Tool Condition Monitoring and Replacement for Tubesheet Drilling

A Thesis Submitted to the College of

Graduate Studies and Research

in Partial Fulfillment of the Requirements

for the Degree of Master of Science

in the Department of Mechanical Engineering

University of Saskatchewan

Saskatoon

By

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Abstract

Tool Condition Monitoring (TCM) methods have shown significant potential to automatically detect worn tools without intervention in the machining process, thus decreasing machine downtime and improving reliability and part quality. Previous research on TCM systems have used a wide variety of time-domain and frequency-domain features extracted from cutting force related parameters as well as mechanical and acoustical vibrations to infer the wear state of tools. This project concerns the process of drilling thousands of tight-tolerance holes on tubesheets and baffles of heat exchangers using large diameter indexable insert drills on a horizontal boring machine. To address the issues involved in the process, the aim of this research is to develop a non-intrusive, indirect, online TCM system on the horizontal boring machine to monitor the drill wear and hole quality while drilling. The specific objectives are to establish an indirect TCM system for the drilling process, to develop models to predict tool wear and the machining accuracy of the drilled holes, and to develop an optimum tool replacement strategy.

The TCM system developed used two cutting-force related signals on the horizontal boring machine, namely the spindle motor current and the axial feed motor current. Features extracted from these data streams, as well as the machining parameters, the cutting speed and the feed rate, and the number of holes drilled with the current inserts, are the inputs to a series of models to predict the tool wear state and the hole diameter. The first model is an autoregressive model that allows the prediction of the extracted features for the next hole before it is drilled. As each hole is drilled, this model is updated with the most recent data to improve the accuracy of the prediction. The predicted values for the features are then used as inputs to the second and third models which are surface response models, one to estimate the tool wear state and one to estimate 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. Tuning the replacement strategy for tool life resulted in a significant 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 ±0.1mm. The

TCM system ensured that not a single over tolerance hole would have been drilled which is critically important since over tolerance holes can result in a scrapped workpiece.

The proposed 3-model TCM system shows promise in being able to significantly reduce the risk of drilling out of tolerance holes while at the same time increasing tool life and correspondingly decreasing tool change time. The models are able to accurately predict the insert flank wear and as well as the actual hole diameter within acceptable error. The TCM system could be implemented in an industrial settingwith minimal revision and since it is an indirect system there would be no intrusion into the manufacturing operation.

One limitation of the TCM system as proposed is that it is only capable of detecting gradual tool wear and not catastrophic tool failure, a limitation that was known from the outset but was not investigated as it was beyond the scope of this project. The proposed TCM system would allow the integration of additional functionality to instantaneously detect catastrophic tool failure.

Finally, for use in a production environment, the developed models need to be implemented on a standalone device that requires essentially no operator input to monitor continuous drilling operations for tubesheet and baffle applications. This implementation could include automatic detection of the machining parameters using frequency analysis of the motor signals.

Acknowledgments

I would like to express my appreciation to all those that have contributed to this research work.

First of all, I would like to give my sincere gratitude to my supervisor Professor Daniel Chen for his support and guidance throughout this project. His encouragement and support for my Natural Science and Engineering Research Council (NSERC) scholarship application are appreciated. Also, his dedicated efforts on pursuing a NSERC Engage Grant and a NSERC Collaborative Research and Development (CRD) Grant for this research enabled this research to occur.

I would also like to acknowledge Hitachi Powers Systems Canada, Mr. Rob McEachern, and Mr. Tom Kischuk for providing me with a leave of absence to complete this research as well as the direct support in funding the project and making the Toshiba HBM available to complete the experimental research portion of this project was invaluable.

Without the support of many others from the College of Mechanical Engineering and Electrical Engineering including my advisory committee members Professors Richard Burton and Francis Bui, and the technical support from Mr. Doug Bitner, Ian MacPhedran, Ms. Kelley Neale I would not have been able to complete this research.

Finally, I would like to acknowledge the University of Saskatchewan for the Dean's Scholarship, NSERC for the Alexander Graham Bell Scholarship, and the additional assistance from Professor Daniel Chen and the Department of Mechanical Engineering as well as the College of Graduate Studies and Research each for the financial support provided.

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List of Abbreviations and Symbols

a	Number of holes drilled
AE	Acoustic Emission
ANOVA	Analysis of Variance
AR	AutoRegressive
ARX	AutoRegressive with Exogenous Inputs
CNC	Computer Numeric Control
E_D	Mean Diameter
f	Feed Rate [mm/rev]
FFT	Fast Fourier Transform
$Fmax$	Maximum mean force for the steady state drilling portion of a hole
HBM	Horizontal Boring Mill
RMS	Root Mean Square
S	Cutting Speed [m/min]
TCM	Tool Condition Monitoring
$Tmean$	Mean spindle torque for the steady state drilling portion of a hole [V]
V_b	Tool Wear [μm]

1. Introduction

1.1. Need for Tool Condition Monitoring

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 online 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. An example of a stainless steel tubesheet being drilled is shown in Figure 1. In this repetitive process even small increases in the life of drills, or using drills until slightly closer to the end of their life, can substantially reduce the 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. On a machining center 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. With the high labour rates in Western Canada this is another extremely important benefit.

Figure 1: Tubesheet Being Drilled

1.2. Tool Condition Monitoring

There has been a lot of research into tool condition monitoring (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 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 (Figure 2). 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], [3], [4]. Cutting forces are proportional to motor currents which allows simple and economical implementation of TCM systems based on these signals [5], [6], [7], [8]. A problem with utilizing cutting forces for TCM is that they are effected by cutting conditions, heterogeneous workpiece material properties, and environmental noise in addition to tool wear [5], [6], [9], [10]. Mechanical vibrations, up to 20 kHz, are also related to tool wear and have been used to infer the tool wear state [11], [12].

Vibrations are also susceptible to being effected 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 [13], [14], [15], [16]. AE is much less susceptible to workpiece materials, cutting conditions, and environmental factors but is sensitive to signal attenuation and part geometry [3], [16], [17]. 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 [18].

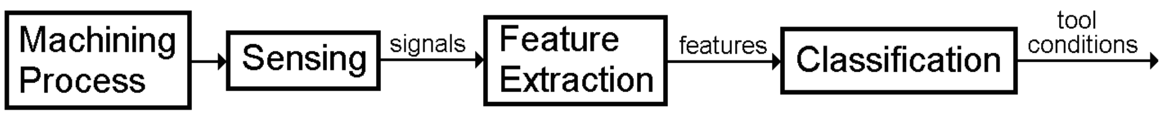


Figure 2: Block Diagram of an Indirect TCM System.

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 [13], [18], standard deviation [18], peak values [19], kurtosis [12], and parameters for time series models of the measured signals [4], [20]. Fast Fourier transforms (FFT) can be used to analyze signals in the frequency domain by determining the distribution of components with different frequencies [3], [11]. The major drawback of the frequency based methods is the FFT calculation tends to attenuate the frequency content of transient phenomena and thus are not very suitable for non-stationary signals such as those found in TCM systems [3]. 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 [14], [20], [21], [22]. 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 [22], neural networks [14], [21], [23], and other pattern recognition approaches [24], [25].

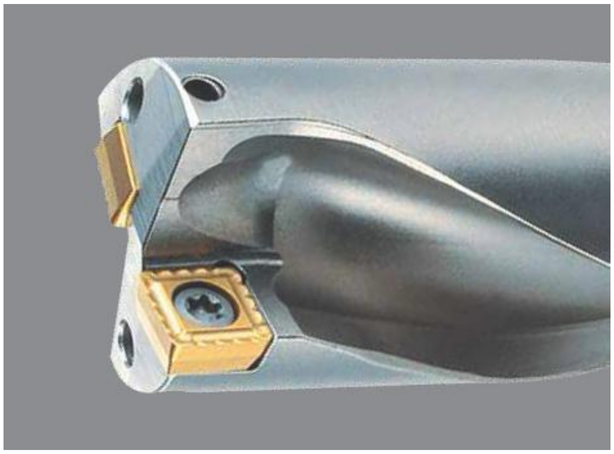


Figure 3: Indexable Insert Drill

All of the referenced research above related to drilling has involved twist drills, most of which were high speed steel and smaller than 20mm in diameter. There has been no research done on TCM systems using 25mm diameter or greater drills. Modern, large diameter drills typically have a steel body with replaceable coated carbide inserts like the drill shown in Figure 3. 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.

1.3. 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 [26]. 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 [15], [27]. 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 [28] and typically have complicated forms and require intensive calculations [27] 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 [29] or the Taguchi method [30], 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 [30]. The response surface model combined with ANOVA and residual analysis are effective for identifying dominating factors and these methods will be employed in the development of models relating hole size and flank wear to the measured current signals for this project.

Much of the research on TCM systems involves models relating the flank wear to measured signals to inform tool replacement [5], [6], [7], [9], [10], [14], [18], [23] but there has only been limited research completed on relating actual hole quality (machining accuracy) to the measured signals [15], [27].

