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Drill wear monitoring using cutting force signals

Huseyin Metin Ertunc *, Cuneyt Oysu

Mechatronics Engineering Department, Kocaeli University, Veziroglu Campus, Izmit, Kocaeli 41040, Turkey

Abstract

Monitoring of tool wear condition for the drilling process, which is one of the major cutting process in machining, is very considerable for the sake of avoiding tool failures, increasing machine utilization and decreasing production cost in an automated manufacturing environment. In the literature, many tool wear condition monitoring techniques have been investigated using a variety of sensors including dynamometers for force and torque, accelerometers for mechanical vibrations, AE sensors for acoustic emission and current probes for current/power measurement of spindle and feed motors. New techniques are proposed in this paper for real time identification of tool wear status based on cutting force and torque measurements from dynamometer during metal drilling. These techniques utilize hidden Markov models (HMM), phase plane method, transient time method and mechanistic approach.

Keywords: Tool wear condition monitoring; Drilling process; Monitoring systems; Hidden Markov models

1. Introduction

Drilling is a material removal process that has been widely used in manufacturing since the industrial revolution. When the repetition of the cutting processes is considered, drilling is one of the most common machine tool operations among the metal cutting operations such as turning, milling and grinding. It was reported that drilling accounts for nearly 40% of all the metal removal operations in the aerospace industry [1]. On the other hand, recent years have witnessed a dramatic increase in the complexity and capabilities of metal cutting technology. Simple machine tools have been replaced by flexible and computer-integrated manufacturing systems. The

* Corresponding author. Tel.: +90-532-430-6758; fax: +90-262-335-2812.
E-mail address: hmertunc@kou.edu.tr (H.M. Ertunc).

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computer numerically controlled (CNC) machine tools are now widely used in industry for achieving productivity performance goals.

As manufacturing technology has been moving to the stage of full automation over the years, monitoring of tool wear condition has gained substantial importance in order to prevent tool failures. Thus, it is possible to increase machine utilization and decrease production cost in an automated manufacturing environment. Yet, tool wear and tool breakage are still unsolved primary problems in metal cutting process, though a considerable amount of research has been done in the literature [2].

Wear is a loss of material at the cutting lips of drill bit because of physical interaction between the cutting tool and workpiece material. Abrasion, adhesion, diffusion and fatigue are the basic mechanisms that cause wear in cutting tools. Tool wear in drilling is a progressive procedure but it occurs at an accelerated rate once a drill becomes dull. During this procedure, the cutting forces increase, temperature of tool rises, drill point deformation and immediate loss of sharp edges occur. After a certain limit, tool wear can cause catastrophic and sudden failure of the tool without any warning that causes considerable damage to the workpiece and even to the machine tool. This scenario can be illustrated in Fig. 1 by classifying the wear stages as initial wear, slight wear (regular stage of wear), moderate wear (micro breakage stage of wear), severe wear (fast wear stage) and worn-out (or tool breakage) as a function of tool life [3].

Measuring cutting forces (*thrust*, the force component in the cutting direction; and *torque*, the moment about the axis of rotation of the tool) is one of the most common used techniques for monitoring because of their sensitivity to tool condition [4]. In addition, it is easy to measure cutting forces using dynamometers mounted on a tool holder. Basically cutting forces increase as the drill tool wears and they will jump suddenly when the tool is broken. For monitoring systems, thrust and torque can be selected separately as measurement signals. Thrust force is one of the most useful dynamic parameters in the drilling process. Thangaraj and Wright [5] used the rate of change of thrust force to predict drill failure while Brinksmeir [6] selected torque to predict tool fracture. On the other hand, Li et al. [7] chose both thrust and torque as monitoring parameters in their “multi-signature extraction technique”.

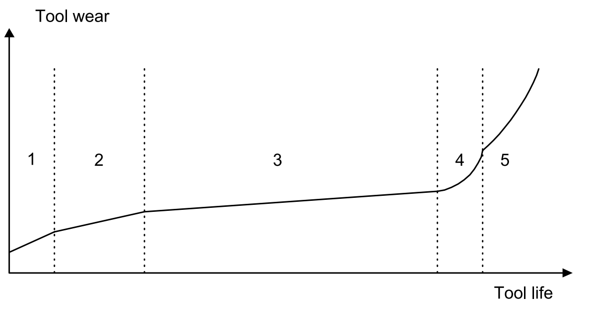

Fig. 1. Tool wear evolution (1. initial wear, 2. slight wear, 3. moderate wear, 4. severe wear and 5. worn-out).

The major drawback of cutting forces is the dependency on cutting conditions (cutting velocity, feed and depth of cut).

In this paper, different monitoring techniques, namely the bargraph method based on hidden Markov models (HMM), a phase plane method, a transient time method and mechanistic approach based on torque signal prediction are presented in order to monitor tool wear in drilling operations in real time. Next sections of the paper illustrate the experimental setup, give concise theoretical background of HMM; then explains how to use the proposed techniques for monitoring drill wear. The proposed techniques are evaluated for thrust and torque signals collected during the drilling operations. Finally experimental results are presented and discussed.

