitude of the cutting forces changed when the tool wore out. Based on this observation, use of a wear coefficient was satisfactory to include the tool wear into the analytical MEMO model. The experimental normal direction cutting force of the new and worn (pre-failure) tools when the NAK-55 steel workpiece is cut (test 1) is presented in Fig. 7, and critical values are listed in Tables 1, 5–8. The average ratio is around 1.4.

The pictures of the cutting edges of new and worn tools are presented in Fig. 8 and Fig. 9.

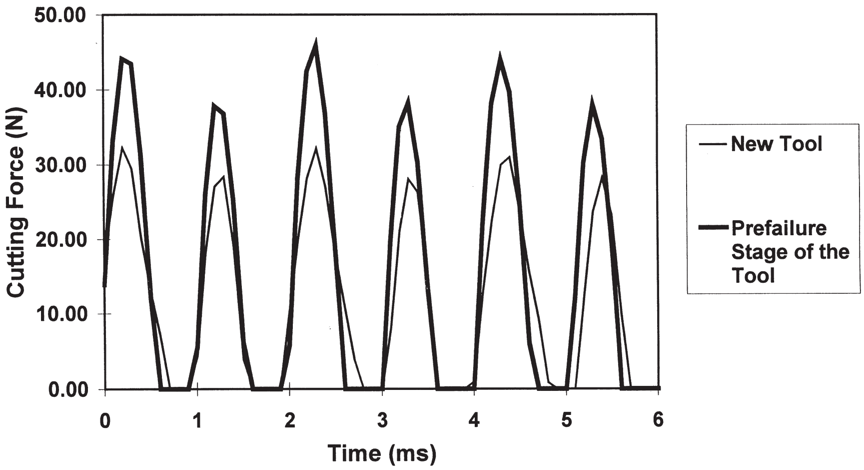

Fig. 7. Comparison of the cutting force profiles between a new tool and pre-failure stage of the tool.

Table 1
Tool wear coefficient (the ratios of the cutting forces at the two extreme stages of tool life)

Tool rotation Angle (degree)	Normal direction cutting force (N) New tool	Pre-failure tool	Ratio
0	17.40	13.84	0.80
18	25.80	33.20	1.29
36	32.28	44.12	1.37
54	29.44	43.44	1.48
72	20.20	31.40	1.55
90	12.80	12.00	0.94
108	7.00	0.00	0.00
126	0.00	0.00	–
144	0.00	0.00	–
162	0.00	0.00	–
180	4.36	5.48	1.26
198	18.28	25.92	1.42
216	27.04	37.84	1.40
234	28.40	36.80	1.30
252	19.20	25.36	1.32
270	3.92	6.04	1.54
288	0.00	0.00	–
306	0.00	0.00	–
324	0.00	0.00	–
342	0.00	0.00	–
360	10.04	5.80	0.58

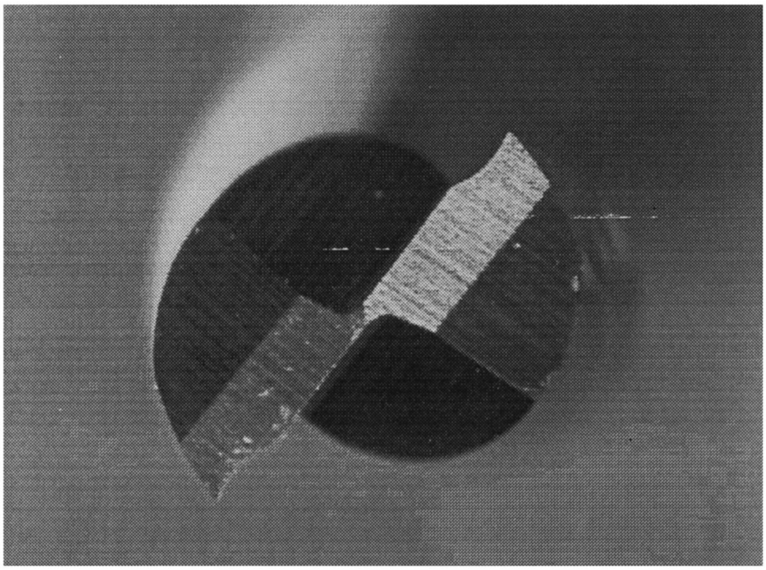

Fig. 8. Cutting edges of a new tool.

