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Genetic tool monitor (GTM) for micro-end-milling operations

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Abstract

Almost all existing tool condition monitoring methods require either the critical parameters of models which are experimentally found or the self-learning algorithms that are trained with existing data. Genetic Tool Monitor (GTM) is proposed to identify the problems by using an analytical model for micro-end-milling operations and genetic algorithm. The current version of the GTM is capable to monitor the micro-end-milling operations without any previous experience and is able to estimate symmetrical wear and local damages at the cutting edges of a tool. Genetic algorithms (GA) are found as a promising health monitoring tool if an expression exists and the necessary computational time is allowable in that particular application. GTM generates meaningful information about the ongoing operation and allows the establishment of rules based on the operators' experience.

Keywords: Genetic algorithms; Manufacturing applications; Process monitoring; End-milling; Micro machining

1. Introduction

The consistency of the machining quality is very important in an automated manufacturing. Many monitoring techniques have been developed to detect tool breakage and to estimate tool wear by evaluating the most important characteristics of the signals coming from sensors such as dynamometer, accelerometer(s), acoustic emission sensors, thermocouples, and microphones. The first approach was to evaluate the characteristics of the signal at different tool conditions and to set the limits or to relate them to tool wear. Later, intelligent computational algorithms such as neural networks were used to automate this task. To use these methods effectively, the operating conditions such as speed, feed rate, depth of cut, and the tool-material couple should be identical or very close to the test conditions. GTM was developed to interpret the cutting force signals by using analytical expressions. Theoretically, once the key parameters are estimated in a single test from the data of any cutting force component, cutting operations can be monitored by measuring any cutting force at any operating condition by using this method. However, GTM should be used very conservatively to eliminate false alarms and to ensure that the wear estimations are performed accurately within an acceptable time frame using a low cost computational hardware. In this study, the performance of GTM will be evaluated on simulated and experimental cutting force data by considering the micro-end-milling of soft electrode materials.

The genetic algorithm [1–3] estimates any number of parameters of an analytical expression by using a search method. It works with linear and non-linear analytical expressions, and very complex conditional statements can be included in the objective function. The GTM concept was developed to estimate the key parameters such as the cutting force coefficient and run-out of the analytical model [4–8] during micro-end-milling operations. Other researchers have used GA to determine the optimal cutting conditions [9–12] in machining and monitoring of turning [13,14] operations.

Generally, in academic studies, continuous monitoring of the machining operations have been aimed, while the workpiece is cut and the cutting conditions vary. However,

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GTM was developed for micro-end-milling of the graphite like electrodes of electrical discharge machining (EDM) by considering the following two requirements:

(a) The magnitude of the cutting forces required to remove the typical electrode material of the EDMs is small with respect to the noise. It is necessary to cut an aluminum type material periodically to collect the data with acceptable signal to noise ratio without wearing the tool.
(b) A continuous monitoring system inspects the machining operation many times per second during the actual machining operation. Unexpected force profiles are always encountered when the cutting conditions vary. Even 0.01% wrong estimations will give several false alarms every hour. Machining of electrode with the same micro-tool sometimes takes a few days and operation continues during the off-duty hours of the operators. False errors should be completely eliminated.

The proposed GTM estimates the cutting force coefficient from the periodically collected data. In some cases, also the run-out was estimated. Cutting force coefficient indicates the dullness of the cutting edge and continuously increases while the operation continues. Contact length of the cutting edge can be calculated when the run-out is estimated from the same data. Although, the genetic algorithm of the GTM [15] may identify most of the cutting parameters theoretically, the computational time will be unacceptable in the practical applications and the maximum two variables will be estimated in this study.

In the following sections, the theoretical background, the proposed GTM, the simulation, the experimental data collection, results and conclusion will be presented.

