Int J Adv Manuf Technol (2016) 86:2011–2020
DOI 10.1007/s00170-015-8325-2

ORIGINAL ARTICLE

Tool wear monitoring and replacement for tubesheet drilling

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Received: 13 August 2015 / Accepted: 29 December 2015 / Published online: 15 January 2016

Abstract Indirect Tool Condition Monitoring (TCM) methods have shown significant potential to automatically detect worn tools without intervention in the machining process. This paper presents the development of a non-intrusive and online TCM system for large diameter indexable insert drills. The TCM system developed used two cutting force-related signals of a horizontal boring machine, namely the spindle motor current and the axial feed motor current, and features extracted from these signals were taken as the inputs to a series of models to predict the tool wear state and the hole diameter. A tool replacement strategy based on applying limits to the predicted hole diameter was also developed. Adjusting these limits allows the strategy to be tuned for either hole accuracy or tool life depending on the requirements of a specific application. Experiments of drilling of 39.0-mm-diameter holes in 2205 Duplex stainless steel in an industrial field were designed and performed with the results to illustrate the effectiveness of developed TCM and strategies. Specifically, the TCM system ensured that none of over tolerance holes would have been drilled, which is critically important since any over-tolerance hole can result in the failure of an entire finished product of tubesheet; the replacement strategy for tool life resulted in a 44 % increase in tool life and a non-trivial reduction in machine down time due to fewer tool changes while holding a hole diameter tolerance of ±0.1 mm.

Keywords Cutting · Machine tools · Manufacturing automation · Monitoring

1 Introduction

Optimizing tool life in machining operations is a continuous challenge for machine shops. A balance between productivity and tooling costs must be found in order to maximize profit. Drilling holes is a common machining operation where tool life is critical. If a drill fails while drilling, it often results in a hole with the diameter and/or surface finish out of tolerance. To prevent this, drills are changed at regular intervals prior to failure. This usually prevents out of tolerance holes but often results in prematurely changing drills that are still capable of drilling significantly more holes. A method for real-time monitoring of the drill condition (tool condition monitoring, TCM) would allow drills to be consistently used to their maximum life while preventing out of tolerance holes.

The manufacture of heat exchangers requires drilling thousands of identical holes through plate varying from 6 mm thick up to 600 mm thick for tubesheets and baffles. Some heat exchangers can require 30,000 plus holes per unit in materials such as stainless steel, chrome alloys, inconel, and low alloy steels. In this repetitive process, even little improvement over the life of drills, or using drills until slightly closer to the end of their life, can substantially reduce the

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manufacturing time and overall cost of a heat exchanger. Another significant benefit to utilizing a TCM system is the ability to allow unmanned drilling operation. With an automatic tool changer and a reliable TCM system, the only operator input required would be to change inserts one or two times per shift allowing the operator to run several machines at once or allow machines to be run completely unmanned in between shifts.

1.1 Tool condition monitoring

There has been a lot of research into TCM systems over the last several decades. These systems can be broken down into two broad streams, direct and indirect systems [1, 2]. Direct TCM systems rely on direct measurements of tool wear through visual inspection [3] or computer inspection. This prevents them from being used online while machining, making them less efficient than indirect systems that rely on measurements of process parameters such as cutting forces or vibration to infer the wear of the tool. The online monitoring capabilities of indirect systems make them preferable in industrial settings. An indirect system typically involves sensing, feature extraction, and classification to estimate the tool condition (Fig. 1).

Cutting forces such as feed force and spindle torque as well as related parameters such as feed and spindle motor currents have been widely measured [2, 4, 5]. Cutting forces are proportional to motor currents which allows simple and economical implementation of TCM systems based on these signals [6–11]. A problem with utilizing cutting forces for TCM is that they are affected by cutting conditions, heterogeneous workpiece material properties, and environmental noise in addition to tool wear [8, 9, 12, 13]. Mechanical vibrations, up to 20 kHz, are also related to tool wear and have been used to infer the tool wear state [14, 15]. Vibrations are also susceptible to being affected by the same factors as cutting forces. Vibrations of higher frequencies which are referred to as acoustic emission (AE), typically over 100 kHz, have also been used to infer the tool wear state [16–19]. AE is much less susceptible to workpiece materials, cutting conditions, and environmental factors but is sensitive to signal attenuation and part geometry [4, 19, 20]. Each of the mentioned signals have pros and show promise for TCM but also have limitations and drawbacks; therefore, more than one parameter is typically measured and data fusion is used to increase system reliability and robustness [21].

It is difficult to infer the tool wear state based on the raw sensor data so features that enable classification are often extracted. These features can be in either the time or the frequency domain. Some commonly extracted features in the time domain are the arithmetic mean [1], the root mean square (RMS) value [16], standard deviation [21], peak values [22], kurtosis [15], and parameters for time series models of the measured signals [5, 23]. Fast Fourier transforms (FFT) can be used to analyze signals in the frequency domain by determining the distribution of components with different frequencies [4, 14]. The major drawback of the frequency-based methods is the FFT calculation tends to attenuate the frequency content of transient phenomena and thus is not very suitable for non-stationary signals such as those found in TCM systems [4]. Time-frequency methods such as the wavelet transform or one of its modified forms allow the extraction of both time domain and frequency domain information from the signals simultaneously [17, 23–25]. Classifiers are then used to divide the feature space into regions representing the different tool wear states. Some classifiers that have been used in TCM systems are rule-based expert systems [25], support vector machines [3], neural networks [10, 17, 24, 26–28], and other pattern recognition approaches [29, 30].