2. Experimental setup

The experimental setup used in this study is illustrated in Fig. 2. The drilling life tests were conducted on a MAHO 700S, which is a computer numerical controlled (CNC) five axis machining center, with movement in three perpendicular axes and a rotary/tilt table. A special CNC program was run to track force as a function of wear. The thrust force (F_z) and torque (T) were measured by a Kistler two-component dynamometer (Kistler Model 9271A). The dynamometer consists of a two-component force transducer fitted under high preload between a base plate and a top

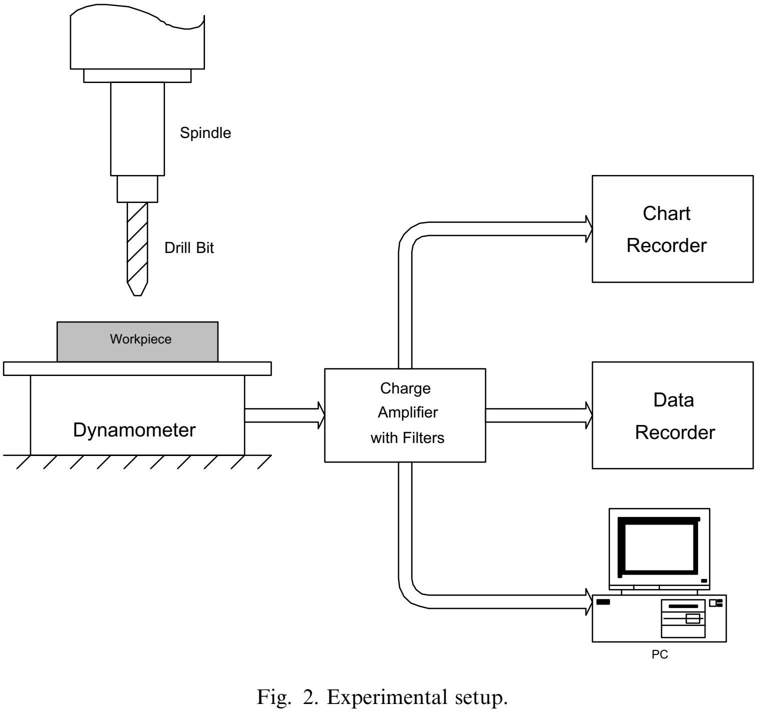

Fig. 2. Experimental setup.

plate. The force transducer contains two sets of quartz disks arranged in a circular configuration. One set is sensitive to pressure in the z direction and yields a charge proportional to F_z (thrust), while the other responds to shear stress and gives a charge proportional to T (torque). The resulting signals are converted into output voltages proportional to the forces sustained and then two charge amplifiers amplify these voltage signals.

Force signals were simultaneously recorded to a DAT tape by a Sony PC216Ax data recorder with a 12 kHz sampling rate. As seen from Fig. 2 collected signals could be monitored in real time either on the computer screen or on the chart recorder. The data recorded was loaded into a Pentium II computer via PCScan MKII software for data analysis after the test. The data were resampled at 1 kHz and saved to the hard disk of the computer.

Holes were drilled on a steel workpiece material using a M7 cobalt split-point twist drill bit, which has 5/16-in. diameter, and 135° point angle. The holes were drilled to a depth of 1/2 in. The feedrate was kept constant at 11 in./min and different spindle speeds in the range of 1825–2500 rpm were used to obtain different tool wear rates. The cutting conditions (speed, feed rate, depth of hole) remained constant throughout the test.

All tests were performed without using any cutting fluid, i.e. under dry cutting conditions. The workpiece material was fairly homogeneous and its geometrical features were not considered.

3. Hidden Markov models

Hidden Markov models (HMM) were introduced by Baum and his colleagues at the end of the 1960s. Then Baker and Jelinek implemented this theory for speech processing applications in the 1970s [8]. Currently, HMM is a state-of-the-art technique for speech recognition because of its elegant mathematical structure and the availability of computer implementation of these models. Recently, HMM applications have been spreading steadily to other engineering fields that include target tracking, machine tool monitoring, fault detection and diagnosis, robotics and character recognition [9].

HMM is an extension of Markov chains. A Markov chain is a random process of discrete valued variables involving a number of states linked by a number of possible transitions. At different times, the system is in one of these states, each transition between the states has an associated probability, and each state has an associated observation output (symbol). State transition probabilities only depend on current state, not on past states. Unlike Markov chains, HMM are doubly stochastic process; i.e., not only is the transition from one state to another state stochastic, but the output symbol generated at each state is also stochastic. Thus the model can only be observed through another set of stochastic processes. The actual sequences of states are not directly observable but are ‘‘*hidden*’’ from observer. This is why these models are called hidden Markov models.