2. Theoretical background

2.1. Genetic algorithms

Genetic algorithms [1–3] use a repeating six-step process to find the optimal solution by following the natural selection rule of the genetic evaluation. The user selects the resolution of the parameters, population size, mating pool size and the number of the children from each couple according to the problem, application and resources. The six-step process includes selection of mating couples (parents), selection of the hereditary chromosomes of the next generation, gene crossover, gene mutation, creation of next generation and evolution. Hereditary chromosome can be selected from the stronger one of the mating couple, or one of them in turn, or selected randomly in the second step. Fixed-point or uniform crossover is used in the third step according to the problem. Jumping or creeping mutation can be used mostly with similar end results in the forth step. The six-step procedure is repeated until the fitness reaches the desired level.

2.2. Modeling the milling operations

Bao and Tansel [6–8] modeled the micro-end-milling operations by considering the trajectory of the tip of the cutting edges of the tool. The following expressions were derived by considering the tool run-out

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

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

where

$$F_u = \frac{K_m r f_t}{2\tan\beta}$$

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

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

$$C_5 = \pm\frac{2r_o}{\pi r}\sin\gamma,$$

$\pm$ for both cutting edges, respectively,

$$C_6 = \pm\frac{4r_o}{f_t}\cos\gamma,$$

$\pm$ for both cutting edges, respectively.

Tool cutter angle ψ is defined as $\Psi = 2\pi/Z$, workpiece cutting angle φ is defined as $\varphi = \arccos[(r-a)/r]$, engagement angle α is defined as $\alpha = b\tan\beta/r$. In the expressions, r is tool radius, r_o is run-out length (in.), p is proportional factor, θ is tool cutting angle, β is tooth helix angle, f_t is feed per tooth, γ is run-out angle, K_m is the cutting force coefficient.

2.3. Genetic tool monitor (GTM)

Two generations of Genetic Tool Monitor, GTM1 [4] and GTM2 [15] were prepared by using the modified

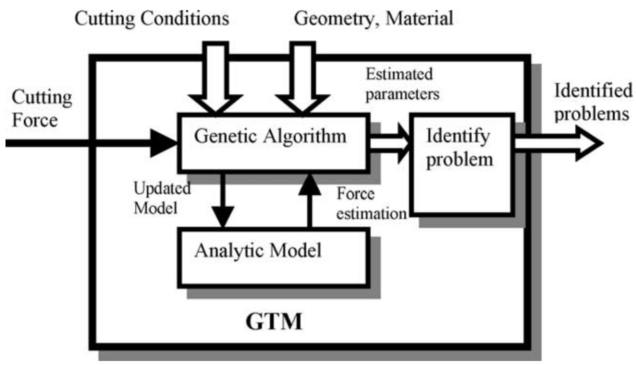

Fig. 1. Block diagram of the GTM2.

versions of Eqs. (1) and (2). They are very similar outside of the complexity of the analytical equation. The diagram of the Genetic Tool Monitor (GTM) is presented in the Fig. 1. The user gives the program all the known parameters including the operating conditions, and tool geometry. Depending on the operating conditions, one or more parameters can be estimated. The objective is mostly to estimate the key cutting parameters such as cutting force coefficient, and tool run-out. Depth of cut, entry and exit angles, and other parameters can also be estimated if an on-line monitoring of the machining operation is considered. However, computational time will increase while the accuracy of the estimations is compromised.

The genetic algorithm estimates the selected parameters. Cutting forces are estimated by using the analytical model and by using the estimated parameters. The accuracy of the estimated parameters is evaluated by comparing the sampled and estimated cutting force(s). The genetic algorithm updates the estimated parameters to minimize the error. The process is repeated until the allowed iteration number is reached. The value of the cutting force coefficient increases when the cutting edges wear out and get dull. The chipped away segments of the cutting edges reduce the effective cutting length of the tips. The tip and run-out estimations start to vary with time.

3. Generation of the simulated data

The simulated data was generated by using the analytical cutting force model [6–8] and micro-end-milling operations were considered. The considered trajectory of the cutting tips and the estimated cutting force is presented in Figs. 2 and 3, respectively.