All of the referenced research above related to drilling has involved twist drills, most of which were high speed steel and smaller than 20 mm in diameter. There has been no research done on TCM systems using 25 mm diameter or greater drills. Modern, large diameter drills typically have a steel body with replaceable coated carbide inserts like the drill shown in Fig. 2. Preliminary research has shown significant potential for utilizing cutting force related signals (based on the spindle current and the feed motor current) in a TCM system for large drills.

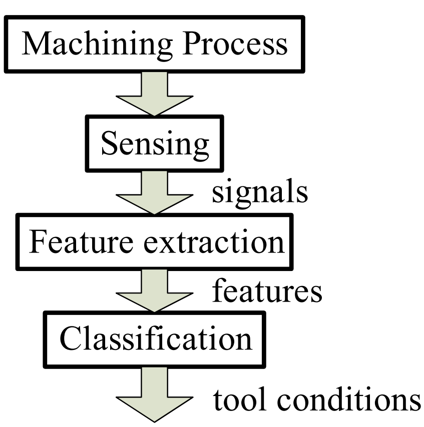

Fig. 1 Block diagram of an indirect TCM system

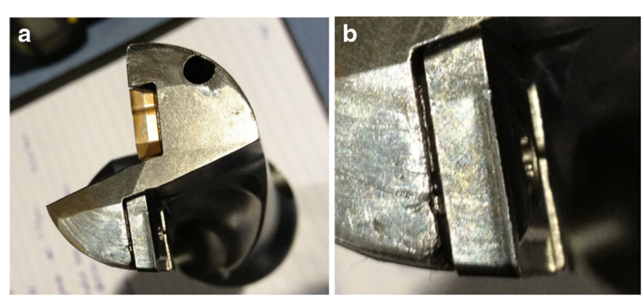

Fig. 2 Drill with inserts **a** full drill and **b** outside insert closeup

1.2 Machining accuracy prediction

Machining accuracy is the variance between desired geometry of a part and the actual geometry. Inaccuracies can come in a number of different forms: size, geometrical position, and surface finish [31]. For the drilling process, machining accuracy is comprised of the hole position, hole size, and surface finish. Inaccuracies can be caused by cutting forces, cutting conditions, tool wear and deflections, and thermal-induced deformation of machine tools [18, 32]. Two types of models have been developed to predict machining errors: physical models and phenomenological models. Physical models are based on the governing physical laws [33] and typically have complicated forms and require intensive calculations [32] limiting their usefulness in industry. Phenomenological models relate machining errors to the contributing factors mathematically with limited consideration of the underlying physics. Rigorously selecting the mathematical equations based on experimental data can result in models with simpler structures compared to physical models.

Typically, the development of phenomenological models involves three steps. First, dominating factors are identified and selected as the inputs to the models to represent the machining errors. Second, drilling experiments, as designed by experiment design methods such as the central composite design method [34] or the Taguchi method [35], are performed while the machining errors are measured and evaluated. Last, specific model structures, such as the response surface models and linear polynomial models, are chosen to represent the relationship between the selected factors and the machining errors. Model coefficients are then identified from the recorded experimental data, and methods such as analysis of variance (ANOVA) and residual analysis are often employed for model validation and improvement [35]. The response surface model combined with ANOVA and residual analysis are effective for identifying dominating factors. As such, these methods were adopted and employed in the development of models relating hole size and flank wear to the measured current signals in the present study.

Most of the research on TCM systems involves models relating the flank wear to measured signals so as to inform tool replacement [8–11, 13, 17, 21, 26]; little research has been completed on relating actual hole quality (machining accuracy) to the measured signals [18, 32]. Furthermore, research on TCM systems for large diameter drills has not been reported in the literature. The goal for this study is to develop a TCM system to monitor the hole quality, along with the tool wear, for large diameter tube drilling and on this basis, to develop strategies for the tool replacement so as to maximize tool lifetime while ensuring hole accuracy. Cutting experiments in an industrial field (Mitsubishi Hitachi Power Systems Canada, LTD) were designed and performed with the results to illustrate the effectiveness of developed TCM and strategies.

2 Model development for tool wear and replacement

In this paper, hole accuracy is represented by the mean diameter (E_D), which is evaluated from three points of a hole. Surface finish is another aspect of hole quality and accuracy that is important in some heat exchanger designs and many drilling applications; however, it is typically a secondary consideration to the hole size and was not considered in this paper. Hole accuracy is related to the wear state of the drill inserts, and previous research has shown that the wear state of a drill is related to the spindle and feed motor currents [4, 9, 10, 25, 36] providing a link between the measured signals and the desired output namely the hole accuracy.

The tool wear (V_b) is represented by the wear on the flank surface of the drilling insert cutting edges and is measured optically with a microscope. For this project, only the flank wear on the outside insert was considered since the outside insert typically wears twice as fast as the inside insert as well as the fact that the outside insert is directly responsible for cutting the surface of the hole.