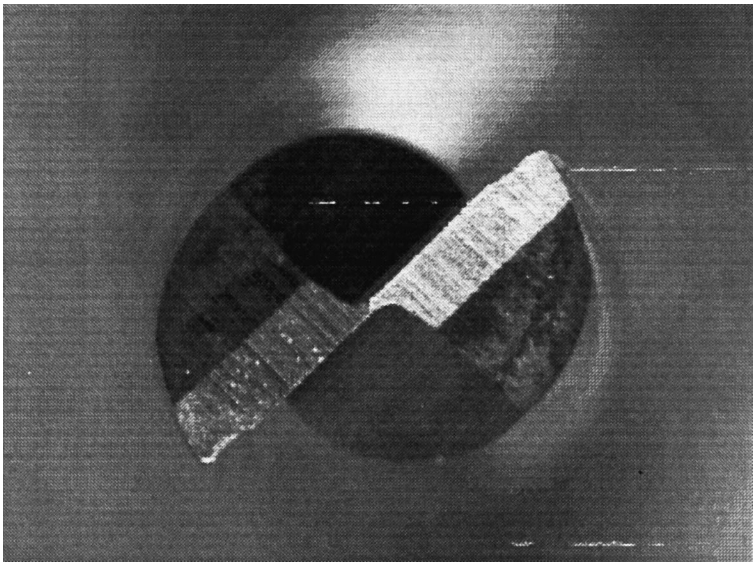

Fig. 9. Cutting edges of a worn tool.

The burr formation was different when the new and worn tools were used. The burr-free and burr slots of an aluminum workpiece machined by a carbide end-mill from new to worn stages are presented in Fig. 10.

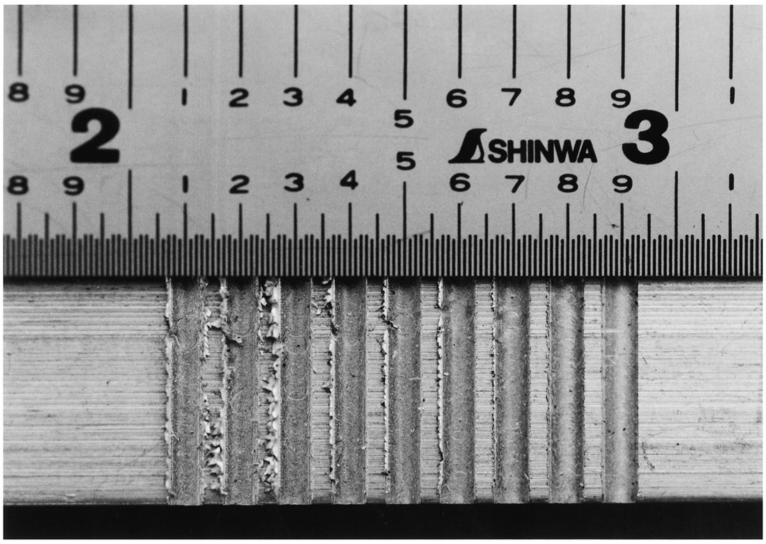

Fig. 10. The burr-free and burr slots of an aluminum workpiece machined by a carbide end-mill from new to worn stages (the scale of the ruler is in inches).

5.2. Verification of the tool wear model

The proposed analytical model used ten parameters and two coefficients to represent the cutting forces of MEMO and CEMO without or with tool runout, at different stages of the tool usage.

- Three working condition variables: spindle speed (n), feed rate (f) and width of cut (b).
- Two tool run-out variables: run-out (r_o) and its angle (γ).
- Two cutting condition variables: tool cutting entry and exit angle, which presents depth of cut (a), and up-and-down-milling.
- Three tool geometry variables: tool diameter ($2r$), helix angle (β) and the number of tool flutes (N).
- Two coefficients: material coefficient (K_m) and wear coefficient (K_w), which are related to the tool and workpiece materials, and tool life.

These parameters and coefficients can be found experimentally.

The proposed model was tested on the experimental data of many MEMO cases and very good agreement was observed between the theoretical and experimental results. The results of two tools' wear test data and the estimations of the developed model are presented in Fig. 11 and Fig. 12. In both experiments, a two-flute carbide end-mill with 0.030″ diameter was used to cut a NAK-55 steel workpiece. 14 and 10 data sets of the cutting forces were recorded during the tool life periods. These two tools were broken at 43.2 N and 38.2 N maximum cutting force in normal direction, and had 42″ and 33″ of tool life, respectively.

The cutting force coefficient of the material was obtained from the single experiment with a new tool. The wear-related C_1 and C_2 parameters of both wear models were determined by using the genetic algorithms for test 1 and test 2 separately. The estimated C_1 and C_2 parameters are listed in Table 2.