3.1. Elements of HMM

In order to characterize a HMM completely, following HMM elements need to be defined using the same notation as given in [8]:

1. N, the number of states of the model. The set of individual states is denoted as $S = \{S_1, S_2, \ldots, S_N\}$.
2. T, the number of observations. A typical observation sequence is denoted as $O = \{O_1, O_2, \ldots, O_T\}$.
3. $Q = \{q_t\}$, the set of states. q_t denotes the current state such that $q_t \in S$ and $t = 1, 2, \ldots, T$.
4. M, the number of observations symbols in the alphabet. If the observation space is "continuous", then M is defined to be infinite.
5. $V = \{v_1, v_2, \ldots, v_M\}$, the set of observation symbols. The observation symbols per state matches the physical output of the model.
6. $A = \{a_{ij}\}$, the set of state transition probabilities of the underlying Markov process with the probabilities,
$$a_{ij} = P\lfloor q_{t+1} = S_j | q_t = S_i \rfloor, \quad 1 \leqslant i, j \leqslant N. \tag{1}$$
This equation describes the probabilistic evolution of the state from S_i at time t to the state S_j at time $t + 1$. The transition probabilities (a_{ij}) satisfy the standard stochastic constraints,
$$a_{ij} \geqslant 0, \quad 1 \leqslant i, \ \ j \leqslant N \tag{2a}$$
and
$$\sum_{j=1}^{N} a_{ij} = 1, \quad 1 \leqslant i \leqslant N, \tag{2b}$$
7. $B = \{b_j(k)\}$, probability distribution of observation symbols for each states with
$$b_j(k) = P[v_k t = t | q_t = S], \quad 1 \leqslant j \leqslant N, \ 1 \leqslant k \leqslant M, \tag{3}$$
where v_k denotes the kth observation symbol in the alphabet. $b_j(k)$ is the probability of symbol v_k given that q_t is in state j, and must satisfy the following constraints
$$b_j(k) \geqslant 0, \quad 1 \leqslant j \leqslant N, \ 1 \leqslant k \leqslant M, \tag{4a}$$
$$\sum_{j=1}^{N} b_j(k) = 1, \quad 1 \leqslant j \leqslant N. \tag{4b}$$
8. The initial state distribution, $\boldsymbol{\pi} = \{\pi_i\}$ is given by
$$\sum_{j=1}^{N} b_j(k) = 1, \quad 1 \leqslant j \leqslant N, \tag{5}$$
where π_i is the probability of being in state S_i at the beginning of the observation sequence.

If the observation is continuous signals, a continuous probability distribution function in the form of a finite mixture is assigned to each state instead of a set of discrete probabilities. In this case, the parameters of the continuous probability distribution function are often approximated by a weighted sum of M Gaussian distribution η,

$$b_j(O_T) = \sum_{m=1}^{M} c_{jm}\eta(\mu_{jm}, U_{jm}, O_t), \quad 1 \leqslant j \leqslant N, \tag{6}$$

where c_{jm} is a weighting (mixture) coefficient, μ_{jm} is the mean vector, U_{jm} is the covariance matrix and M is the number of mixture components. Note that $\eta(\mu, U, O)$ is a multivariate Gaussian probability density function with mean vector μ and covariance matrix U.

The c_{jm} must also satisfy stochastic constraints, i.e.,

$$c_{jm} \geqslant 0, \quad 1 \leqslant j \leqslant N, \ 1 \leqslant m \leqslant M, \tag{7a}$$

$$\sum_{m=1}^{M} c_{jm} = 1, \quad 1 \leqslant j \leqslant N. \tag{7b}$$

Thus, the compact representation for a HMM with a discrete output probability distribution is given by

$$\lambda = (A, B, \pi) \tag{8}$$

and the model with a continuous output distribution is given by

$$\lambda = (A, c_{jm}, \mu_{jm}, U_{jm}, \pi). \tag{9}$$

In the next section, we present a real time monitoring technique by processing the cutting forces (thrust and torque) in drilling operation on the models based on HMM. In general, HMM is a very efficient method to model pattern classes that consist of time series data and to compare patterns to recognize, or classify new data. Here, cutting forces (thrust and torque) are time series to develop HMM models and to determine the tool wear condition of drilling operation. It must be noted that, cutting forces depend on the machining conditions such as spindle speed, feed rate, workpiece/tool type, and depth of hole. However, the data signals are expected to be quite similar in terms of shape and amplitude under the same machining conditions. Therefore, we have collected the cutting force signals and applied the proposed monitoring techniques for drilling operations with the same machining parameters, cutting tool properties, workpiece material and geometry.

4. The proposed monitoring bargraphic methods

The theories of four different methods for the drill wear monitoring based on bargraphic representation are explained briefly in the following subsections.