Given that the tool wear and the hole accuracy depend on cutting conditions as well as the cumulative cutting time for a particular insert, i.e., the number cumulative number of holes drilled (a), it is rational to model them as a dynamic system where the inputs are the cutting conditions, i.e., the cutting speed (S) and the feed rate (f), and the features extracted from the drilling process by the current sensors (i.e., $F_1$and F_2) are treated as system states, characterizing the system dynamics. Figure 3 is a block diagram of the proposed model, which consists of three sub-models to represent the system states, tool wear, and hole accuracy.

The first model, $\mathbf{M_1}$, could be any discrete dynamic model. Data related to this project that was collected previously indicated that the autoregressive-with-exogenous-inputs (ARX) or one of its modified forms was promising. An ARX model for modeling each of three features extracted from the steady state drilling portion over the life a set of drilling inserts is:

$$F_j(n) = -\sum_{k=1}^{N} c_k F_j(n-k) + \sum_{k=0}^{M} a_k f(n-k) + \sum_{k=0}^{L} b_k S(n-k) + e(n) \quad (1)$$

where F_j are the features being modeled, f is the feed rate, S is the surface speed, and e is the error.

However, in order to determine the coefficients a_k, b_k, and c_k, the inputs $f(n)$ and $S(n)$ must be “rich” or have persistence of excitation. For tubesheet drilling in general, the feed rate and the surface speed are not normally changed throughout the life of the insert; thus, the inputs for the equation above are constant over the life of each time series and therefore do not

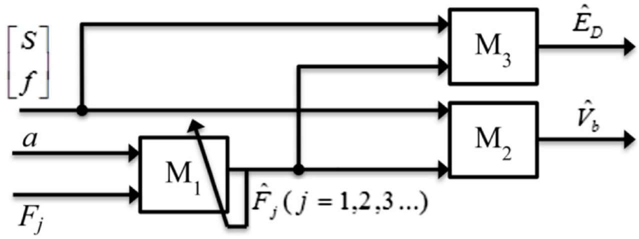

Fig. 3 Block diagram of the proposed dynamic model

qualify as rich inputs. Removing the terms associated with the inputs results in an autoregressive (AR) model of the following form, which is only dependent on the previous outputs that can be measured:

$$F_j(n) = -\sum_{k=1}^{N} c_k F_j(n-k) + e(n) \tag{2}$$

A number of features make an AR model attractive. First of all, depending on the number of terms used in the model (the model design parameter N), the model provides a degree of smoothing to the actual data. Secondly, the AR model allows forecasting of the value of $\hat{F}_j$ up to N holes into the future, thus permitting the forecasting of future hole diameters and allowing inserts to be changed prior to drilling holes with a high potential to be out of tolerance.

To allow the AR models to accurately predict the extracted features, $\hat{F}_j$, for the initial holes drilled in a time series (i.e., $n<N$), surface response models can be used. $F_j(n-k)$ for$k>=n$, F_j can be estimated with a polynomial model with inputs of feed rate and spindle speed.

$$F_j = f(x_1, x_2, \cdots x_k) + \varepsilon \tag{3}$$

The second and third models, $\mathbf{M_2}$ and $\mathbf{M_3}$, shown in Fig. 3 are also surface response models. These models are not dynamic since the relationship between the measured signals and the tool wear and subsequently the hole accuracy does not change with time. The second model will use the machining parameters, feed rate, f, and spindle speed, S, as well as the predicted values for $\hat{F}_j$ to predict the flank wear on the outside drilling insert using up to second-order polynomials of the form shown in Eq. (3). The proposal for the third model to predict the hole diameters has the machining parameters and the predicted features as inputs to a polynomial surface response model similar to model 2.

3 Experimental methodology

3.1 Experiment design

There are many factors that may influence the life and accuracy of a drill including the machining parameters (spindle speed and feed rate), drill type, insert grade, insert shape, type of insert chip breaker, use of coolant, coolant volume, coolant pressure, machining center rigidity, and part/setup rigidity. In this paper, the influence of two factors of machining parameters, i.e., spindle speed and feed rate, was investigated, while the others were held constant in the cutting experiments. With two varying factors, a simple and efficient experiment design is a two factor–two level full factorial design with 4 different test conditions, which, however, only provides information enough for identifying a linear model. Adding an additional test condition in the center of the 4 test conditions provides additional data to test for non-linearity. If further test conditions are added along each axis, enough information could be obtained for quadratic, 2nd order models. This design is called a central composite design, which is an efficient design for fitting up to 6 coefficients in two factor 2nd order models. This design includes 8 runs plus the runs at the center point (typically 3 to 5 runs). These runs at the center point provide an idea of the variability of the process being studied, especially where only a single replicate can be run at each of the other test conditions.

The center point of the experiment was chosen based on Hitachi's current operating conditions, specifically a feed rate of 0.130 mm/rev at a surface speed of 130 m/min for the steady-state portion of the hole. All of the test conditions for the experiment are shown in Table 1.

As mentioned above, the remaining factors were held as constant during the cutting experiments. Specifically, a Toshiba BF-130A horizontal boring mill (HBM) with high pressure, through the tool, coolant at 700 psi was used for all testing. All tests were completed with the same drill, on the same workpiece, and in the same setup.