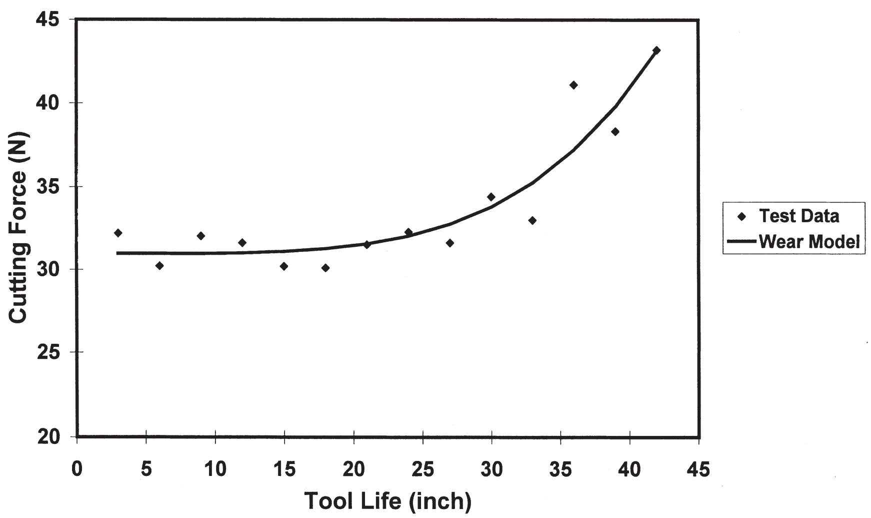

Fig. 11. Wear model of the NAK-55 steel wear test 1.

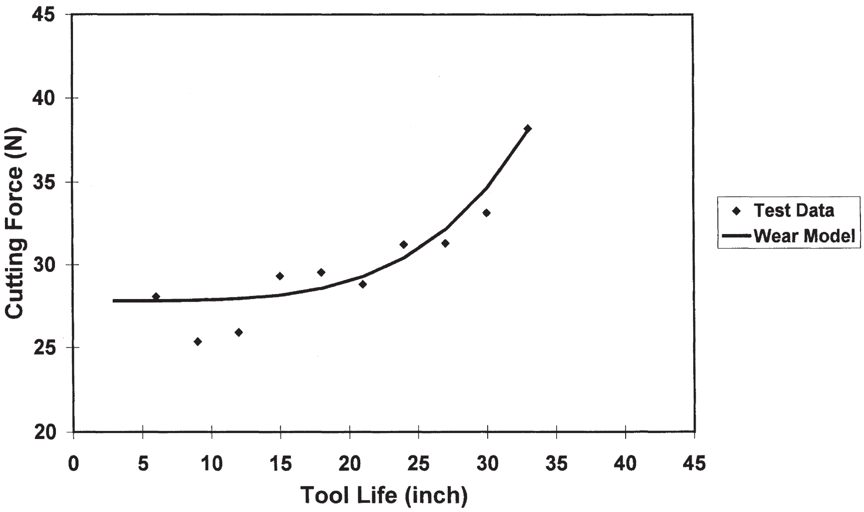

Fig. 12. Wear model of the NAK-55 steel wear test 2.

Table 2
Accuracy of the cutting force estimations by using the proposed model

	Cutting Conditions	C_1	C_2	Error	%Error
Test 1	30,000 rpm spindle speed 2.5 ipm feed rate 0.015″ width of cut 0.015″ depth of cut	0.0192	4.352	±1.1 N	3.3%
Test 2	20,000 rpm spindle speed 1.25 ipm feed rate 0.0225″ width of cut 0.015″ depth of cut	0.0240	4.287	±2.0 N	7.1%
Average		0.0216	4.320	±2.2 N	8.0%

The experimental data was very close to the estimations of the proposed model. The average deviations of both models were 3.3% and 7.1% for test 1 and 2, respectively. The averages of C_1 and C_2 parameters were used to estimate the maximum cutting force at 24 different conditions. The estimation error was less than 8% for both tests. These results indicate that wear progress characteristics were very similar in different cutting conditions.

The average parameters C_1 and C_2 were used to calculate the wear coefficient K_w of the analytical model (Eq. (1) and Eq. (2)). The cutting forces were simulated at different usage levels of a tool when NAK-55 steel was machined. The simulated and experimental cutting forces in normal direction of a new and worn (pre-failure) tool of test 1 are presented in Fig. 13 and Fig. 14. They are almost identical in both figures.