1.4. Research Objectives

The aim of this research is to develop a non-intrusive, indirect, online TCM system for large diameter indexable insert drills so as to monitor the hole quality while drilling. This research focuses solely on drilling 39 mm diameter holes in 31.8 mm thick 2205 Duplex Stainless Steel, which was chosen based on the fact that the industrial sponsor for this project (i.e., Hitachi Power Systems Canada Ltd.) has had a significant amount of experience with this specific application. This experience provided a solid knowledge base of expected drill performance and potential issues the TCM system needs to handle. This main objective can be broken down into the following specific objectives:

1. Establish a non-intrusive On-line TCM system for the drilling process.

An on-line TCM system requires a data acquisition system and the necessary algorithms to interpret the data. The data acquisition system needs to measure and record the spindle motor current and the z-axis feed motor current at a sufficient data capture rate to ensure that all relevant details in the signal are captured. The spindle motor current and the z-axis feed motor current are proportional to the spindle torque and axial feed force [6] and a TCM system utilizing them can be implemented on a milling machine without any interference with the machining operation and without any changes to the machining setup or process. Algorithms will be developed to parse the data streams and provide useful features for the predictive models.

2. Develop models to predict tool (insert) wear and the machining accuracy of the holes.

To determine the coefficients of the models for predicting tool wear and machining accuracy for a variety of machining parameters, drilling tests are required. The experiment design needs to maximize the information obtained regarding the drilling process, while remaining within the constraints of cost, machine time, and material availability. The data collected in the experiments will be analyzed and used to develop a series of models and to determine the associated coefficients to allow the prediction of tool wear and the estimation of the machining accuracy, which is the hole diameter for this project.

3. Develop a strategy for optimum tool replacement to maximize tool life while ensuring acceptable hole quality.

The final objective is to develop a strategy for automatically deciding when a tool needs to be replaced using the models determined above. This goal of this tool replacement strategy is to maximize tool life and productivity while minimizing the risk of out of tolerance holes. The strategy should be flexible enough to allow it to be tuned for particular situations where tool life may be the most important or where machining accuracy is critical and tool life can be sacrificed.

1.5. Organization of the Thesis

This thesis consists of 7 chapters. In addition to this one, the remaining 6 chapters are organized as follows:

Chapter 2. Development of Models for Tool Condition Monitoring (TCM)

This chapter presents the development of models for a TCM system specifically targeted towards drilling tubesheet and baffles holes in plate. The TCM system consists of three linked models that ultimately predict the machining accuracy and a tool replacement strategy to inform tool replacement based on the predicted output of the models.

Chapter 3. Experimental Methodology

This chapter details the design of an experiment to provide the information needed to determine the coefficients of the developed models. It also describes the equipment and measuring tools used to measure the insert flank wear and the hole diameters, as well as the data acquisition system that was implemented on a large horizontal boring machine to capture the axial feed motor and spindle motor currents.

Chapter 4. Experimental Results and Data Analysis

This chapter describes the raw data obtained from the experiments including the flank wear measurements, the hole diameter measurements and the recorded currents. The details of the motor current data signals are related to the actual drilling cycle and then the algorithms used for delineating individual holes in the continuous data signals and dividing the holes up into sections based on the drilling cycle are described.

Chapter 5. Model Identification and Verification

The details of the determination of the model coefficients are provided. The models are built and are used to develop a tool replacement strategy. This strategy is then tested on the experimental data to verify its ability to predict the machining accuracy and prompt tool changes in a manner that increases productivity and prevents drilling of out of tolerance holes.

Chapter 6. Discussion of Results

The details of the results for the tool replacement strategy tests in Chapter 5 are discussed and the potential benefits and limitations of the proposed TCM system are reviewed.

Chapter 7. Conclusions and Future Work

This final chapter presents the conclusions drawn from this research and also provides some suggestions for future research that would strengthen and improve the capabilities of the TCM system developed in the present study.

2. Development of Models for Tool Conditioning Monitoring (TCM)

The main objective for this research is to develop an online TCM system to monitor the hole quality while drilling. This requires a model or a series of models to relate the machining parameters and the measured data to the hole accuracy. There are a lot of factors that affect the instantaneous value of the measured signals so the system needs to extract the useful information from the data while discarding extraneous data that is not related to the hole accuracy.

In this project, hole accuracy is represented by the mean diameter (E_D) which is evaluated using a three point hole micrometer which is the standard method for performing quality assurance checks on tubesheet and baffle holes in industry. 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 research. Hitachi's experience indicated that the 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 [3], [6], [7], [22], [31] 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 (the drill has two inserts, one which cuts the center portion of the hole and one that cuts the outer portion of the hole, the outside insert is the black insert shown in Figure 7) was considered, again based on Hitachi's experience that 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 4 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:

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

where F is the feature 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 and for this project in particular 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 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:

$$\hat{F}_j(n) = -\sum_{k=1}^{N} c_k F_j(n-k) + e(n) \qquad (2)$$

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 $\hat{F}_j$ one hole into the future thus permitting the forecasting of the hole diameter in advance and allowing inserts to be changed prior to drilling a hole 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 (ie. 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.

$$F_j = f(x_1, x_2, \cdots x_k) + \varepsilon \quad (3)$$

The second and third models, $\mathbf{M_2}$ and $\mathbf{M_3}$ shown in Figure 4 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 equation (3). The original proposal for the third model was to predict the hole diameters using the machining parameters and the predicted flank wear as inputs to a polynomial surface response model similar to model 2; however, as will be discussed in the results section below, these 3 inputs, feed rate, spindle speed and predicted flank wear do not provide sufficient information to accurately predict the hole diameter. If, instead of relying primarily on the predicted flank wear as the main input of information, all the predicted features, $\hat{F}_j$, are utilized, a significantly improved prediction of the flank wear can be made.

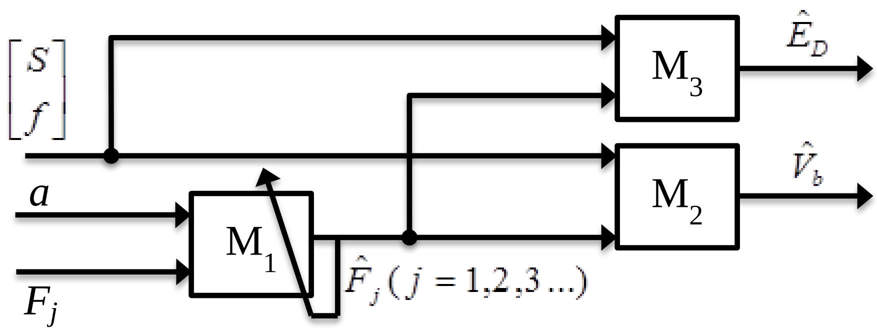


Figure 4: Block Diagram of the Proposed Dynamic Model

3. Experimental Methodology

The main objective of this project is to develop a TCM system specifically for 39 mm diameter indexable insert drills and 2205 Duplex Stainless Steel material. As discussed above, this specific combination of drill and material was chosen because of Hitachi's familiarity and experience with it which provided a solid knowledge base of what to expect for tool life and what machining parameters would perform reasonably.

3.1. Experimental Design

A 31.8 mm thick plate of 2205 Duplex Stainless Steel plate was available for testing that was large enough for approximately 1650 holes. This placed an upper constraint on the number of holes that could be drilled in the experiment. In a production environment with this drill, insert, and material combination, 60 holes would be drilled with each insert edge before both the inside and the outside inserts would be indexed (rotated) to a fresh cutting edge. Experience had shown that this was a safe limit to prevent out of tolerance holes as a result of worn inserts; however, it was also expected that the inserts would potentially last up to two times that long with minimal reduction in hole quality. Assuming an insert life of 120 holes per insert edge limited the number of possible experimental runs to a maximum of thirteen.

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, coolant temperature, the machining center rigidity, and part/setup rigidity. All of these factors except the two machining parameters were held constant throughout the entire experiment.

With two varying factors, a simple and efficient experiment design is a two factor, two level full factorial design with 4 different test conditions. This would allow 3 replicates at each test condition; however, this design only provides enough information for 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 will be obtained for quadratic, 2nd order models. This design is illustrated in Figure 5 and is called a central composite design [29] which is a very 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 multiple 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.

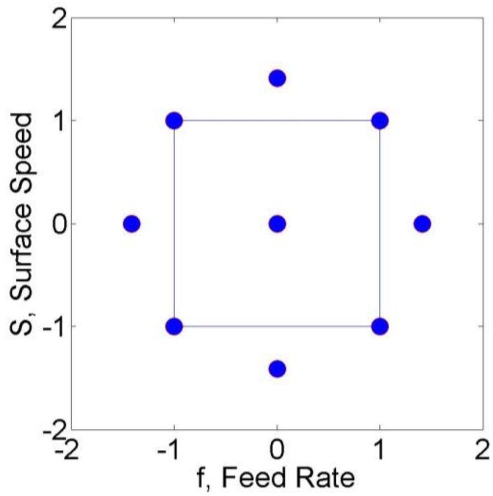


Figure 5 Central Composite Experiment Design with Coded Variables

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. Experience has shown that limiting the feed rate upon entering and exiting the workpiece helps to prevent catastrophic drill failure at these critical times so the drilling program for each hole was:

1. Set the spindle speed per the test conditions for the current run.
2. Drill to a depth of 2 mm with a feed rate of 65 mm/min.
3. Drill to a depth of 28.8 mm (3.0mm from the back of the plate) at the feed rate specified for the current run.
4. Drill the final 3 mm at a feed rate of 55 mm/min.

As mentioned above, all the remaining factors were held as constant as possible. 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 and on the same workpiece in the same setup as shown in Figure 6.