The drill is a 39.0-mm diameter SandvikCorodrill 880 drill capable of drilling to a depth of two times the diameter (Sandvik part number 880-D3900L40-02). This drill requires

Table 1 Experimental conditions

Run	f	s	f (mm/rev)	s (m/min)
1	0	0	0.130	130
2	−1	1	0.090	140
3	1	−1	0.170	120
4	0	0	0.130	130
5	1	1	0.170	140
6	−1	−1	0.090	120
7	0	0	0.130	130
8	−1.4	0	0.074	130
9	0	1.4	0.130	144
10	1.4	0	0.186	130
11	0	−1.4	0.130	116
12	0	0	0.130	130
13	0	0	0.130	130

two indexable carbide inserts, the inside insert used for all the experimental testing is a general machining chip breaker in a 1044 grade (Sandvik part number 880–07 04 06H-C-GM 1044), and the outside insert is a light machining 4024 grade (Sandvik part number 880–07 04 W10H-P-LM 4024). Each insert, both the inside and the outside, has a total of four cutting edges obtained by simply rotating the insert 90°. The aim of the experiment was to drill as many holes with a single cutting edge as possible at each combination of cutting parameters, and both inserts were always indexed prior to starting a new run.

Figure 4a, b shows a new and a worn OD insert with a ×5 magnification of the flank of the outside insert. As these inserts are used, a clear wear line develops along the flank of the inserts. As more holes are drilled, this wear line typically advances across the flank of the insert in a fairly linear fashion with the greatest wear occurring near the tip of the insert. The width of this wear pattern increases sharply upon first use when the insert is new slows to a consistent increase in wear until near the end of the life of the insert when the wear will tend to accelerate again.

The large wear pattern visible near the right side of the insert shown in Fig. 4b is an example of the random increased wear patterns that can develop and which also can affect the resulting hole diameter depending on the where the wear occurs.

The two signals required for the TCM system are the current of spindle motor and the current of axial feed motor. The HBM used for the testing has a built in spindle load meter with a 0–10 V output proportional to the spindle motor current. It did not have a similar meter for the axial feed force, so an Ohio Semitronics CT8-017D RMS current sensor with a proportional output of 0–10 V and an input range of 0–20 Amps was installed. The current signals for the spindle motor and the axial feed motor were both recorded using a National Instruments USB 6351 DAQ and a custom interface written using the Data Acquisition Toolbox of Matlab. Figure 5 shows the experimental setup of the present study.

A 2 kHz sampling rate was used for all data analysis. Since the spindle torque and the axial feed force are proportional to the motor currents, in this paper, the motor currents (measured in volts, V) will be referred to as the spindle torque and the axial force even though actual torques and forces were not calculated.

The results for the wear and hole diameter measurements for the experiment are shown in the following figures. The maximum flank wear for all the runs can be seen in Fig. 6, and the hole diameter for each hole is shown in Fig. 7. The diameter for the four runs at the center point (0.13 mm/rev feed and 130 m/min surface speed) is shown in Fig. 8.

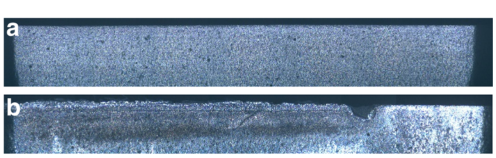

Fig. 4 OD Inserts at ×5 magnification **a** new and **b** 135 Holes Drilled

Since these runs are all at the same machining parameters, this graph provides a good indication of the inherent variability for the Sandvik drill used. There is ±0.075 mm diameter variation with the same drill and the same parameters (the maximum difference in the diameters between the runs up until 60 holes when wear variations starts to increase the variability). This variability indicates the maximum accuracy, i.e., the minimum variability that can be expected for a TCM system using large size indexable insert drills.

The models in the proposed TCM system are based on features extracted from the raw motor currents. In order to extract features from the raw signals, algorithms were developed to recognize the current signature for an individual hole and to identify the steady state drilling portion of each hole. For this project, all the features used for building the TCM models were extracted from the steady state drilling portion of the drilling cycle.

3.2 Parameter identification

The first step to building a dynamic AR model for the extracted features is to model the initial values of the features to accurately predict the initial time series points. The first ten values in the recorded time series were averaged to obtain a single data point for each experimental run. Using ANOVA analysis and a least squares fit the mean torque and force can be calculated by the models shown in Eq. (4), and similar results are shown in Eq. (5) for the initial maximum axial feed force. The axial feed force is mainly influenced by the feed rate with only a small dependence on the spindle speed. There is also more variation in the maximum values of the force that is not accounted for in the model resulting in a lower coefficient of determination of 0.87.

$$T_{\mathrm{mean}}[V] = -1.37 + 10.48f\left[\mathrm{mm}/\mathrm{rev}\right] + 0.017S\left[\mathrm{m}/\mathrm{min}\right] \tag{4}$$

$$F_{\max}[V] = 1.26 + 2.0f\left[\mathrm{mm}/\mathrm{rev}\right] - 0.003S\left[\mathrm{m}/\mathrm{min}\right] \tag{5}$$

Similar models were built for other extracted features such as the mean axial force, the RMS value of the torque, as well as others. However, the two features detailed above, the maximum axial force, and the mean spindle torque provided the best results in models 2 and 3.