4.1. Hidden Markov models

In this method, after drilling a hole in a workpiece material with a sharp drill, the collected thrust and torque signals are trained separately to develop hidden Markov models, i.e., HMM parameters ($A, C_{jm}, \mu_{jm}, U_{jm}$ and π) are determined. Once these parameters are determined, thrust and torque signals collected during the drilling process are processed in real time in the corresponding hidden Markov models to evaluate the wear status of the drill bit. Each model generates a probability which quantitatively represents the similarity between the current signal and the signal used for building the model, i.e., the signals obtained from a sharp drill. The probabilities generated by the model are denoted in a logarithmic scale because the values of the probabilities are extremely small. Then, the probabilities generated from both of the HMM models corresponding to a sharp drill are normalized to *one*, so that the probabilities take values between 0 and 1.

The more the drill wears, the more the thrust force and torque signals differ from those signals which were obtained for a sharp drill, in terms of both magnitude and shape. When the signals are processed through the corresponding HMMs, the probabilities begin to decline indicating the wearing process of the drill. If the normalized probabilities decrease below a certain threshold, it can be concluded that the drill is about to brake and it is time to change the tool. The threshold value corresponds to severe stage of the tool wear evaluation as illustrated in Fig. 1. During the experiment, we determined the tool wear stages empirically based on the expert operator's observations. In general at the severe stage, much higher cutting force, deteriorated surface quality and extreme heat dissipation from the drill can be examined.

4.2. Phase plane method

In the phase plane method, the data signals are plotted on the Cartesian coordinate system (thrust on the y-axis versus torque on the x-axis) basically and the boundary values of a *reference rectangle* for the data come from drilling signals are determined. The steady state values of the data points, both at the exit and entry of force should be inside the rectangle as shown in Fig. 3. *Entry* is the time from the initial contact until the full engagement of the entire cutting lips. *Exit* corresponds to the retraction of the drill bit from the hole at the end of the cutting process. As the boundary values of the reference rectangle are located in the phase plane for the test cutting process, the torque and thrust data signals are plotted on the same plane for successive runs. Since the signals change with tool wear, the percentages of the number of data points falling into the rectangle decreases as drilling and progressive wear continues.

The reference rectangle exploits percentages of the number of data points inside the reference rectangle to track tool wear, like in the HMM approach. This information is in good agreement with the probabilities generated by the HMM models as will be shown in the results of the methods. The phase plane method is very advantageous from the point of view of its simplicity for computer implementation compared to HMM. The reason is that, this method involves much less

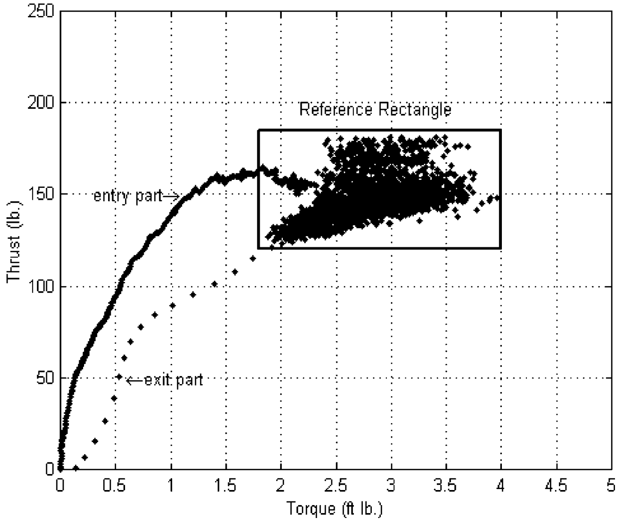

Fig. 3. Phase plane and reference rectangle for torque and thrust signals.

mathematical calculation, but rather checking whether each data point falls into the rectangle or not. On the other hand, the force signal's characteristics like the signature or shape play very important role in the monitoring of tool wear in a drilling process. HMM methods compare the current signal to the reference signal, which was used to develop the corresponding HMM, in terms of not only amplitudes but also the shapes of the force signals.

4.3. Transient time determination

In the drilling operation, the actual cutting action occurs only at the cutting lips (edges) of the tool though the chisel edges penetrate into the workpiece first. As the drill proceed into the workpiece, the cutting area continually increases until all of the cutting lips are engaged. In each drilling process, the torque is close to zero at the beginning and then it gradually increases and finally reaches steady state as shown in Fig. 4. When drilling is finished, the drill bit is extracted from the workpiece material and the torque signal goes to zero at the exit part of the cycle. On the other end, corner wear is known as the most common wear type in the drilling process. Because the cutting speed is maximum and the contact area is the largest at the end points of the cutting lips, the temperature rise is very rapid at the drill corners. Further increase in temperature can cause plastic deformation of the tool material. Therefore the drill bit is more likely to begin to wear from its corners. As illustrated in Fig. 5, as corner wear progresses, the point angle reduces and cutting lips lengthen because the tool loses its sharp edge. Consequently, the transient time, that is the time for entry of the tool into the workpiece, increases.