Table 1: Experiment Test 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

Figure 6: Experimental Setup with Toshiba BF-130A HBM

The drill is a 39.0mm diameter Sandvik Corodrill 880 drills capable of drilling to a depth of two times the diameter as shown in Figure 7 (Sandvik part number 880-D3900L40-02). This drill requires two indexable carbide inserts and the insert grades were chosen based on Hitachi's experience. 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). 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°.

(a) (b) (c)

Figure 7: (a) Sandvik Corodrill 880 Drill, (b) Inside Insert, and (c) Outside Insert

The aim of the experiment was to drill as many holes with a single cutting edge as possible at each combination of cutting parameters. The decision to stop a run was based on two criteria as shown in the decision flowchart in Figure 8. If the insert chipped in a way that would pose a significant risk to damaging the drill body the run was stopped and the inserts were indexed. Caution was required in this regard to prevent damage to the drill body as it was desirable to use the same drill body for the entire experiment to eliminate that potential source of variation. If an insert chipped prior to having sufficient wear to result in diameter starting to change significantly the run was repeated. Both inserts were always indexed prior to starting a new run.

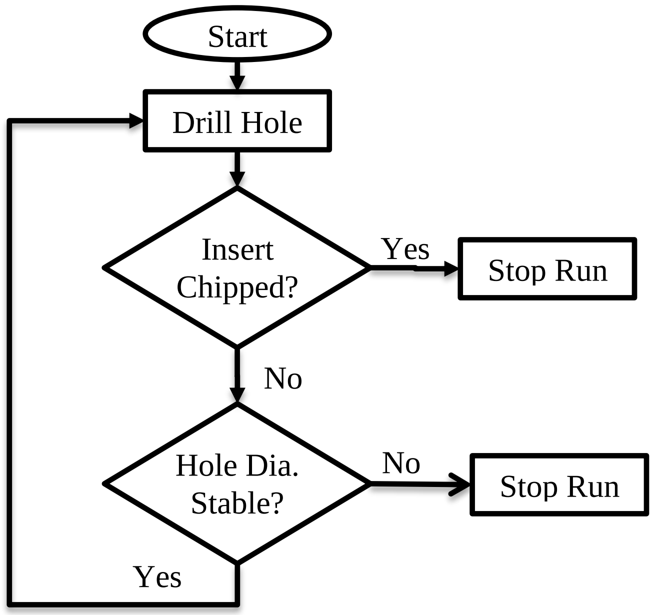


Figure 8: Insert Failure Decision Flowchart

3.2. Wear Measurements

The tool wear state, which was based on the flank wear of the outside insert, was measured at regular intervals throughout each drilling test run. A Nikon MA100 inverted metallurgical microscope was used for all the wear measurements. It is equipped with a digital camera and software from PAX IT was used to merge a series of photos obtained by traversing the width of the insert at a magnification of 5x and then to measure the flank wear. A jig was machined to hold the entire drill in the correct position for inspection on the microscope such that the inserts did not have to be removed for each measurement thus removing a source of potential variability. The setup is shown in Figure 9.

Figure 10 shows a drill with new inserts installed along with a 5x 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 can be seen in Figure 11. 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.

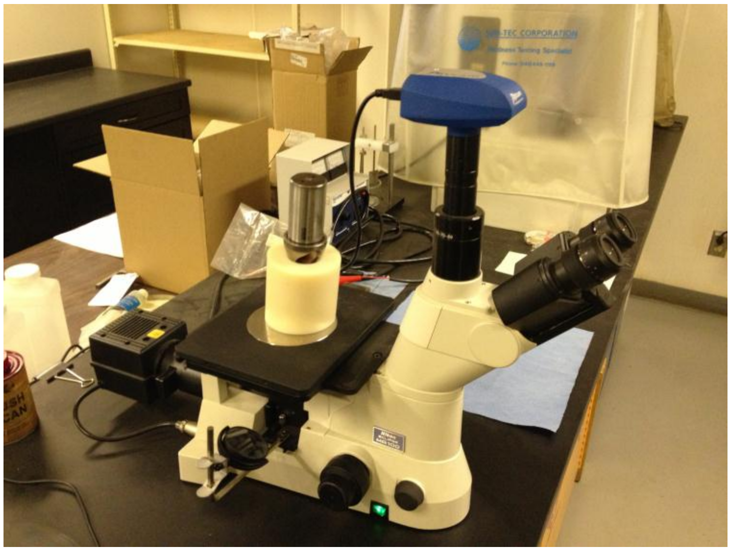
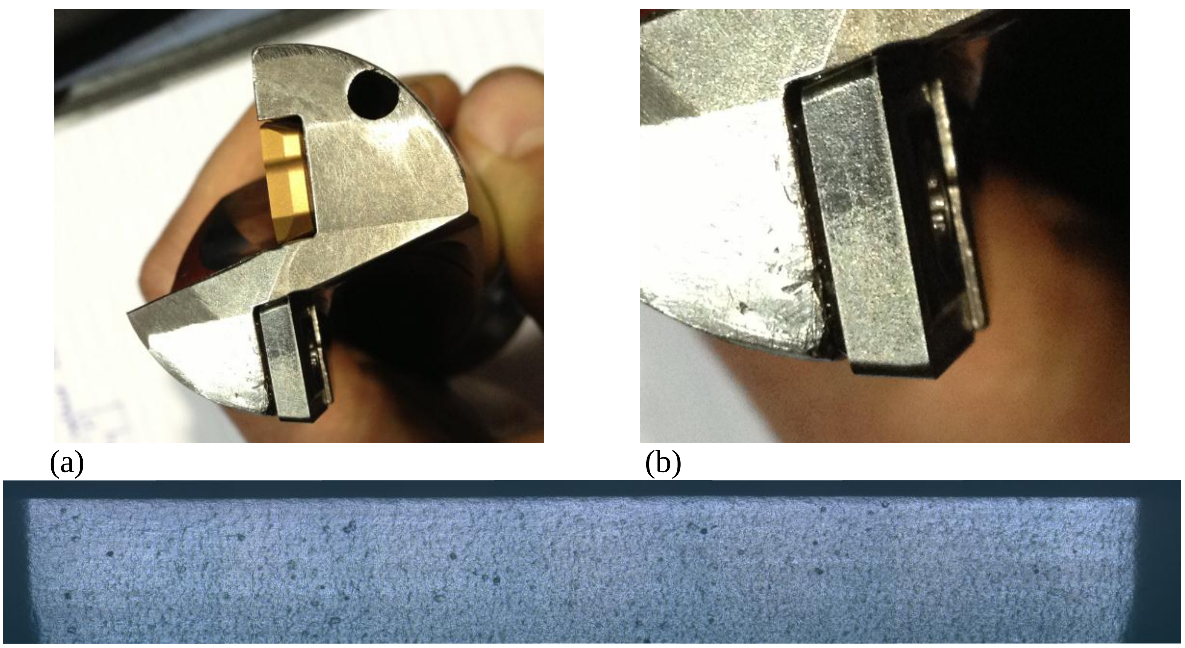


Figure 9: Nikon MA100 Microscope with Drill in Measurement Jig



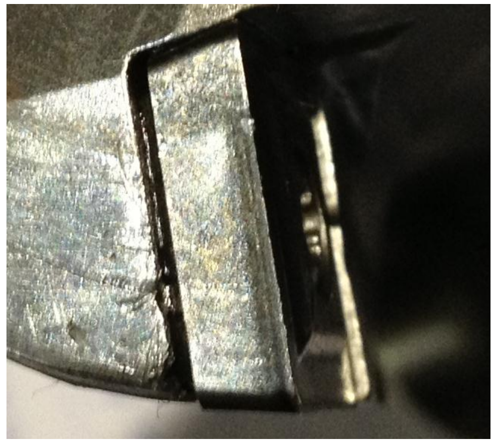
(a) (b)

(c)

Figure 10: Drill with new inserts. (a) Full Drill (b) Outside Insert Closeup (c) Flank of Outside Insert (5x Magnification)

The large wear pattern visible near the right side of the insert shown in Figure 11 c) is an example of the random wear patterns that can develop and which also can affect the resulting hole diameter depending on the where the wear occurs. The series of photographs in Figure 12 shows the increasing width of the wear pattern every 20 holes for experiment run 9.