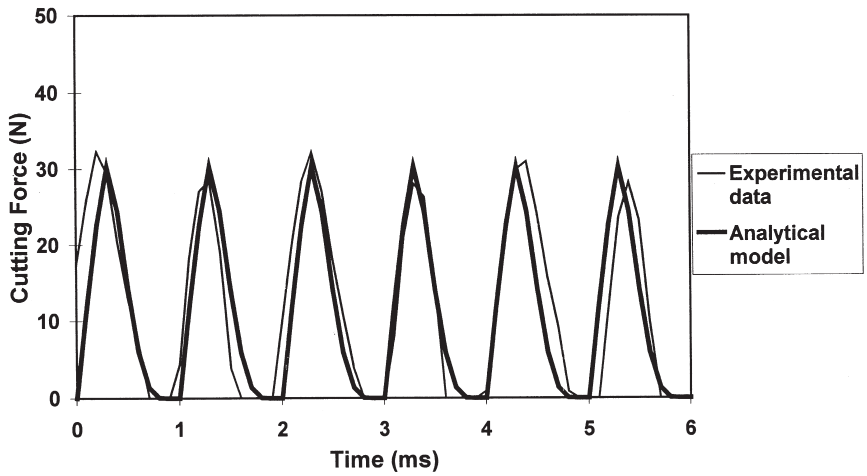

Fig. 13. Simulated and experimental cutting forces during the micro-end-milling operations with a new tool.

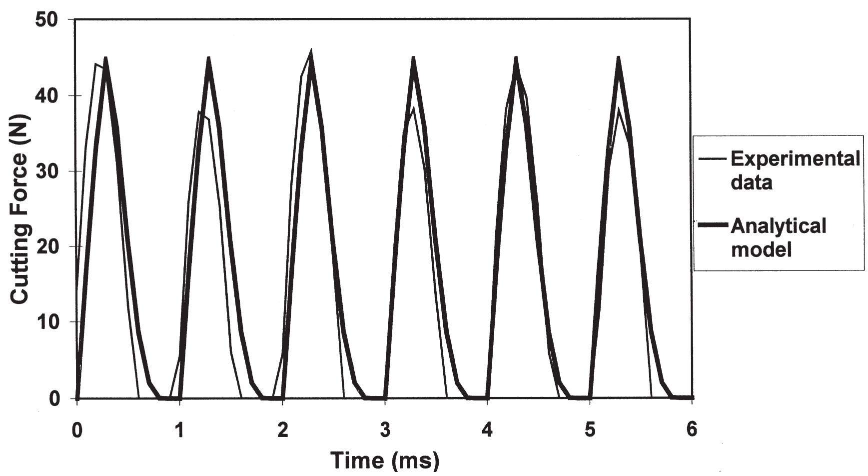

Fig. 14. Simulated and experimental cutting forces during the micro-end-milling operations with a pre-failure tool.

5.3. Estimation of remaining tool life

The remaining tool life estimation accuracy of Eq. (6) was tested on the experimental data collected by using a carbide end-mill to machine a NAK-55 steel workpiece. The cutting conditions of the tests and estimated parameters are presented in Table 2. The critical cutting force in normal direction was selected as 40 N by inspecting the cutting force variations just before the breakage and tool life was estimated at the different stages of tool life by using different parameter pairs (C_1 and C_2 obtained for test 1, test 2, average, all data together). Tool life esti-

Table 3
Tool life estimation accuracy of tool 1 by using the C_1 and C_2 parameters obtained from the data of test 1

Usage of the tool	Actual remaining tool life	Estimated remaining tool life	Error	% Error
21″	21″	18.6″	2.4″	5.7%
24″	18″	14.1″	3.9″	9.4%
27″	15″	17.6″	2.6″	6.3%
30″	12″	7.8″	4.2″	9.9%
33″	9″	11.4″	2.4″	5.7%
36″	6″	0″	6″	14.3%
39″	3″	1.8″	1.2″	2.8%
Average			3.2″	7.7%

mations and errors are presented in Tables 3 and 4. The average error was around 10%. The results indicated that the proposed model could be used to estimate the remaining tool life.

The smallest estimation error was observed when the C_1 and C_2 parameters of the same cutting conditions were used. The average error was around 7.7% and 9.2% for tools 1 and 2.

The average estimation error was very reasonable (around 9.1% and 10.0% for tools 1 and 2) when the C_1 and C_2 parameters of the other test condition were used to estimate the remaining tool life. The results are presented in Table 5 and Table 6.