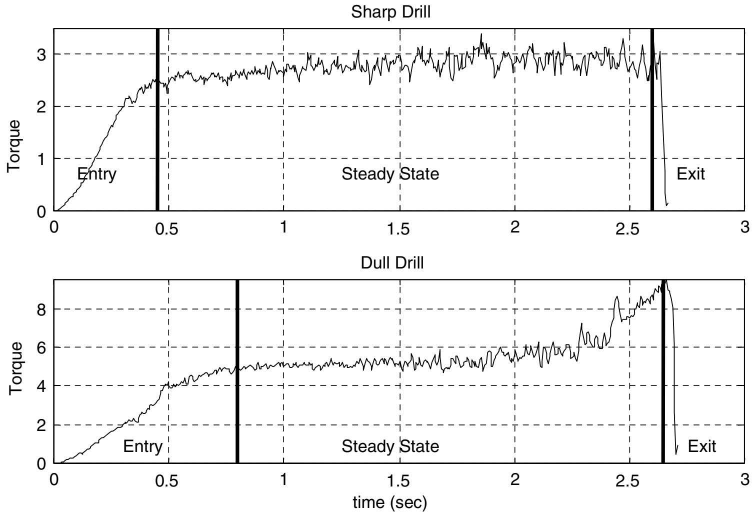

Fig. 4. The different parts of torque signal.

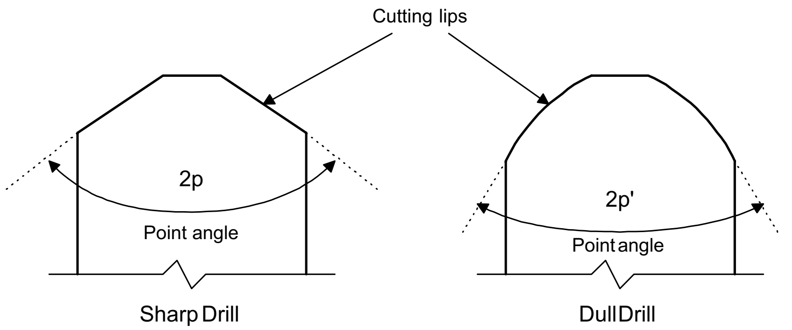

Fig. 5. Corner wear illustration in a drill bit.

If the corner wear is too large, then the transient time increases considerably and therefore can be used as a parameter to monitor tool wear. In order to determine the exact transient time, the torque signal is first filtered; the time where the derivative is approximately zero corresponds to end of the transient time. Usually drills fail when all the cutting lips are fully engaged inside the workpiece material. Thus, if the transient time is above a threshold value, and then the process is stopped before the drill penetrates further into the workpiece.

4.4. Mechanistic approach

Over the years, researches have developed different mechanical/mathematical models to simulate the drilling process and hence to predict thrust and torque by using cutting parameters such as drill diameter, drill chisel edge length, feed rate, material hardness, etc. These models can be used for tool condition monitoring by tracking the variation of some of the model parameters as a function of tool wear. Due to the complex geometry of the drill and the nonlinear nature of machining, most of the models are empirical models based on analyzing experimental data given the cutting conditions. Using the geometry of the process, Chandrasekheran et al. [10] have developed mechanistic models to predict thrust and torque profiles among the cutting lips and chisel edge of a conventional conical point drill, separately. The following formula gives the torque for the cutting lips at entry when drilling with a pilot hole,

$$T_{\mathrm{CL}}(t) = \frac{C_2 R^2 f}{(b+2)}\left[\left(\frac{r(t)}{R}\right)^{b+2} - \left(\frac{r_{\mathrm{p}}}{R}\right)^{b+2}\right] - \frac{C_2 f w^2 \sin^2 p}{2b}\left[\left(\frac{r(t)}{R}\right)^{b} - \left(\frac{r_{\mathrm{p}}}{R}\right)^{b}\right], \tag{10}$$

where R is the radius, $2p$ is the point angle, $2w$ is the web thickness, f is the feed, C_2 and b are the model coefficients, r_{p} is the pilot hole radius, $r(t)$ is the radial distance of an element on the cutting lips. They calibrated the torque model by determining the model coefficients (C_2 and b) using experimental data from drilling tests with different pilot hole sizes. It is clear that C_2 is related to magnitude of the torque signal. b is the velocity coefficient that can be determined from drilling experiments at varying spindle speed at a constant feedrate [10].