(a)


(b)

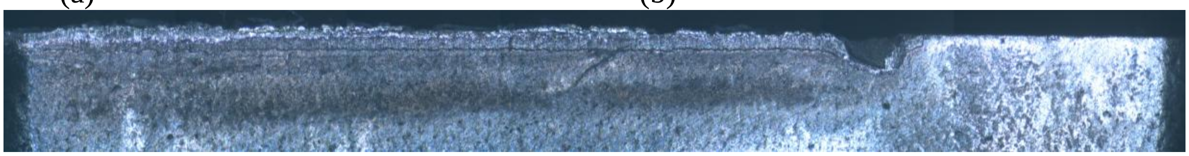
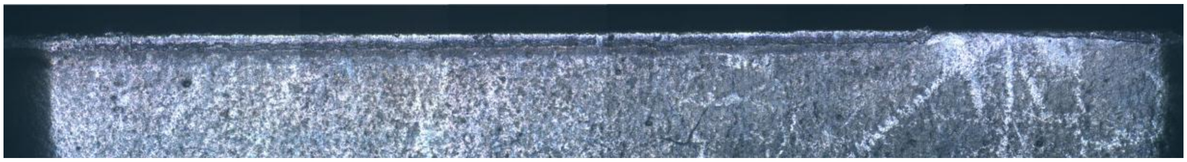

(c)

Figure 11: Drill with Worn Inserts (Run 7 after 135 holes) (a) Whole Drill (b) Outside Insert Closeup (c) Flank of Outside Insert (5x Magnification)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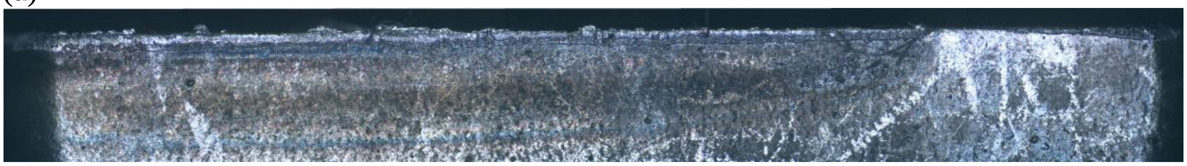
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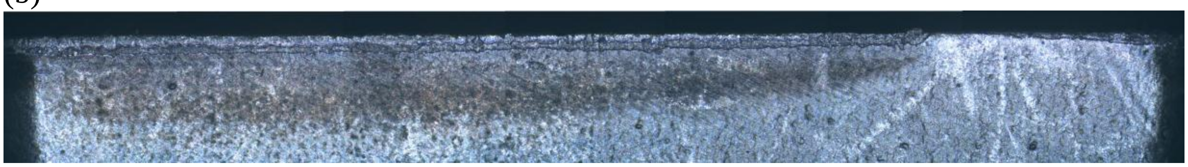
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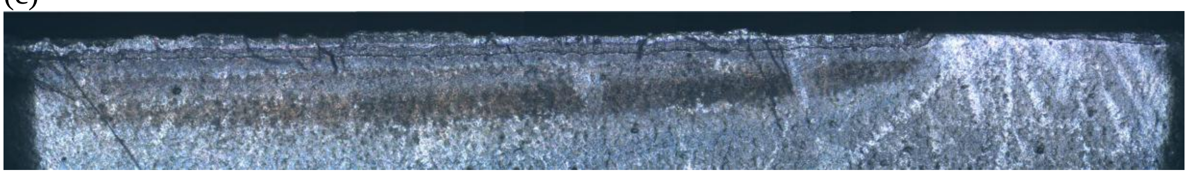
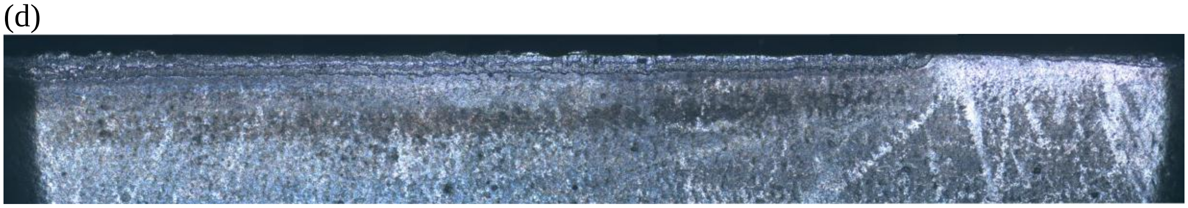
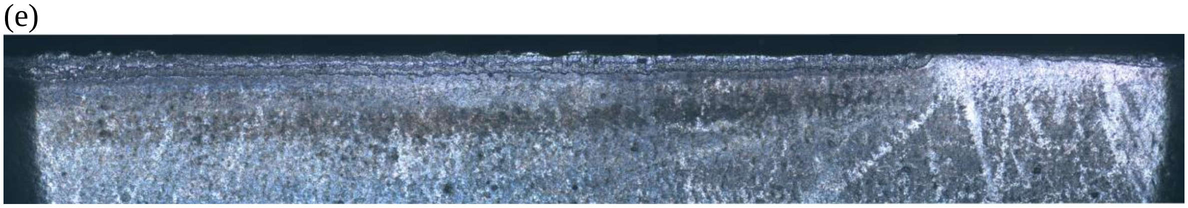
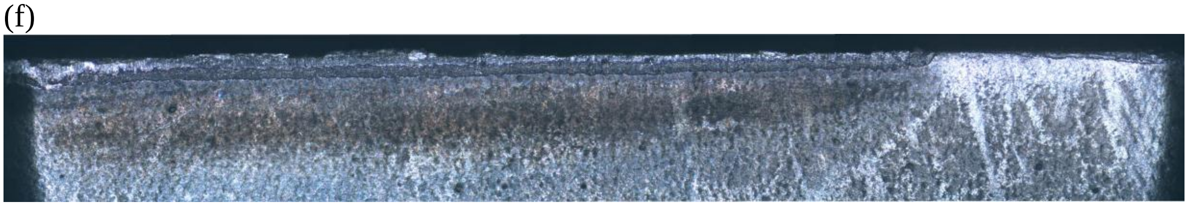
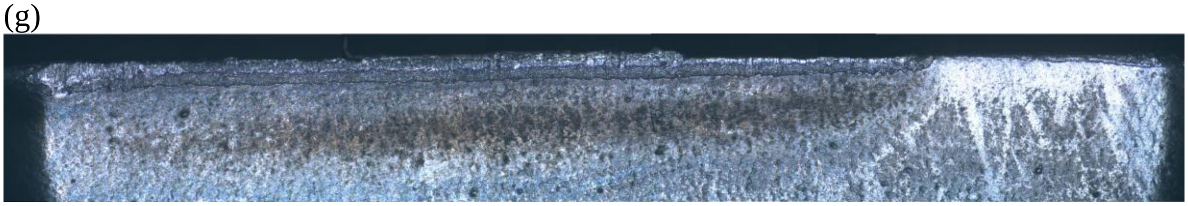

(d)

(e)

(f)

(g)

(h)

Figure 12: Flank Wear for Run 9 every 20 holes (a) 20 holes … (h) 140 holes

3.3. Hole Accuracy Measurement

In manufacturing tubesheets and baffle plates for heat exchangers with a computer numeric control (CNC) milling machine it can be assumed that the holes will be in the correct location with sufficient accuracy; however, the hole diameter is very dependent on the wear of the drill or drilling insert. For this project the machining accuracy is defined as the diameter of the holes. The diameter of each hole drilled was measured with a Mitutoyo Series 568 Digimatic Borematic 3 point micrometer as shown in Figure 13. This micrometer provides a quick and accurate indication of the average diameter of the hole. The diameter was checked in three locations (depth wise) for each hole to indicate if the diameter was changing throughout the hole.

Figure 13: Mitutoyo Series 568 Digimatic Borematic 3 Point Micrometer

3.4. Data Acquisition

The two signals required for the TCM system are the current for the spindle motor and the current for the axial feed motor. The HBM used for the testing has a built in spindle load meter with a 0-10V output proportional to the spindle motor current. It didn't have a similar meter for the axial feed force so an Ohio Semitronics CT8-017D RMS current sensor with a proportional output of 0-10V 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 National Instruments USB 6351 DAQ and a custom interface written using Matlab's Data Acquistion Toolbox. A schematic for the data acquisition system is shown in Figure 14.

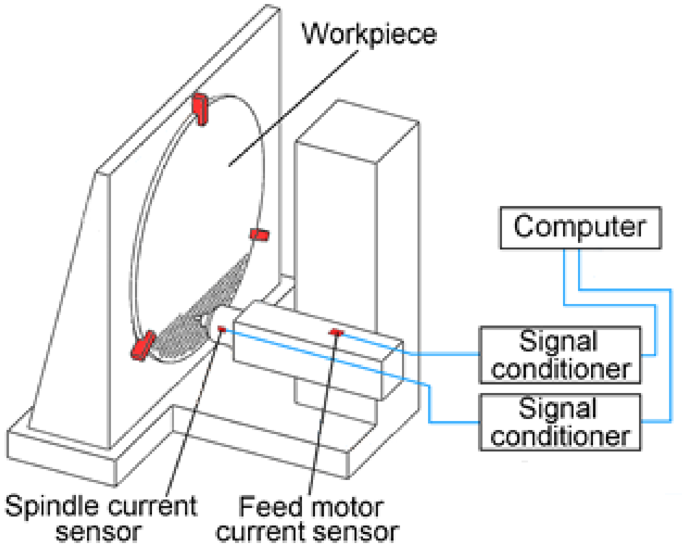


Figure 14: Data Acquisition Schematic

Initial testing of the data acquisition system revealed a significant amount of noise that completely masked the desired signals. Applying a moving average to the signals resulted in a clear signal as shown in Figure 15. To ensure the moving average wasn't masking details in the data that might be useful, both signals were recorded at a sampling rate of 100 kHz for the entire duration of the experiment and then a 1000 point moving average was applied afterwards. Therefore, each data point was averaged over a total of 1/100th of a second. Finally, all the data was subsampled down to 2 kHz for further data analysis. Since the spindle torque and the axial feed force are proportional to the motor currents, in this report the motor currents (measured in V) will be referred to as the spindle torque and the axial force even though actual torques and forces were not calculated.