Feed, thrust and resultant forces of worn out tools were simulated in this study by considering three different conditions. In the simulations, the cutting force coefficient and the contact length of one of the cutting edges was kept constant. The other edge was assumed to get dull and/or partially chiped away when the tool wears out. The contact length of a cutting edge is the section of a tooth which actively removes material from the workpiece. The contact length of the perfect cutting edge was taken as 0.001 in. Different levels of dullness and contact length loss were simulated to evaluate if the GTM2 would be able to recognize the difference. The cutting force coefficient of one of the edges was increased first 10% in three simulations with partial cutting edge loss at three different levels. In the other three simulations, cutting force coefficient was increased 20%. For partially chipped away cutting edges, the contact length was reduced to 0.0009, 0.0008, and 0.0007 in. The center of rotation (run-out) and diameter of a tool were changed to simulate the cutting force of a tooth with partially chipped away cutting edge.

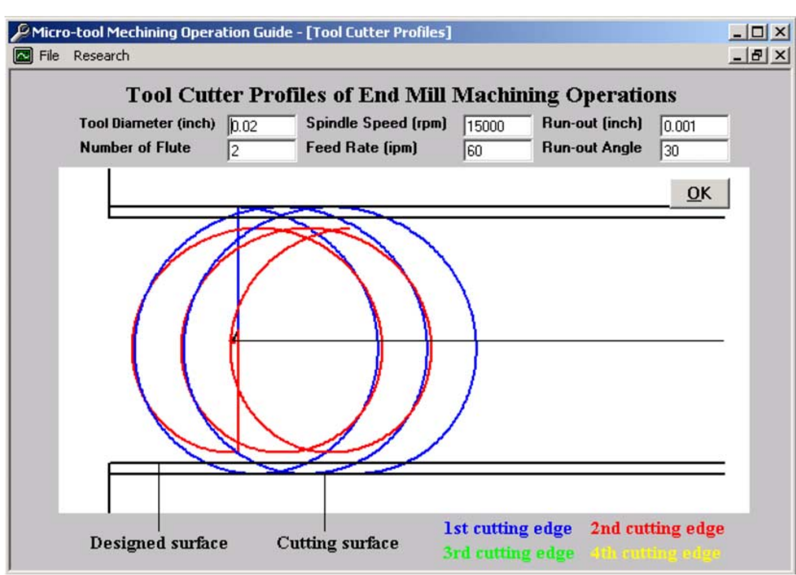

Fig. 2. Trajectory of the tool tip of the analytical model.

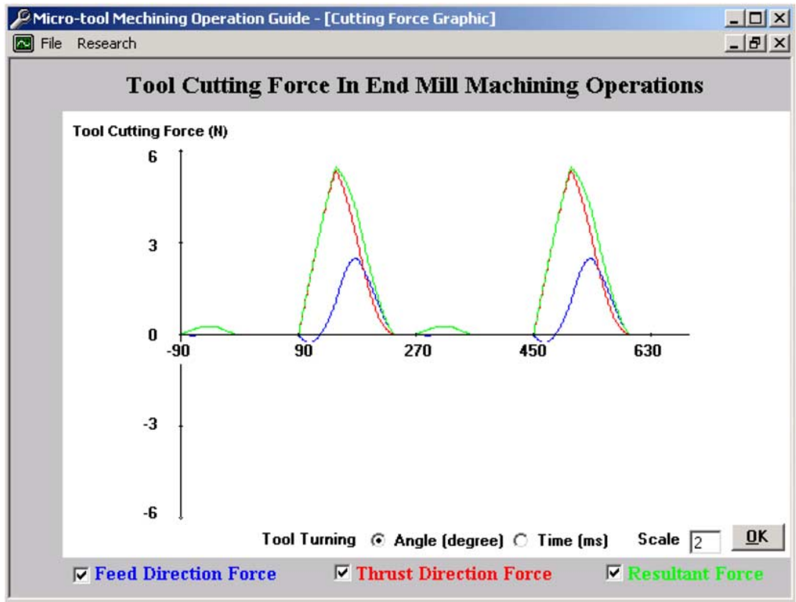

Fig. 3. Estimated cutting forces.