The approach in the present paper is to estimate the model coefficients from the real data and to relate them with tool wear. The transient time for the torque signal is assumed to be a constant, say 0.5 s; in other words the initial portion of the torque data up to 0.5 s is considered and *simplex search method* is used to find the minimum model coefficients starting with at an initial estimate. Fig. 6 shows the real data and the simulated torque using the estimated values obtained for C_2 and b. Experimental results show that the model coefficients (C_2 and b) increase with tool wear. Unlike the experiments done by Chandrasekheran et al. [10], a pilot hole is not used in the present work, therefore r_{p} (pilot hole radius in the above equation) is replaced by half of the chisel web length (w) which is very small when compared with the radius of the split-point drill. Because the contribution of the chisel edge to torque is very small, the torque due to the indentation zone is neglected.

5. Experimental results and discussions

Using a split-point twist drill, many holes were drilled in a steel workpiece material and numerous sets of data were collected. The results of the proposed methods are presented for three sample data sets running under the same experimental conditions given in Table 1. All the experiments started with a sharp drill and the tool eventually became worn by drilling many holes, then finally it was broken. For the

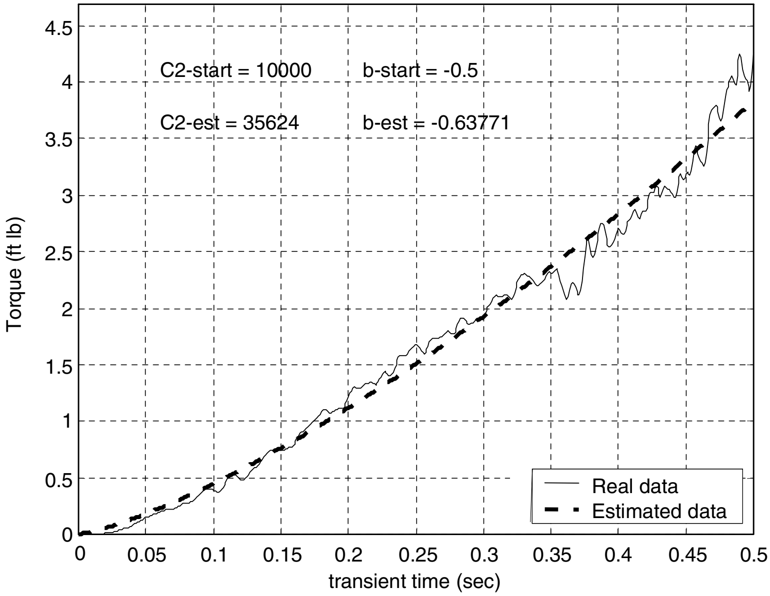

Fig. 6. Estimation of force coefficients in torque model.

Table 1
Experimental conditions

Test no.	RPM	Feed rate (in./min)	Depth of hole (in.)	Workpiece material	Drilled holes
1	1825	11	1/2	Steel	7
2	1825	11	1/2	Steel	69
3	1825	11	1/2	Steel	93

first drill bit, only seven holes were drilled because it was worn from its corner of cutting edges purposely so that the wear rate could be increased. The tool wear occurred naturally in the second test and the run numbers in the figures correspond to drilling of holes 1, 14, 28, 41, 55 and 68, respectively. For Test 3, the run numbers correspond to the drilling of holes 1, 15, 28, 42, 55, 69, and 82, respectively.

Figs. 7–10 show the bargraphic results of hidden Markov models, phase plane method, transient time determination method and mechanistic approach, respectively. As seen from the figures, the condition of the tool can be clearly monitored from the bargraphics. Note that, even though the drill was failed at the 93rd hole in Test 3, the last sample of torque and thrust data was obtained at the 82nd hole and the drill was still in a workable condition at this time. Therefore, the last values of bargraphs in Test 3 were still high compared to the ones in the previous tests.

The values of bars in Fig. 7 are given in normalized logarithmic probabilities because the numerical values of the actual probabilities generated by the hidden Markov models are very small, e.g. 10^{-36} for the sharp case in Test 1. The more the tool wears, the smaller the numerical values of logarithmic probabilities. All the

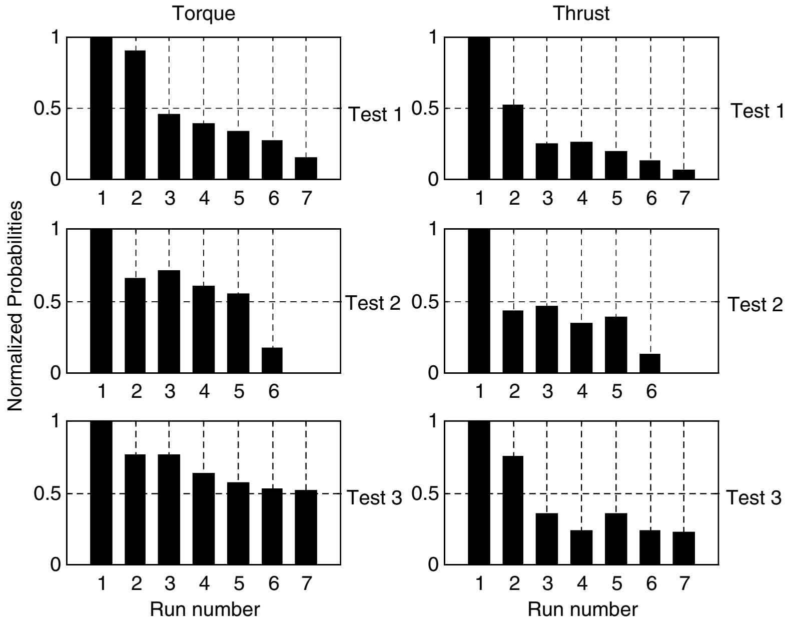

Fig. 7. The results of the hidden Markov models.