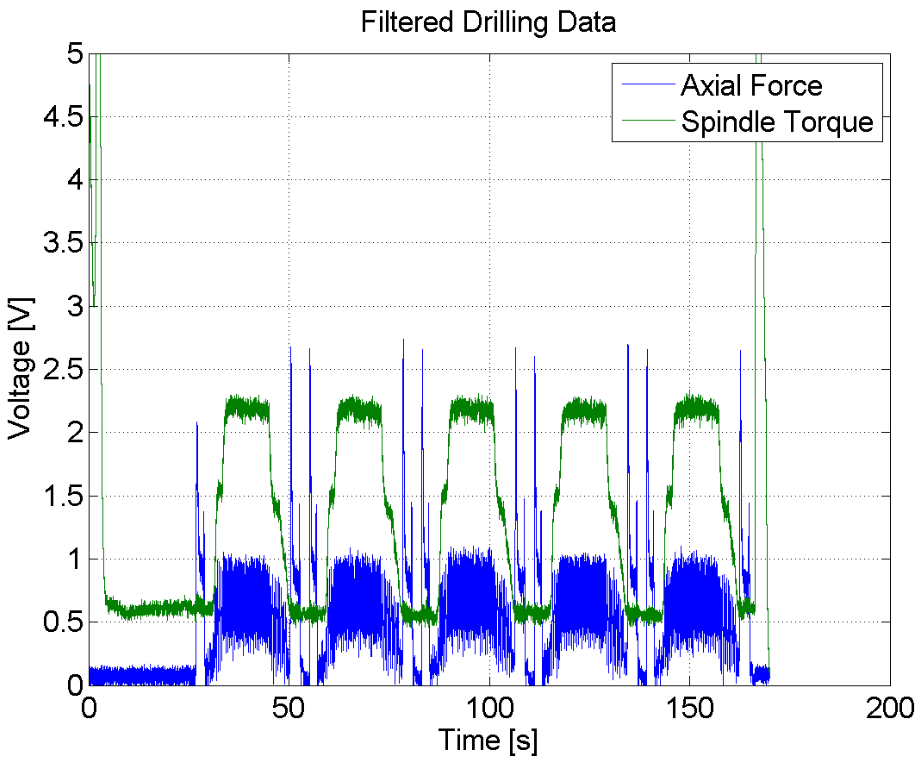


Figure 15: Filtered Spindle Motor and Axial Feed Motor Signals

4. Experimental Results and Data Analysis

4.1. Raw Experimental Results

The results for the wear and hole diameter measurements for the experiment are shown in the following figures. Figure 16 shows a set of typical flank wear measurements for a run, Run 02 in this case. A number of different measurements were taken to see which would have the most correlation to the features extracted from the motor current data during the modeling phase of the project. As shown, the wear increases rapidly within the first few holes and then levels off to a fairly consistent wear rate until near the end of the life of the insert where the wear rate increases sharply. The maximum flank wear for all the runs can be seen in Figure 17.

The hole size measurements for Run 02 are shown in Figure 18. The minimum measurement for each hole is shown in Figure 19. The minimum measurements were used for all models. The minimum diameter for the runs at the center point (0.13 mm/rev feed and 130 m/min surface speed) are shown in Figure 20. Since these runs are all at the same machining parameters this graph provides a good indication of the variability that can be expected with the Sandvik drill used. This diameter variation of about ±0.075 mm with the same drill and the same parameters indicates the accuracy that can be expected for a TCM system using large size indexable insert drills.