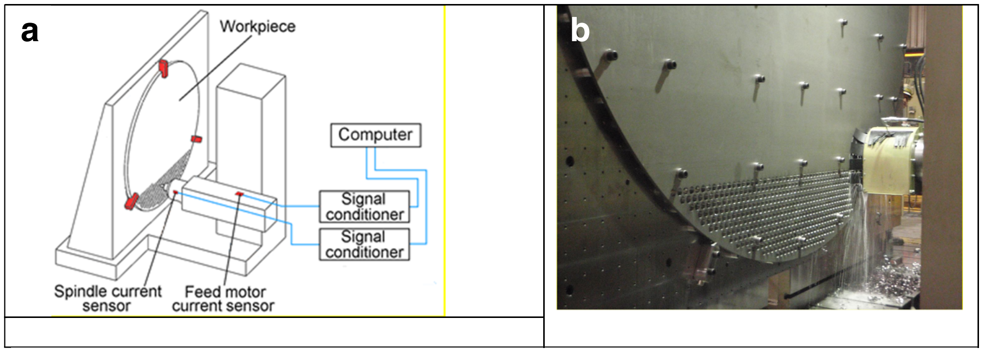

Fig. 5 Experimental setup: **a** schematic of TCM system and **b** drilling a tubesheet on a boring machine

Development of the AR models required the determination of the optimum form of the models as well as the coefficients for the chosen model order to predict the maximum axial force and the mean spindle torque. Potential coefficients for the mean spindle torque AR model were determined for each run (each run is an individual time series) using the least squares method for up to a ninth order model. Run 9 was not used in the training of any of the models since it was used for verification.

The 12 values for each coefficient (for each order) needed to be combined into a single value for use in the final AR model. Several methods were used to determine the best way to perform this consolidation including visualization and ANOVA analysis. There is no apparent correlation between the input parameters, feed rate and spindle speed, and the coefficients. Similarly, ANOVA analysis indicated that there is no statistical correlation between these input parameters and the coefficients. Since there was no correlation, an arithmetic mean was used to combine the 12 calculated coefficients into a single value for the AR model. The same process was carried out for the maximum axial force with similar results. The value of the coefficients has limited change as the model order is increased beyond a 6th order model, and the 6th order model also performed better as inputs to the subsequent models than lower order models, so the 6th order coefficients were chosen. The model output is demonstrated on run 09 in Fig. 9.

The proposed model for predicting the insert flank wear is a polynomial surface response model. A variety of inputs were investigated for this model including the machining parameters as well as many different features extracted from the current measurements. A number of flank wear measurements were used in the analysis were the overall maximum wear at any point on the insert. Each of these indications of the insert wear was investigated during the building of this model. The input data and the measured flank wear data were aggregated together for all the runs, except for run 09 which was used for validation, to allow ANOVA analysis and the determination of the model coefficients using the least squares method. The predicted values for the extracted features were used in place of the actual measured values as inputs to the model. The best combination of inputs was found to be the feed rate and the maximum axial feed force. The final model is shown in Eq. (6), and the model was validated using run 09 which is shown in Fig. 10, where the model reasonably matches the shape of the actual data.