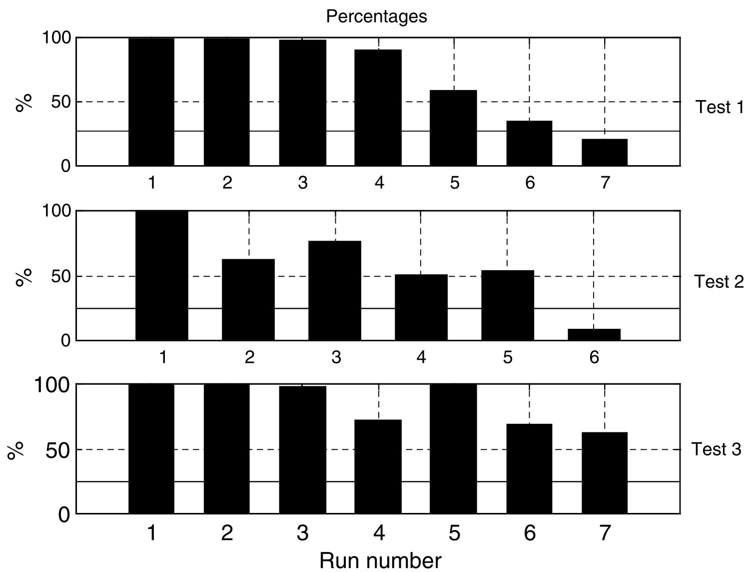

Fig. 8. The results of phase plane method.

probabilities are normalized according to the one obtained from the first sharp drilling, as explained in Section 4.1. Note that in Fig. 7, the probabilities for the

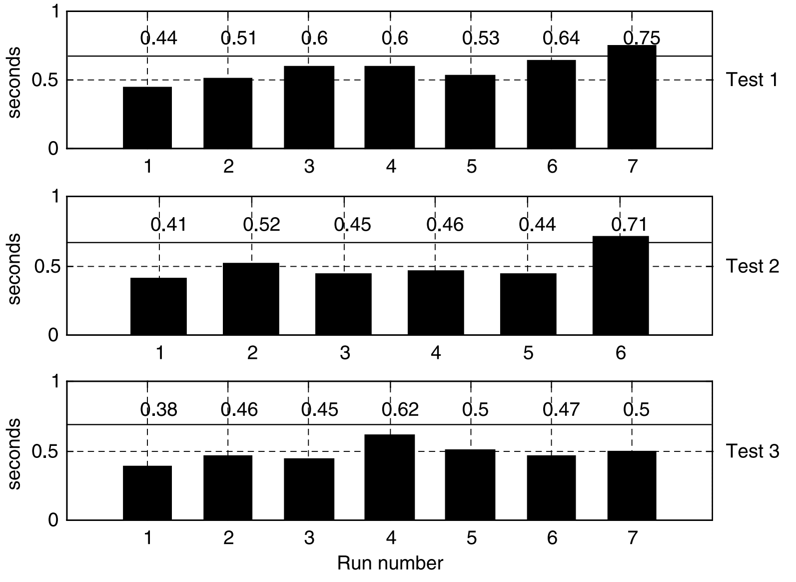

Fig. 9. The results of determination of transient time.

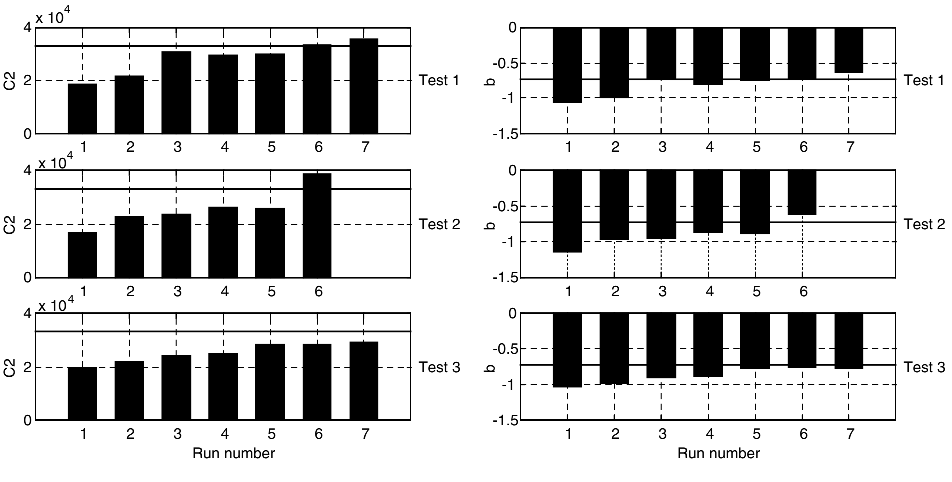

Fig. 10. The results of mechanistic approach.