4. Experimental data collection

The data was collected using the experimental set-up shown in Fig. 4 [6–8]. A POCO-EDM-C3 electrode was assembled on a Kistler dynamometer. The aluminum test piece was attached on the electrode and used to collect the experimental data. Two components of the cutting force on the horizontal plane were digitized by using a Nicolet 310 digital oscilloscope.

A 1/16 in. carbide tool was used to cut the POCO EDM-C3 part and the aluminum test piece. The spindle speed was 15,000 rpm in all the tests regardless of the material of the workpiece. The POCO EDM-C3 electrode material was machined with a 20 in./min feed rate and a 0.030 in. depth of the cut. Experimental data was collected by cutting the aluminum test piece at 15,000 rpm with a 5 in./min feed rate and a 0.015 in. depth of cut.

5. Results and discussion

The performance of the proposed GTM was evaluated on the simulated and experimental cutting force data. GTM estimates the dullness index (DI) when the single parameter is estimated in both cases. The first estimated cutting force coefficient value with the new tool is used as reference $(K_m)_1$ value. $(DI)_n$ is calculated from the data of the cutting force profile of one tool rotation by $(K_m)_n/(K_m)_1$. For a new tool, DI fluctuates around 1. Smoothly increasing DI values during the machining indicates that the tool is getting dull.

If a cutting edge is damaged, its cutting force profile differs from a normal one. The run-out of the tool appears to be changed. In addition to the DI, the contact length of a cutting edge was estimated from the simulated data when two parameters were estimated. The objective was to see if the genetic algorithm could distinguish the variation of the force profile due to changes in the cutting force coefficient or the contact length of a cutting edge. On the experimental, primarily the DI was estimated to evaluate the wear when two parameters were considered. The run-out was estimated without any unit just as an advisory value and it was called run-out index (ROI). The ROI of a new tool depends on the type and condition of the tool holder and adjustment. Since the feed per tooth is extremely small in micro-end-milling, it is common to perform the machining operation by using only a single cutting edge. In this study, ROI is mainly used to improve the accuracy of the DI estimation. Under the perfect conditions, both of the cutting edges of the tool wear out and gets dull simultaneously. ROI will fluctuate and have very small values. If one of the cutting edges were chipped, or broken, the contact length of one of the cutting edges decrease, and the ROI would increase drastically. This drastic increase indicates that both of the cutting edges do not remove the same amount of material.

5.1. Performance of the GTM on the cutting force data

The cutting force coefficient and the contact length of one of the cutting edges was estimated from the resultant (Figs. 5 and 6), feed (Figs. 7 and 8), thrust direction (Figs. 9 and 10), and cutting forces. To demonstrate the performance of the prosed approach, simulated and estimated values of the DI and contact length estimations were compared in the figures. The genetic algorithm was stopped after 500 iterations in all the test cases. The DI is the ratio of the estimated cutting force coefficient over the theoretical value