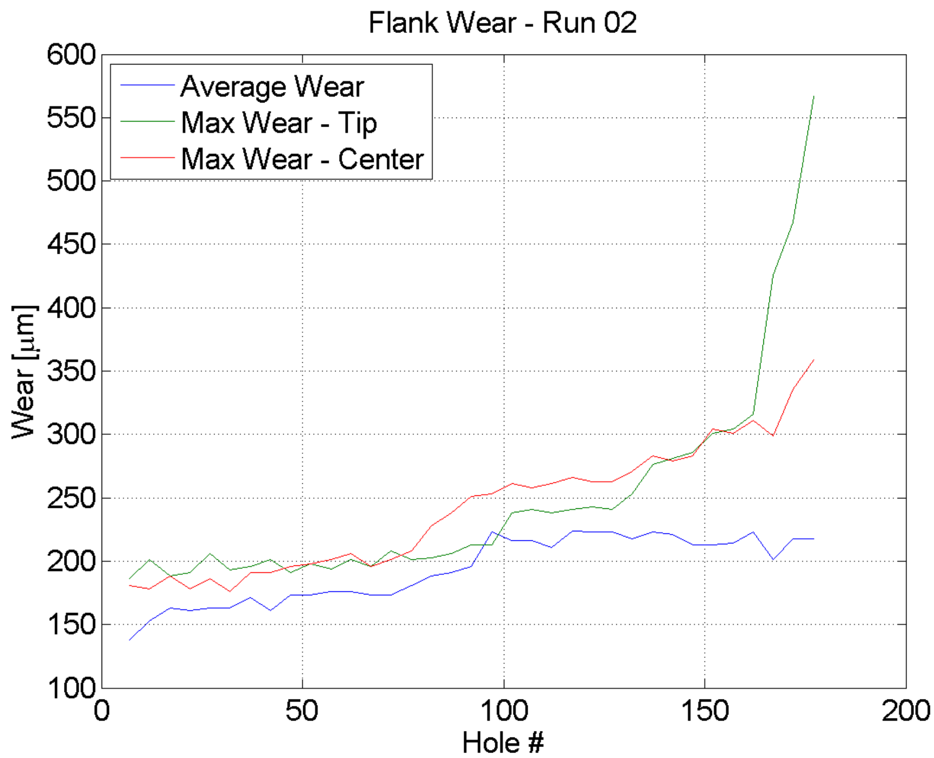


Figure 16: Flank Wear Measurements for Run 02

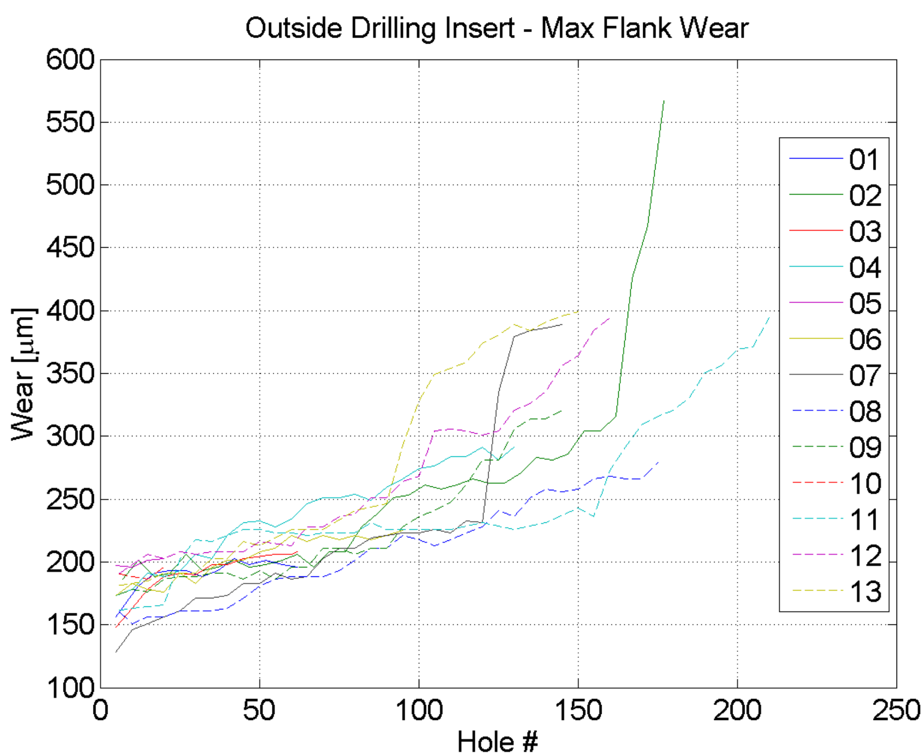


Figure 17: Maximum Flank Wear for All Runs

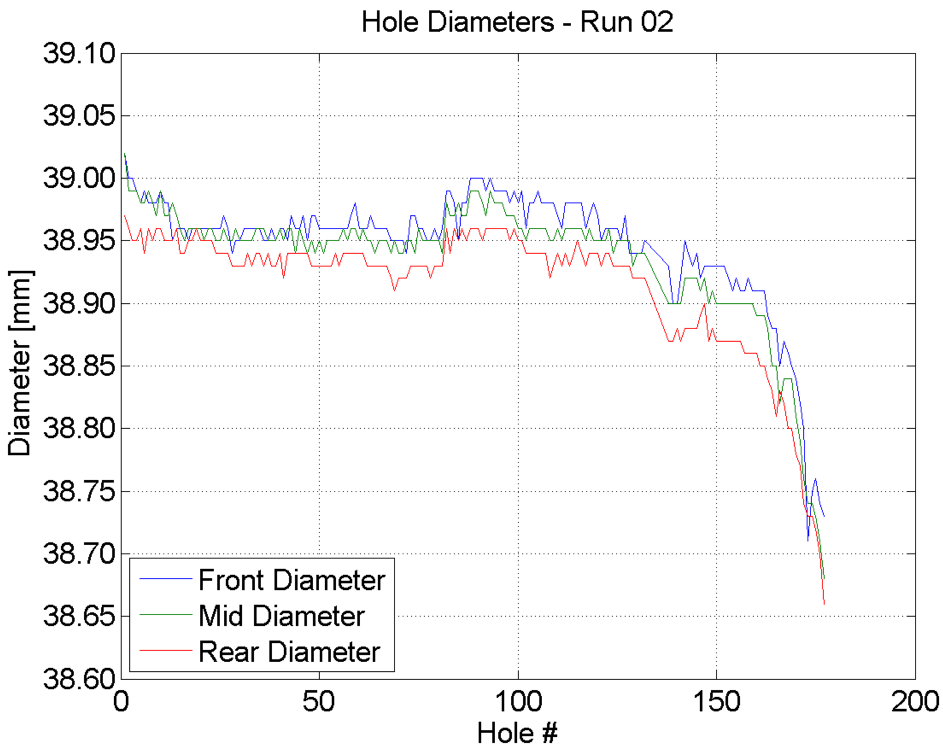


Figure 18: Hole Diameters for Run 02

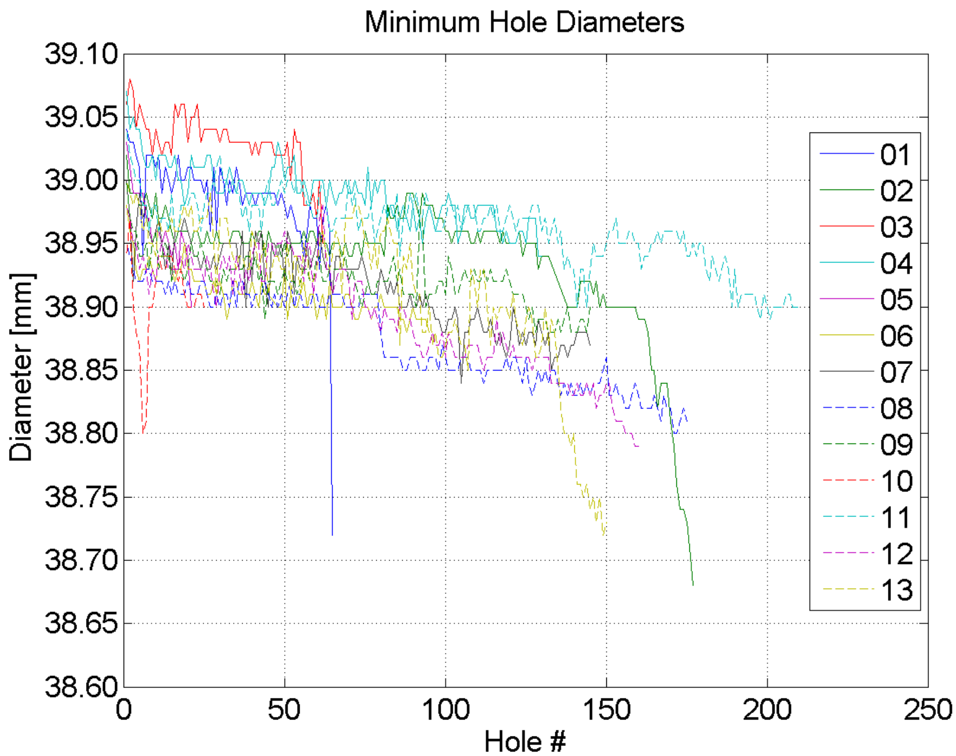


Figure 19: Minimum Hole Diameter for All Runs

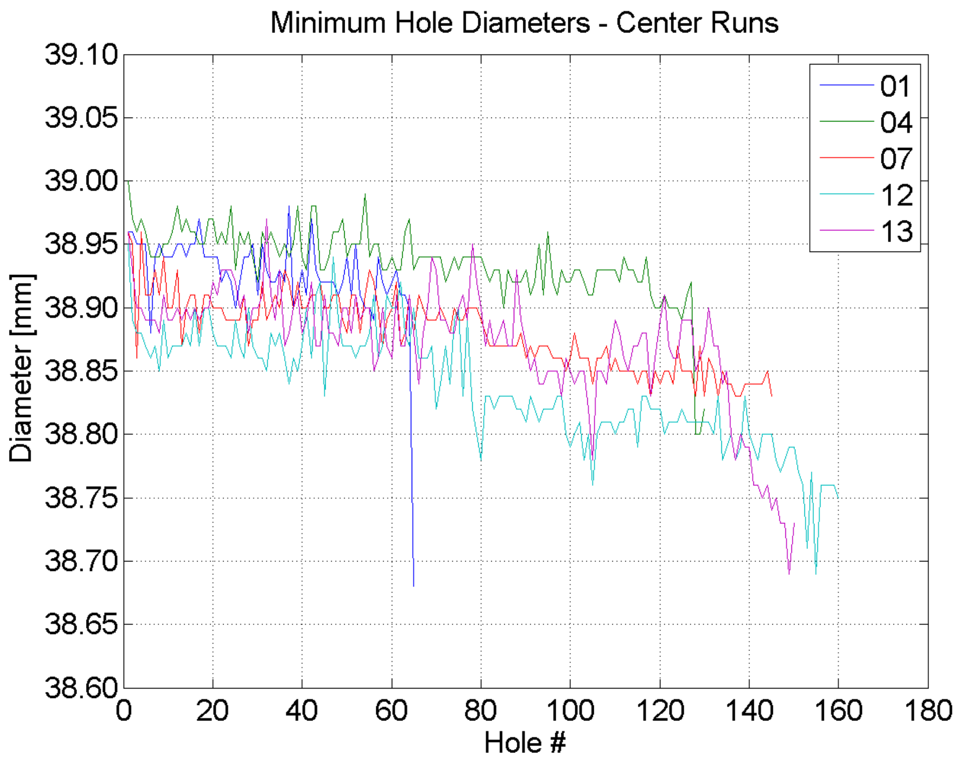


Figure 20: Minimum Hole Diameters for All the Center Runs (Same Parameters)

4.2. Hole Recognition and Feature Extraction Strategy

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 it is necessary to know what the current state of the hole drilling cycle is. The filtered data from Run 05 is shown in Figure 21. Since the Toshiba HBM used for this testing does not have any way to output the current state based on the CNC program, this information needs to be determined directly from the data. The first step required in order to be able to extract useable features from current data is to identify individual holes and the second step is identifying the steady state drilling portion of each hole. The steady state drilling portion of each hole is the time that the drill is feeding at the feed rate specified for the individual experimental run. An individual hole drilling cycle and the steady stead drilling portion are clearly identified in Figure 22.