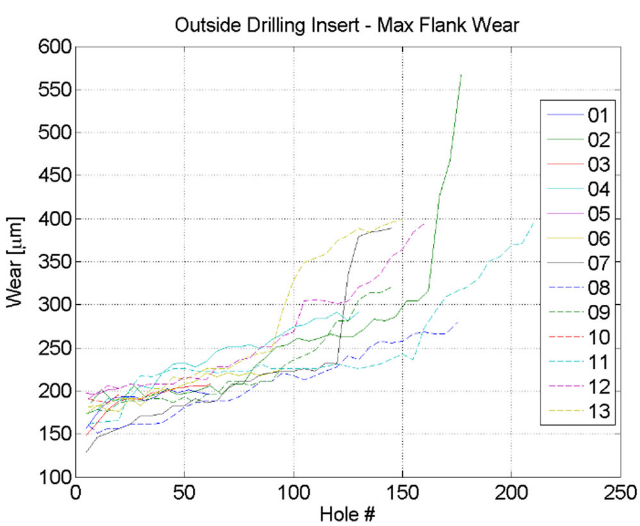

Fig. 6 Maximum flank wear for all runs

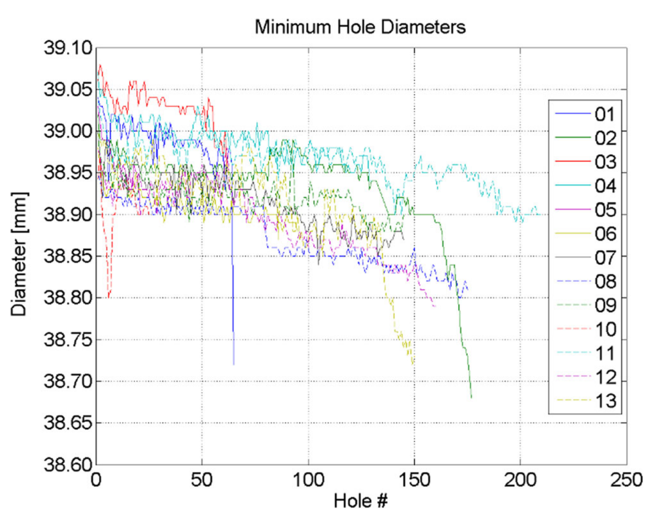

Fig. 7 Minimum hole diameter for all runs

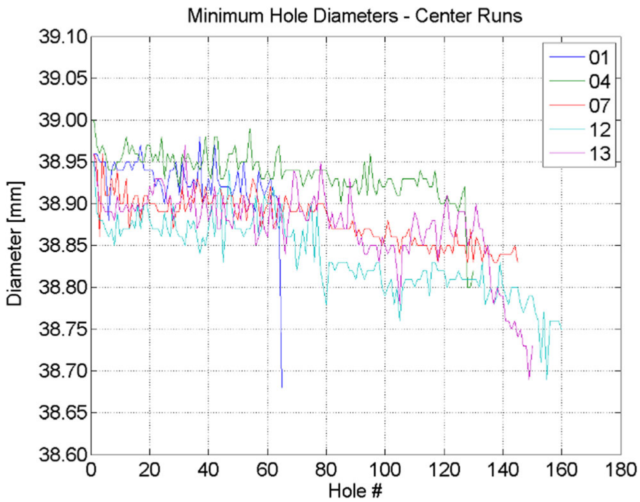

Fig. 8 Minimum hole diameters for all the center runs (same parameters)

$$\hat{V}_b = 1916 + 14135 \times f - 4978 \times \hat{F}_{max} + 3169 \times \hat{F}^2_{max} - 13422 \times f \times \hat{F}_{max} \tag{6}$$

3.3 Hole diameter model

The final model of the TCM system is a surface response model to predict the machining accuracy of the drill or the hole size in particular. The proposed model was a polynomial model with the machining parameters, the extracted features, and the predicted flank wear from the second model as inputs and the minimum hole diameter as the output. The same process as was used to determine the coefficients for the second model were used to develop this model. The best results obtained with the proposed inputs resulted in the model given by Eq. (7). The data and the fitted model are shown in Fig. 10, where the green vertical lines show the division between individual experiment runs. The model is not able to fit the data with a high degree of accuracy, but it is able to capture most of the overall trends. The data and the fit for Run 04 are an example of this. The model captures the downward trend in the diameter but is not able to accurately predict the actual

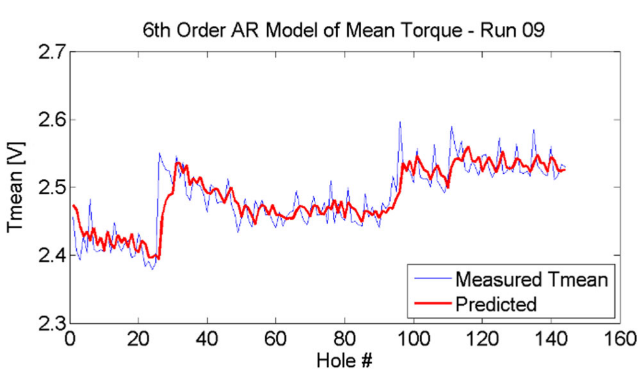

Fig. 9 AR model results for run 09 mean torque

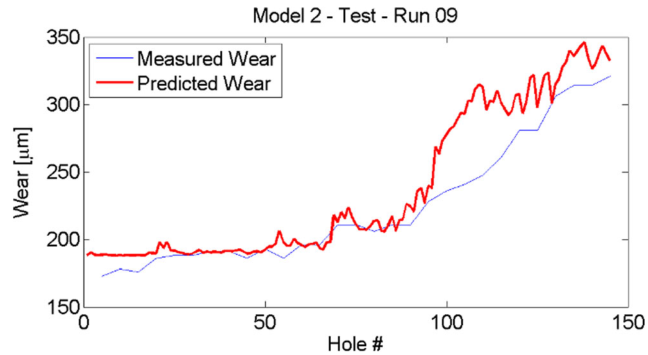

Fig. 10 Model 2: flank wear model validation

diameters. There are a number of reasons for this including: variability in insert size or the possibility of the insert not seating exactly in the pocket. Neither of these problems would cause a significant change in the axial feed force or the spindle torque, so the model cannot predict the hole size accurately but they would directly affect the hole diameter.

$$\hat{E}_D = 38.5 - 4.07 \times f - 0.0026 \times S - 0.19\hat{F}_{max} + 1.41 \times \hat{T}_{mean} - 0.24 \times \hat{T}^2_{mean} - 0.36 \times \hat{F}_{max} \times \hat{T}_{mean} + 1.44 \times f \times \hat{F}_{max} \times \hat{T}_{mean} \tag{7}$$

The validation run using the data from run 09 is shown in Fig. 11. The model predicts the hole diameter within about 0.05 mm with a downward trend as shown in the actual data. An item of interest that is shown by this plot can be seen around hole 100. Just before hole 100, the model predicts a sudden drop in the hole diameter while the actual hole diameter increased slightly (a similar occurrence can be seen by looking at the data for run 02 in Fig. 10 above). The reason for this behavior and why the model cannot accurately predict the diameter in these instances is that all wear on the inserts, either the inside or the outside insert appear to result in increased axial feed force and increase spindle torque. However, depending on the location of the wear, if it is on the tip of the outside insert or on the inside edge of the inside insert, the diameter can either temporarily decrease or increase. The overall trend is for the diameter to decrease over the life of