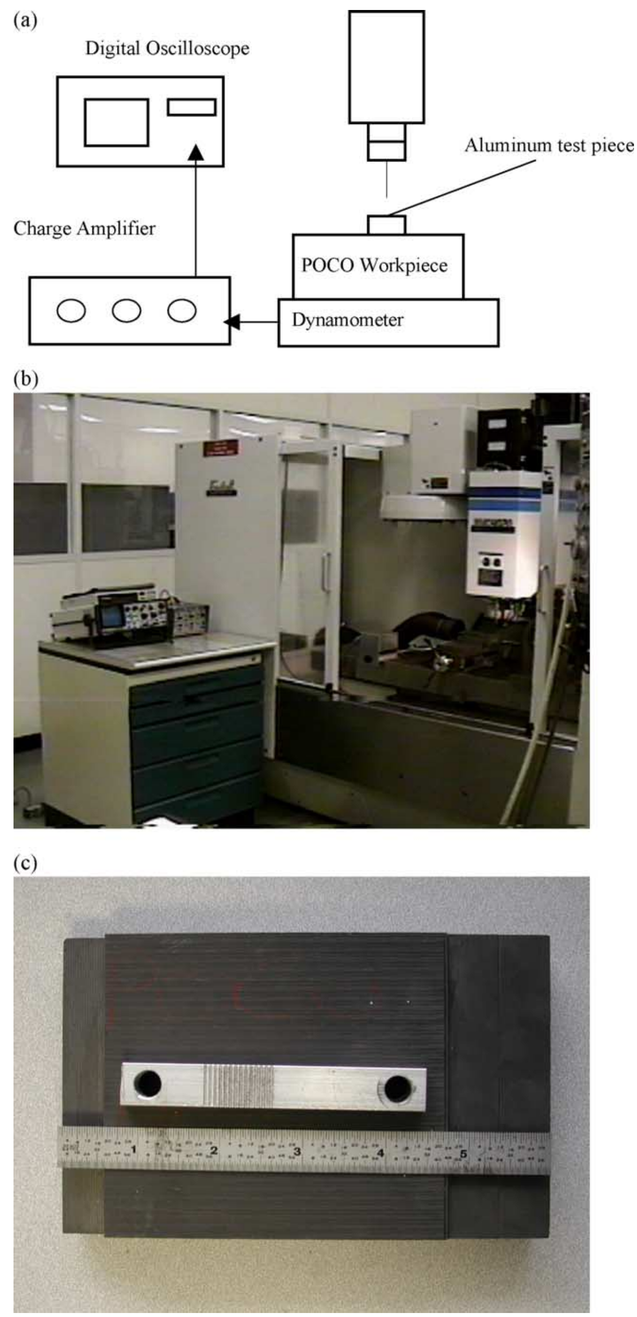

Fig. 4. Experimental set-up: (a) diagram of the experimental set-up; (b) picture of the set-up; (c) POCO workpiece and aluminium test piece with slots.

of the same coefficent for the perfect tool. The contact length is the section of the cutting edge which removes the material.

The cutting force coefficient was estimated with less than 1% error in all the studied cases, either the resultant force or the single force component was used. The contact length estimation error was less than 10% when the GTM made the estimations from the resultant force. The estimation error was less than 2% when a single force component was used to estimate the contact length. These results indicated that

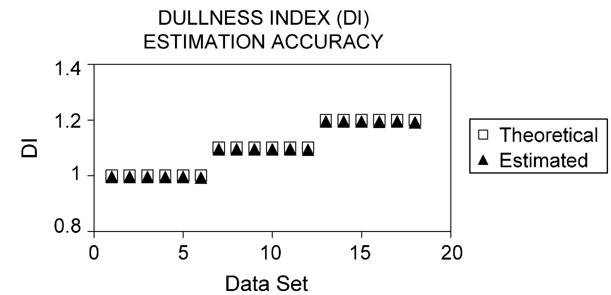

Fig. 5. Cutting force coefficient estimation accuracy of the GTM when the resultant cutting force is used for estimations (values were taken from Ref. [15]).

GTM was capable to distinguish the variation of the cutting force coefficient and the change of contact length.

5.2. Performance of the GTM on the experimental data

The resultant cutting force data was calculated from the sampled two cutting force components. The data segments, which correspond to one revolution, were isolated starting from the lowest force value. Then, these were used to make the estimation of the considered parameters. The considered segment and the estimation of the genetic algorithm is presented in Fig. 11.

First, GTM was used to estimate the DI of three cutting force segments collected at eight wear levels, and results are presented in the Fig. 12 [15]. DI stayed around unity when the tool was sharp at the beginning. It quickly increased and

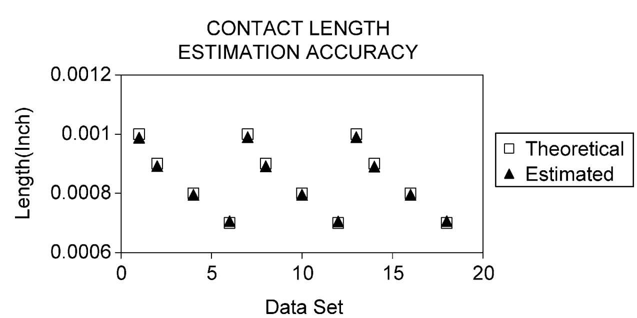

Fig. 6. Contact length estimation accuracy of the GTM when the resultant cutting force is used for estimations (values were taken from Ref. [15]).