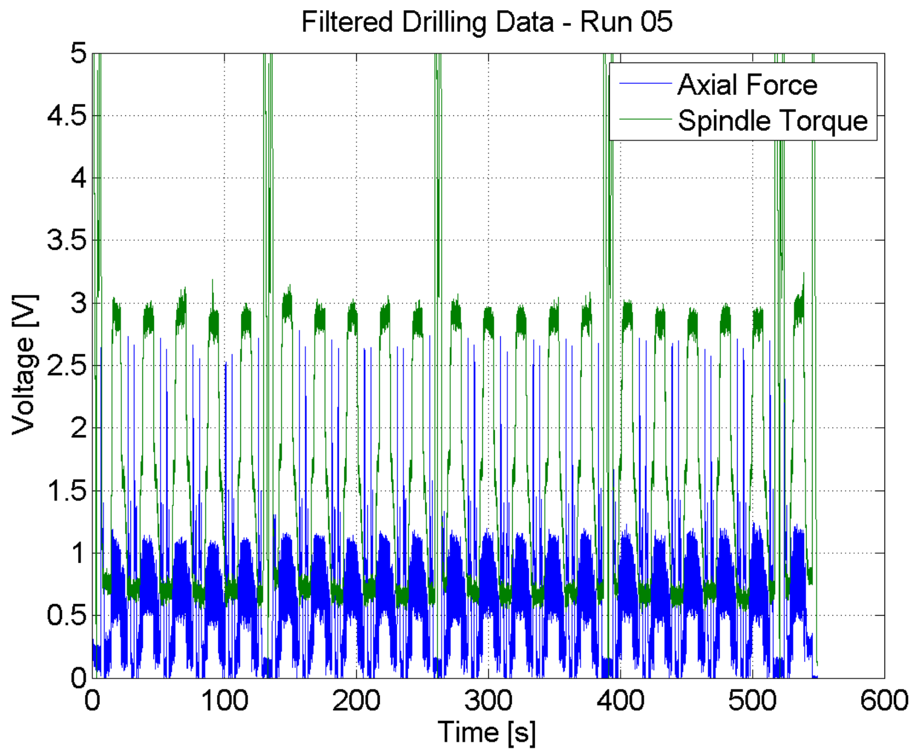


Figure 21: Filtered Data from Run 05

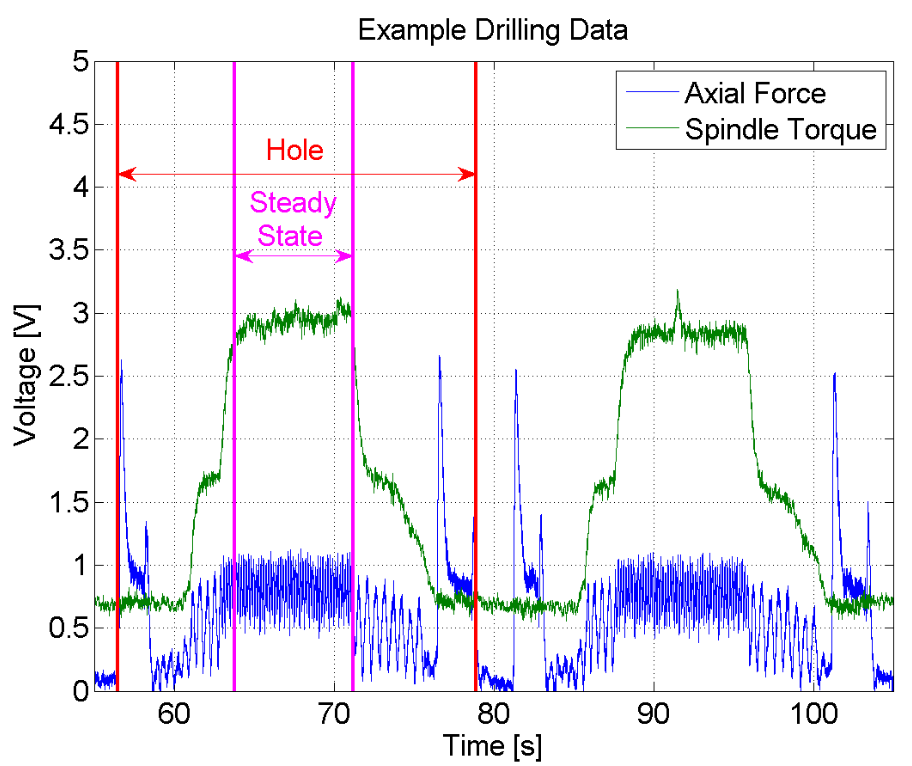


Figure 22: Example Data – Division of Holes and Steady State Drilling

4.3. Description of a Hole Drilling Cycle and the Current Data

At any point in time the drilling cycle can be categorized into one of the following 8 states:

1. Spindle off or outside of drilling cycle
2. Start of drilling cycle – feeding in towards material
3. Transition 1 – drill begins to engage the material
4. Drilling at constant feed rate of 65 mm/min
5. Transient 2 – feed rate is increased to the desired steady state feed rate
6. Steady State drilling at desired feed rate
7. Transient 3 –feed rate is decreased to 55 mm/min and then drill breaks through the back of the plate
8. Retraction of the drill

State 6 is the critical state that needs to be defined for every hole to allow the desired features to be extracted. The states are illustrated in Figure 23.

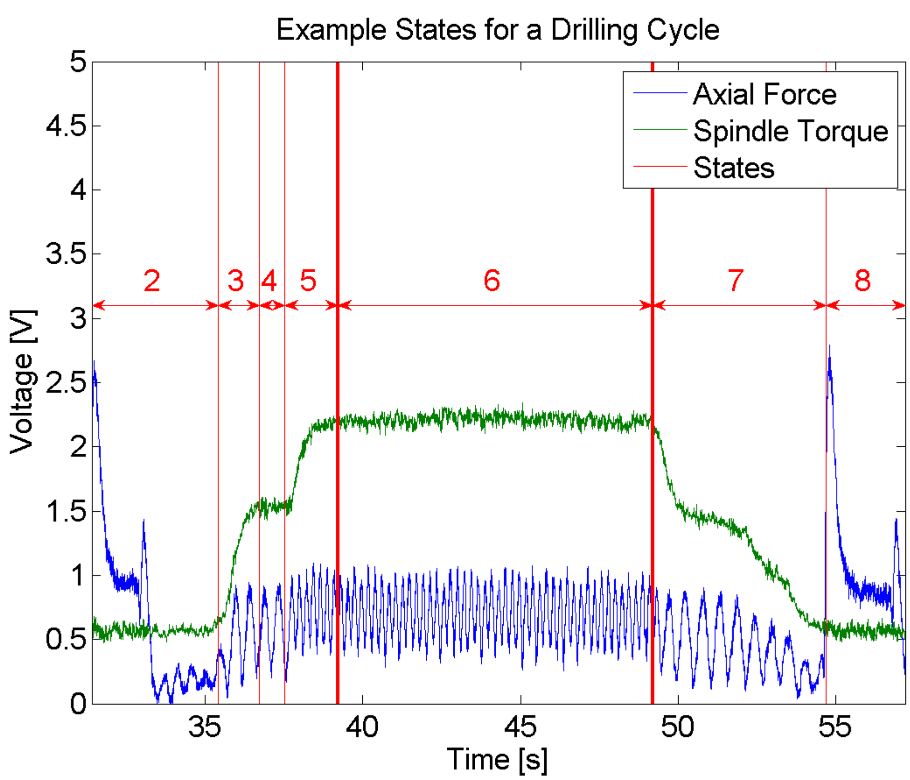


Figure 23: Drilling Cycle States

4.4. Hole Recognition and Drilling State Detection Algorithms

The axial force data shown in Figure 22 above reveals that there are sharp changes in the axial force before and after each hole in a defined, repeatable pattern. These spikes in the axial feed force are a result of the acceleration and deceleration the spindle in the axial direction. At the start of a hole cycle the spindle accelerates towards the plate at a high feed rate (the larger spike) and then quickly slows down to the drilling feed rate just before the drill touches the plate (the smaller spike). After the drill has drilled completely through the plate there is another, almost identical spike in the axial feed force as the spindle is accelerated in the reverse direction to retract the drill from the hole and then decelerated to a stop before the HBM moves to the next hole. Detecting these when these spikes in the axial feed motor current exceed 2.0 volts provides a reliable indication of the beginning and the end of a hole.

The process for dividing the identified holes up into individual states is more difficult. For this process the spindle motor current or spindle torque provides the necessary information. The basic algorithm for this process is:

1. Filter the torque data with an alpha-beta filter to create as smooth a curve as possible with minimal time lag.
2. Take the derivative of the alpha-beta filtered torque data.
3. Take the 2^{nd} derivative of the alpha-beta filtered torque data.
4. Calculate the standard deviation of the 1^{st} derivative of the torque data which was calculated in step 2 above.
5. Each time the 2^{nd} derivative of the torque becomes greater than or less than plus/minus one standard deviation of the 1^{st} derivative is an indication of a significant change in the spindle torque and a change in the state.

These algorithms were refined until they were capable of detecting and dividing the holes automatically without user input for all the different machining parameters used throughout the experiment.

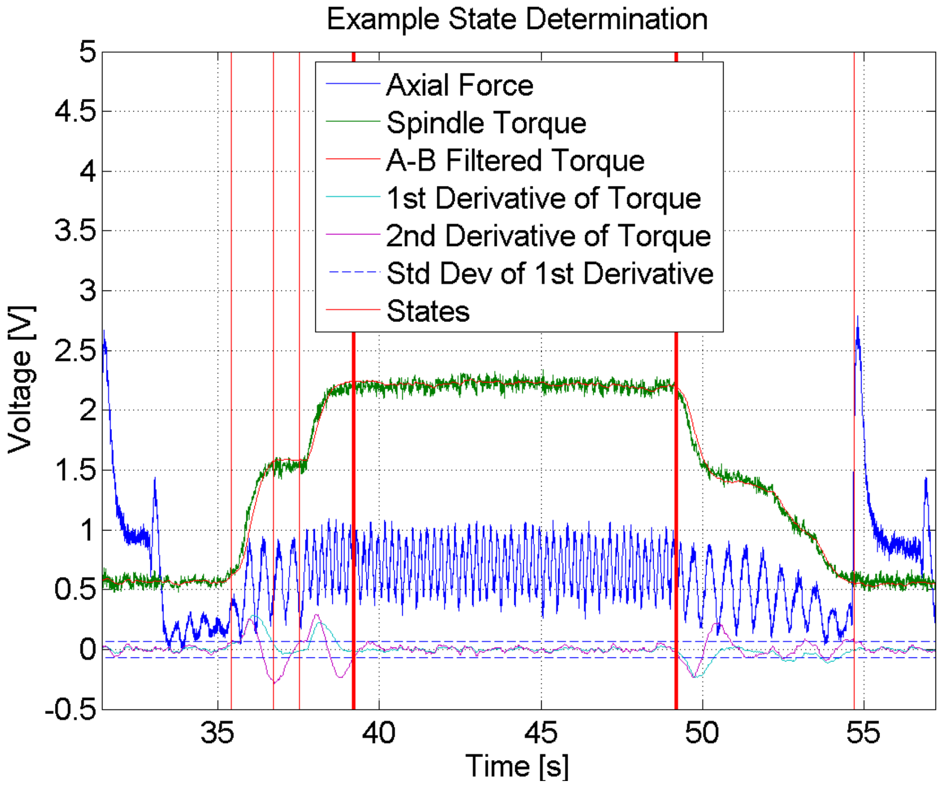


Figure 24: Example Hole with Data for State Determination

4.5. Feature Extraction

For this project all the features used for building the TCM models were extracted from the steady state drilling portion of the drilling cycle. A number of the features that were investigated for use in the models are illustrated in Figure 25. These extracted features provide an indication of how the spindle torque and axial feed force are changing as an insert wears out. The maximum value of the axial feed force for the steady state portion of each hole, shown by the green dashed line in the figure, shows the greatest change over the life of the insert indicating that it would likely be a good candidate as an input for the TCM models.