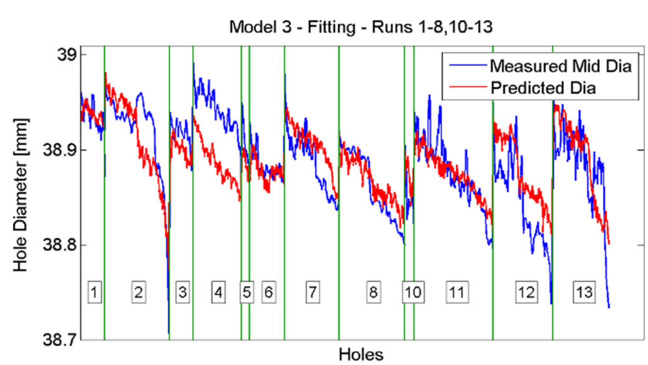

Fig. 11 Model 3: hole diameter model fit using extracted features

the inserts since the majority of the wear does occur on the outside insert and the tip of the outside insert tends to have the most wear. Chips which were observed on the inside insert around hole 100 are most likely the cause of the increase in diameter. Looking back at Fig. 12, the data for the maximum feed force and the mean spindle torque are shown and both show increases just before 100 holes matching the change in predicted diameter and the wear observed on the inside insert.

3.4 Tool replacement strategy

The final step in a TCM system is determining when the tool being used needs to be replaced, i.e., in this instance, when the drilling inserts need to be indexed or replaced. For this project the tool replacement strategy was based on the following process:

1. Drill the first hole and record the predicted diameter of the first hole (based on the machining parameters and the measured features).
2. Set limits for the hole diameter based on the first hole.

    a. Upper limit – the minimum of:

        i. 1st hole predicted diameter + upper offset or
        ii. Absolute upper limit (a maximum upper limit to reduce the risk of oversize holes)

    b. Lower Limit – the maximum of:

        i. 1st hole predicted diameter – lower offset or
        ii. Absolute lower limit (a minimum lower limit to reduce the risk of undersize holes)

3. Predict the diameter for the next hole, if the prediction is outside the limits, stop drilling.
4. Drill another hole, average the predicted diameters of the first 2 holes and automatically adjust the limits based on the rules in step 2.
5. Repeat steps 3 and 4 for the first 5 holes (continue adjusting the limits based on the average of the first 5 holes).

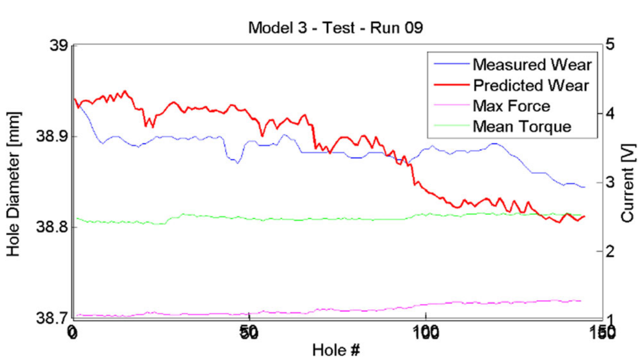

Fig. 12 Model 3: hole diameter model validation (using extracted features)

6. After the fifth hole, continue drilling. For each hole, if the predicted diameter of the next hole is out of the limits, stop drilling.

This process is completely automatic and the results of implementing it are illustrated in Fig. 13 with average limits to minimize the risk of out of tolerance holes and maintain a tolerance of 38.925 mm ± 0.1 mm. The following limits were set:

1. Minimum Diameter Tolerance – 38.825 mm
2. Upper Offset – 0.035 mm
3. Lower Offset – 0.045 mm
4. Absolute Upper Limit – 39.00 mm
5. Absolute Lower Limit – 38.85 mm

Figure 13 illustrates how the TCM system can detect the changing hole diameter and stop drilling prior to drilling out of tolerance holes. The model limits can be adjusted tighter or looser depending on the required hole tolerance and the consequences of out of tolerance holes. A limitation of the TCM system as described in this paper is that the current models are not capable of detecting sudden tool failure. The models in the TCM system as described are only designed to detect incremental tool wear and are only capable of determining the tool wear state after each hole is completely drilled. An instantaneous tool failure can result in an out of tolerance hole that these models cannot detect. A robust TCM system also requires another model to detect sudden changes that occur during catastrophic tool failure and stop the drill immediately. With the settings listed above, the system failed to indicate that tool replacement should occur on four experimental runs, runs 1, 3, 5, and 6. Runs 3 and 6 had no out of tolerance holes, but the insert chipped on the last hole drilled and drilling was stopped by the operator to prevent damage to the drill. Run 5 was drilled at parameters that caused significant vibration resulting in an extreme wear rate and