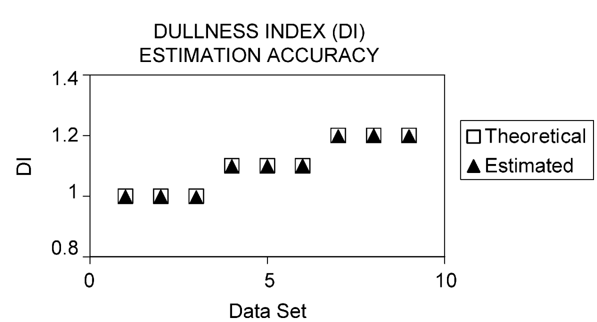

Fig. 7. Cutting force coefficient estimation accuracy of the GTM when the feed direction cutting force is used for estimations (values were taken from Ref. [15]).

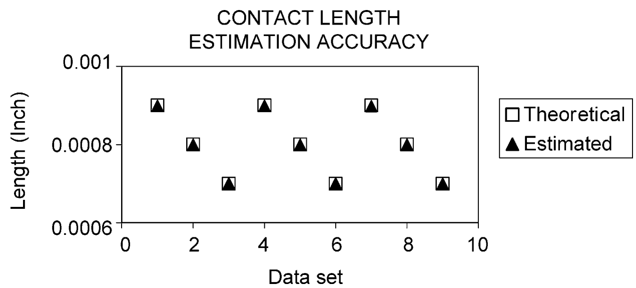

Fig. 8. Contact length estimation accuracy of the GTM when the feed direction cutting force is used for estimations (values were taken from Ref. [15]).

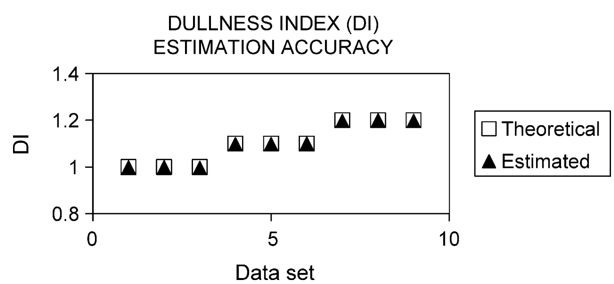

Fig. 9. Cutting force coefficient estimation accuracy of the GTM when the thrust direction cutting force is used for estimations (values were taken from Ref. [15]).

stayed at the next level. The DI values of the samples were very consistent at the same wear levels.

GTM was also used to estimate DI and ROI at the same time from the same data [15]. DI values were almost the same when one or two parameters were estimated. ROI had very small values and fluctuated slightly at the beginning. It increased very slightly when the tool worn out. The results are presented in Figs. 13 and 14.

6. Conclusion

Genetic Tool Monitor (GTM) was introduced and its performance was evaluated on the simulated and experimental data. The user does not need to have any expressions for a system when time series analysis, fuzzy logic and neural networks are used. It is necessary to study the characteristics of the data at many different cutting conditions, and to determine the most important indicators of the wear. Based on these observations, sampling of the data, preliminary processing, proper use of the method, and interpretation of the final results should be determined. In case of neural networks, training data should be provided at all the cutting conditions. These methods work reliably only if the operating conditions are similar to the previously considered ones.

It is necessary to have either an analytical or an empirical expression to be able to use the genetic algorithms. A carefully obtained analytical or experimental expression

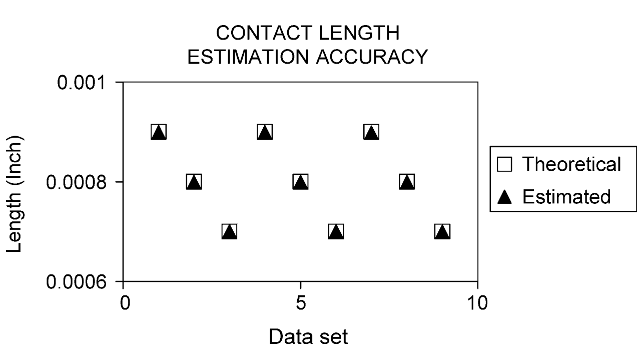

Fig. 10. Contact length estimation accuracy of the GTM when the thrust direction cutting force is used for estimations (values were taken from Ref. [15]).