thrust signal compared to the torque signals have a wider range between the sharp and dull status of the tool. Therefore, it can be concluded that thrust signals are better indicators of tool wear than torque signals in this particular application.

Fig. 8 shows the results of *phase plane method*. When drilling holes in a steel workpiece material, the average values of force signals during the drilling of the final holes are usually 100% greater than for the drilling of the initial holes. Thus, a *reference rectangle* is constructed in the thrust–torque plane so that the reference rectangle contains the normal operating data, i.e. the data obtained from drilling using a sharp tool; and the height (thrust) and the width (torque) are extended to be two times the maximum values during the normal operation. Further, the minimum steady state values of thrust and torque obtained from the first run in Test 1 run were chosen as the lower-left corner of the corresponding reference rectangle. This reference rectangle determined in Test 1 is used in the other tests (Tests 2 and 3) for verification of the proposed approach. Tool wear can be monitored by observing the decreasing trend of the percentages of the data points, which fall into the reference rectangle. Coincidentally, tool failure occurred when the percentages were below 20% (shown by horizontal line in the figure) in the experiments.

It must be noticed that there are some fluctuations in the values of percentages, i.e., the percentages do not increase uniformly and they make some unexpected jumps as can be seen from Fig. 8. Even though this may cause confusion, the dull status of the tool can be fortunately determined, because the force drastically increases. Therefore the percentages of the data points inside the reference rectangle decrease noticeably at this stage of tool wear.

Fig. 9 shows the calculated transient times for the tests. When the drill is about to break the transient time is almost doubled as compared to that of a sharp drill in Tests 1 and 2. Because of the same reasons as explained previously, it is not possible to detect the failure in Test 3. The authors noticed in the experiments that the drills usually fail when all the cutting lips are fully engaged inside the workpiece material. So, determining the transient time and taking action if the transient time is above a threshold value (indicated by a line in the figure), could prevent the failure. Although this method has a good advantage for the early prediction of tool failure using only the transient part of the torque signal, it may not be easy to determine the *exact* value of transient time because filtering of the signal is required before computing the derivative, and this can change the signal and affect the computation.

Using the formula given in Eq. (10), the torque force coefficients are estimated for a certain transient time (0.5 s) of torque signals in each one of data set. The increasing trend of model coefficients (C_2 and b) can be used to monitor tool wear as seen from Fig. 10. As long as C_2 and the absolute value of b are below the threshold, the tool is considered as *workable*. Whenever they exceed the threshold value, the process is stopped before a possible breakage due to excessive wear occurs. The mechanistic model of torque can predict the failure in Tests 1 and 2. Because the torque data is not available near the last failure, the tool wear can only be observed in Test 3, but not the breakage.

6. Conclusion

Several monitoring methods for tool wear detection in drilling operations were presented based on the measurements of force signals (thrust and torque). The overall purpose of these methods is to track progressive tool wear so that catastrophic tool failure can be avoided by taking necessary corrective counteractions such as stopping the feed rate and spindle rotation, in sufficient time.

Experimental results show that the reliability of the proposed methods. The use of HMM seems to have promise as a real time and data trainable system that does not require any mechanical and/or mathematical model of the machine tool. Because both the shape and amplitude of the force signals vary with tool wear, HMM is effective in comparing the data signals during the drilling operation. Moreover, the proposed HMM methods can be implemented on-line since the computation of the probabilities which indicate the status of tool wear can be performed during the noncut time between two consecutive drilling operations.

Even though, it seems very simple, *the phase plane method* gives satisfactory criteria for monitoring tool wear, because this method is based on the increment of force signals. The percentages decline is in good agreement with probabilities generated by the HMM models. The basic advantage of the phase plane method when compared to HMM is its simplicity from the point of view of computer implementation. Because, it is not necessary to implement too many calculations for this method, but rather checking whether each data point falls into the reference rectangle.

The transient time method for torque signal has the advantage of early prediction of outer corner wear before full engagement of the drill bit with the workpiece. Corner wear is usually the dominant wear type in drilling operations and the transient time of the torque signal increases with corner wear.

A torque model in the literature [10] is modified to predict the force signals along the cutting lips a drill bit while it is operating. Using the simplex search method, the force coefficients (C_2 and b) for torque signal were estimated and correlated tool wear. These constants increase with dullness of the drill.

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