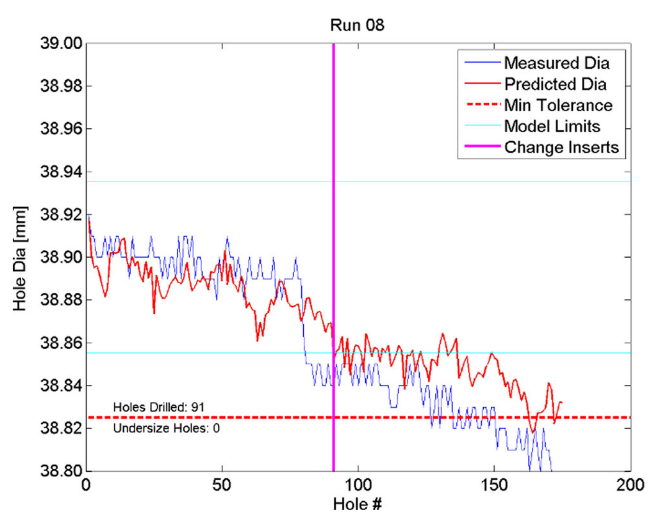

Fig. 13 Tool replacement strategy

drilling was stopped by the operator, again to prevent damage to the drill. A total of 4 holes out of 989 were slightly undersize and there were no oversize holes. Not including runs 5 and 10, which were run at very high machining parameters and were beyond the capabilities of the inserts for the given material, 87 holes were drilled per insert on average which is a significant improvement to the prior operating procedure to change the inserts every 60 holes. The TCM system was able to automatically indicate when inserts should be changed and prevented any significantly out of tolerance holes. The small number of holes which were slightly out of tolerance on the small side which is not a significant problem since a small hole can easily be made larger. Holes that are out of tolerance on the large side of the tolerance are a much bigger concern as there is often no method available to fix the hole, especially on tubesheets and baffle where welding not usually allowed.

Overall, this test shows that the TCM system with the drill used for this experiment would be capable of holding the holes to a ±0.1 mm diameter tolerance with approximately a 44 % increase in tool life and a significant reduction in the risk of out of tolerance holes.

4 Conclusions and discussion

The present study concerns the process of drilling over thousand tight-tolerance holes on a single tubesheet accomplished by means of a horizontal boring mill. To maintain the hole accuracy and protect the boring mill from damage during the process, it is vital to ensure the drill or tool is in good condition. Unfortunately, models of tool wear and hole accuracy for such a drill process are not available in the literature. In this paper, a TCM system involving three models was developed for the tool wear monitoring and hole accuracy prediction, thus determining the time when the tool needs to be replaced, and experiments of drilling holes with a diameter 39.0 mm on tubesheets of 2205 Duplex stainless steel were designed and performed for testing the effectiveness of the developed TCM system. The results obtained illustrated that the TCM system with the drill used for this study is capable of holding the holes to a ±0.1 mm diameter tolerance with approximately a 44 % increase in tool life and a significant reduction in the risk of out of tolerance holes. It should be noted that if this TCM system is implemented into a production environment, the hole recognition and state determination algorithms would be performed in real time allowing the features to also be extracted in real time. The extracted features are all that would need to be saved to allow optimization and updating of the model coefficients for changing tooling or materials.

The AR models for the maximum axial force and the mean torque for each hole were simple and useful models. The initial values for each feature were modeled with a very simple surface response model and then the AR models allowed forecasting the extracted features a number of holes into the future as well as providing some smoothing to the measured data. After each hole is drilled, the data can be used to update the model and allow a more accurate forecast based on the new information. If the extracted features are stored for each hole that is drilled, the TCM system could automatically recalculate the AR model coefficients at the completion of each run (insert life).

The 2nd model in the system to predict insert flank wear was accurate with a very simple 2nd order model based only on the feed rate and the axial feed force. The main discrepancies between the fitted model and the actual data are attributable to the challenges in measuring the flank wear. For this project, the flank wear measurements were taken at a limited number of points and only on the outside insert. By taking more data points on the outside insert as well as some on the inside insert, a more robust method of averaging the wear could likely be developed and an even better fit between the model and the data could be determined. However, due to the inherent randomness in the drilling process, the benefit of this is limited. Measuring the flank wear is a time-consuming and difficult process that requires a microscope and image analysis software which limits the ability to have it measured on a regular basis in a production environment making it difficult and impractical to update the model fit over time.

The 3rd model in the system, used to predict the hole diameter, was significantly less accurate and the model fit was lower than that for the 2nd model. However, the accuracy of the model was sufficient to provide a reliable indication of the hole diameter. An advantage of the 3rd model over the second model is that the hole diameters can be measured easily on the shop floor which allows the model coefficients to be updated as a machining job progresses.

The main reason for the relatively poor model fit for the hole prediction model is the fact that the location of the wear points on the drilling inserts has a significant effect on the non-axial forces in the drill resulting in an increased or decreased drilling diameter depending on the wear locations. However, the increased wear appears to have a similar effect on the feed force and the spindle torque regardless of where the wear occurs. This results in the model typically predicting a decrease in diameter with any increase in forces instead of accurately predicting the actual machined diameter.

A reasonably accurate tool replacement strategy can be implemented as long as changes in the wear state result in measureable changes in the motor currents. A tool replacement strategy was tested using the experimental data and the testing showed that using these drills, a tolerance zone of ±0.1 mm can be held reliably with a significant 44 % increase in tool life and a non-trivial reduction in machine down time due to fewer tool changes. A tolerance zone of ±0.1 mm is acceptable considering that the variation in hole diameters with new inserts at the same machining parameters is ±0.075 mm as shown previously in Fig. 7.

As anticipated, the main limitation to the TCM system as tested is that it is not capable of detecting catastrophic failure of inserts that are not worn out. The TCM system as described in this project would detect the damaged insert on the next hole, but it would not detect it quickly enough to prevent the drill body from being damaged beyond use or repair since the models only update after every hole.

Acknowledgments The financial support to the present study from the Natural Sciences and Engineering Research Council (NSERC) of Canada and Mitsubishi Hitachi Power Systems Canada, LTD is acknowledged.

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