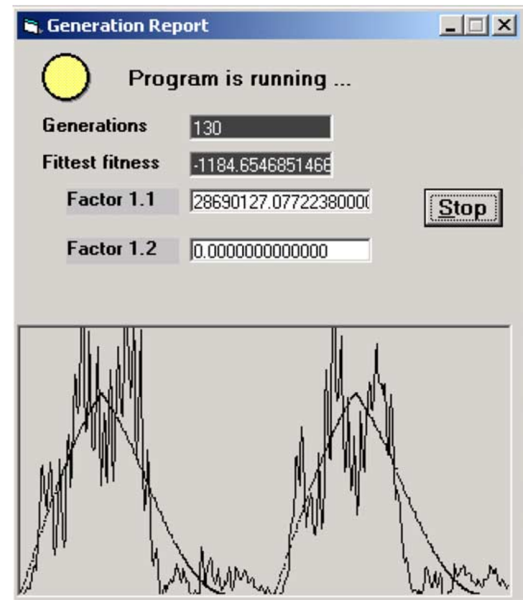

Fig. 11. The experimental data of one tool revolution and the estimated model by the GTM [15].

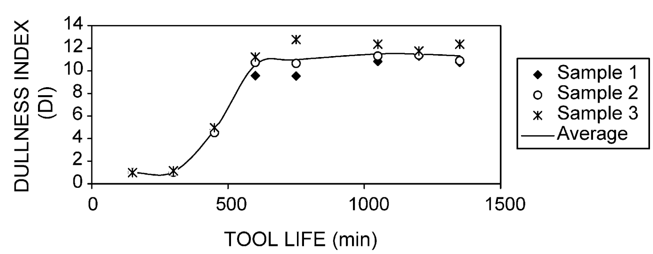

Fig. 12. Variation of the DI with tool wear. GTM2 estimated single value (DI) (values were taken from Ref. [15] and modified).

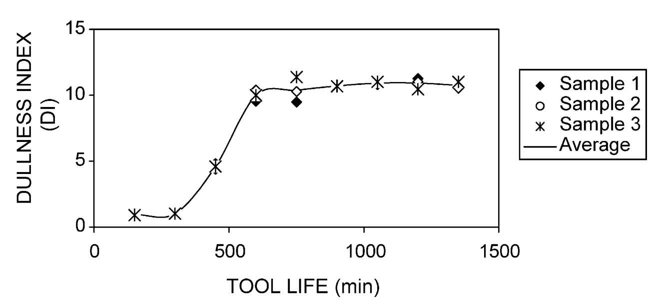

Fig. 13. Variation of the DI while the tool wears out. DI and ROI were estimated simultaneously (values were taken from Ref. [15] and modified).

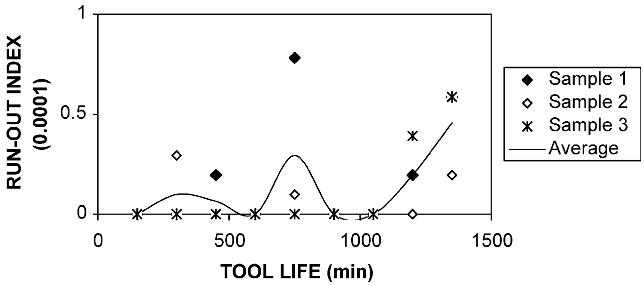

Fig. 14. Variation of the ROI while the tool wears out. DI and ROI were estimated simultaneously (values were taken from Ref. [15] and modified).

provides very valuable information about the characteristics of the system. A genetic algorithm estimates one or more key parameters of this expression from the incoming data. Since the genetic algorithm-based diagnostic tools know the characteristics of the system, once the key parameters are estimated they can start to monitor the signals without any previous training, and they are more robust against noisy signals. If they estimate any parameters of the operating conditions, they are supposed to continue to operate reliably even if that parameter changes during the machining operation and take values, which was never tested before. Theoretically, a tool condition monitor can be developed which estimates all the cutting parameters, and it should be able to estimate the wear continuously while a very complex part is cut. However, each estimated parameter would increase the computational time and reduce the accuracy. In this study, all the cutting conditions were fixed to increase the reliability of the estimations, to minimize false alarms, and to detect when any of the components of the system fails.