The errors listed in Tables 3–6 indicate that operating conditions have very little influence on the C_1 and C_2 parameters. It is possible to use the averaged wear parameters obtained from tests at different operating conditions to estimate the remaining tool life. Estimation errors obtained by using this approach are presented in Table 7 and Table 8. The average error was around 7.7% and 8.6% for tools 1 and 2 when the average of the C_1 and C_2 parameters is used.

6. Conclusion

The characteristics of the cutting forces of the new and worn tools were studied and an analytical model is proposed to simulate the cutting forces of MEMO at different usage levels. The parameters of the models were estimated by using the genetic algorithms.

Table 4
Tool life estimation accuracy of tool 2 by using the C_1 and C_2 parameters obtained from the data of test 2

Usage of the tool	Actual remaining tool life	Estimated remaining tool life	Error	% Error
15″	18″	13.2″	4.8″	14.5%
18″	15″	12.5″	2.5″	7.6%
21″	12″	15″	3.0″	9.2%
24″	9″	8.8″	0.2″	0.6%
27″	6″	8.7″	2.7″	8.0%
30″	3″	6″	3.0″	9.1%
Average			2.7″	8.2%

Table 5
Tool life estimation accuracy of tool 1 by using the C_1 and C_2 parameters obtained from the data of test 2

Usage of the tool	Actual remaining tool life	Estimated remaining tool life	Error	% Error
21″	21″	15.0	6.0	14.4%
24″	18″	11.3	6.7	15.9%
27″	15″	14.2	0.8	1.9%
30″	12″	6.3	5.7	13.5%
33″	9″	9.2	0.2	0.4%
36″	6″	0	6.0	14.3%
39″	3″	1.5	1.5	3.7%
Average			3.8	9.1%

Table 6
Tool life estimation accuracy of tool 2 by using the C_1 and C_2 parameters obtained from the data of test 1

Usage of the tool	Actual remaining tool life	Estimated remaining tool life	Error	% Error
15″	18″	16.4	1.6	4.9%
18″	15″	15.5	0.5	1.4%
21″	12″	18.6	6.6	20.1%
24″	9″	10.9	1.9	5.7%
27″	6″	10.7	4.7	14.3%
30″	3″	7.4	4.4	13.4%
Average			3.3	10.0%

Table 7
Tool life estimation accuracy of tool 1 by using the C_1 and C_2 parameters obtained from both test data

Usage of the tool	Actual remaining tool life	Estimated remaining tool life	Error	% Error
21″	21″	18.6″	2.4″	5.7%
24″	18″	14.1″	3.9″	9.4%
27″	15″	17.6″	2.6″	6.3%
30″	12″	7.8″	4.2″	9.9%
33″	9″	11.4″	2.4″	5.7%
36″	6″	0″	6″	14.3%
39″	3″	1.8″	1.2″	2.8%
Average			3.2″	7.7%

Table 8
Tool life estimation accuracy of tool 2 by using the C_1 and C_2 parameters obtained from both test data

Usage of the tool	Actual remaining tool life	Estimated remaining tool life	Error	% Error
15″	18″	14.6″	3.4″	10.2%
18″	15″	13.8″	1.2″	3.6%
21″	12″	16.6″	4.6″	14.0%
24″	9″	9.7″	0.7″	2.2%
27″	6″	9.6″	3.6″	10.8%
30″	3″	6.6″	3.6″	11.0%
Average			2.8″	8.6%

The simulated cutting forces of the proposed model were compared with experimental data of MEMO and very good agreement was observed between the simulated and experimental cutting force profiles. The error of the cutting force simulations for both new and used tools was less than 8%.

The proposed analytical model was modified to estimate the remaining tool life from the cutting force data. The proposed expression estimated the remaining tool life with typically 10% error. Maximum error was 20%.

It is possible to use the proposed model and genetic algorithm-based identification for on-line monitoring of tool condition. All the parameters, which vary with the changing cutting conditions, can be estimated instantaneously together with the cutting force coefficients. With this approach, the change of depth and width of cut will be immediately recognized and cutting force coefficients will be estimated accurately. The reference cutting force coefficients can be estimated when the machining operation starts with a new tool. A monitoring system may update the cutting force coefficients continuously and calculate the remaining tool life. The system needs only a critical value of the cutting force that indicates the tool breakage. This procedure eliminates the need for investigation of the characteristics of cutting forces at different usage levels of that specific tool, workpiece, and cutting conditions.

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