The accuracy of the estimated parameters was the same and even better when the data of either of the single force's component was used instead of the resultant force. However, use of the resultant force was preferred on the experimental data to assure that the method is valid even if the feed direction is not known.

In this study, machining of non-metallic materials with miniature tools was considered, and cutting force data was collected periodically while a test piece was cut. Since the cutting force was very small relative to the noise, use of this approach was inevitable. However, the proposed approach is very attractive to develop low cost tool condition monitoring systems. These systems may use a single load cell to collect the data on a test piece at a carefully selected cutting condition, periodically and estimate wear with a low cost computational hardware. The low development and maintenance cost, high accuracy, and reliability will be the main advantages of them and compensate the disadvantage of non-continuous monitoring capability.

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References

[1] D.E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley, Reading, MA, 1989.
[2] J.H. Holland, Adaptation in Natural and Artificial Systems, A Bradford Book, The MIT Press, Cambridge, MA, 1992.
[3] D.L. Carroll, Chemical laser modeling with genetic algorithms, AIAA Journal 34 (2) (1996) 338–346.
[4] I. Tansel, W.Y. Bao, B. Tansel, R. Shisler, D. Smith, J. Murray, Identification of cutting conditions by using an analytical model and genetics algorithms for micro-end-milling operations, Intelligent Engineering Systems through Artificial Neural Networks 8 (1998) 779–784.
[5] I.N. Tansel, W.Y. Bao, T.T. Arkan, C.V. Kropas-Hughes, Genetic algorithm versus neural network in health monitoring applications, Intelligent Engineering Systems Through Artificial Neural Networks 12 (2002) 255–260.
[6] W.Y. Bao, I.N. Tansel, Modeling micro-end-milling operations. Part I. Analytical cutting force model, International Journal of Machine Tools Manufacture 40 (15) (2000) 2155–2173.
[7] W.Y. Bao, I.N. Tansel, Modeling micro-end-milling operations. Part II. Tool run-out, International Journal of Machine Tools and Manufacture 40 (15) (2000) 2175–2192.
[8] W.Y. Bao, I.N. Tansel, Modeling micro-end-milling operations. Part III. Influence of tool wear, International Journal of Machine Tools and Manufacture 40 (15) (2000) 2193–2211.
[9] F. Cus, J. Balic, Optimization of cutting process by GA approach, Robotics and Computer-Integrated Manufacturing 19 (1–2) (2003) 113–121.
[10] J.P. Davim, C.A.C. António, Optimisation of cutting conditions in machining of aluminium matrix composites using a numerical and experimental model, Journal of Materials Processing Technology 112 (1) (2001) 78–82.
[11] M.S. Shunmugam, S.V. Bhaskara Reddy, T.T. Narendran, Selection of optimal conditions in multi-pass face-milling using a genetic algorithm, International Journal of Machine Tools and Manufacture 40 (3) (2000) 401–414.
[12] Z. Khan, B. Prasad, T. Singh, Machining condition optimization by genetic algorithms and simulated annealing, Computers and Operations Research 24 (7) (1997) 647–657.
[13] T. Szecsi, A DC motor based cutting tool condition monitoring system, Journal of Materials Processing Technology 92–93 (1999) 350–354.
[14] S. Achiche, M. Balazinski, L. Baron, K. Jemielniak, Tool wear monitoring using genetically-generated fuzzy knowledge bases, Engineering Applications of Artificial Intelligence 15 (3–4) (2002) 303–314.
[15] L. Li. Genetic Algorithm based open architecture cutting tool monitoring system, MS Thesis, Florida International University, 2002.