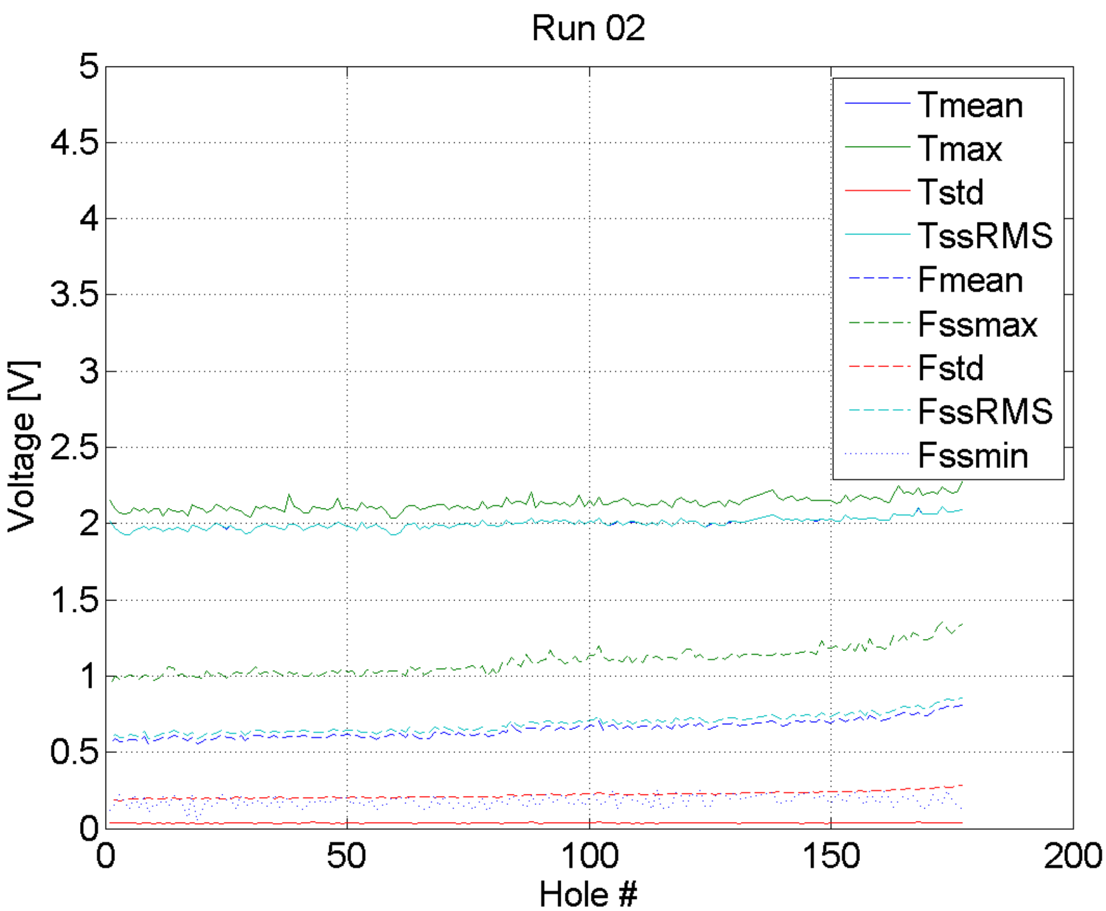


Figure 25: Extracted Features for Run 02

5. Model Identification and Validation

Having developed reliable algorithms to recognize holes in the measured current data, divide the holes into sections identifying the steady state portion, and having extracted a number of features from the data for each hole, the data can be used to identify the coefficients for the proposed models.

5.1. Dynamic Model

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. As an example, the process for building an AR model for the mean value of the spindle torque will be shown. The first ten values in the recorded time series were averaged to obtain a single data point for each experimental run. ANOVA analysis was done to determine if either or both of the machining parameters were correlated to the experimental values and then the least squares solution was found to determine the model coefficients. For the spindle torque, both the feed rate, f and the surface speed, S directly affect the measured values and a simple linear model provides an excellent fit to the data with a coefficient of determination of 0.99. The details of the final model are shown in equation (4) and the resulting plane from the model is plotted in Figure 26 (in green) along with the data points. Similar results are shown in equation (5) and Figure 27 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.

$$T_{mean}[V] = -1.37 + 10.48 f[mm/rev] + 0.017S[m/\min] \qquad (4)$$

$$F_{\max}[V] = 1.26 + 2.0 f[mm/rev] - 0.003S[m/\min] \qquad (5)$$

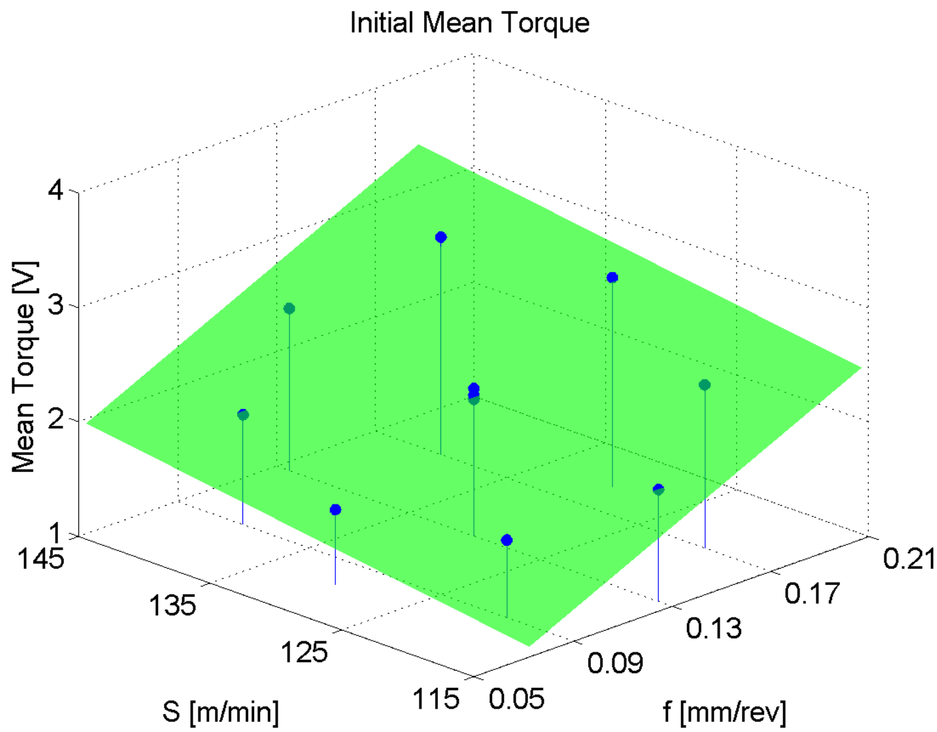


Figure 26: Surface Response Model for Initial Spindle Torque Values

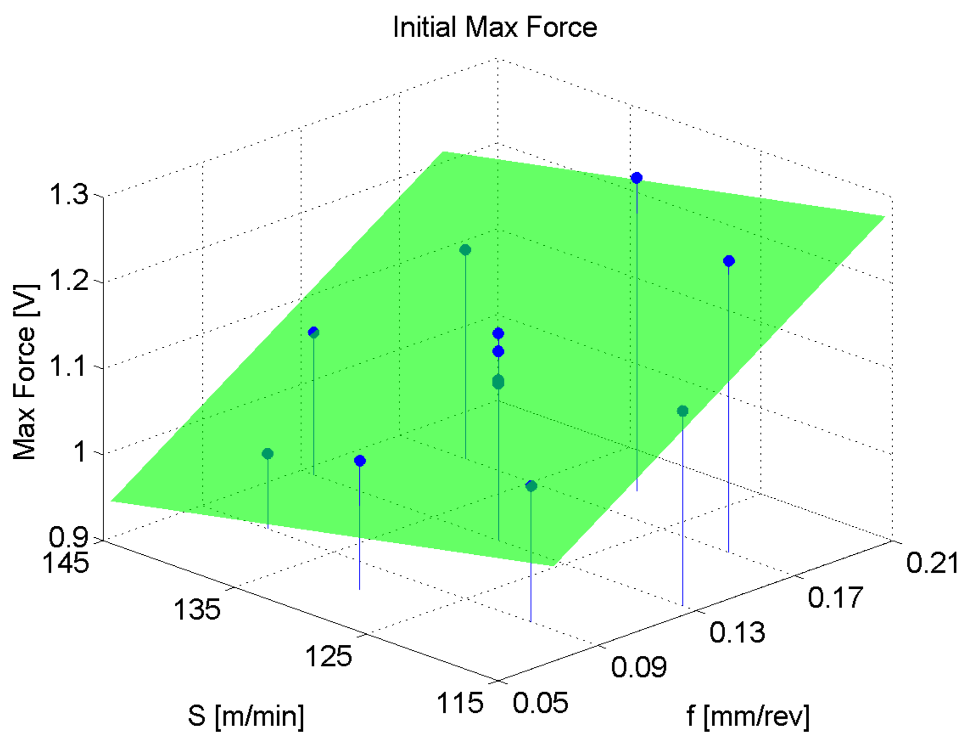


Figure 27: Surface Response Model for Initial Max Force Values

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 two and three.

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 and are shown in Figure 28. Run 9 was not used in the training of any of the models since it was used for verification.

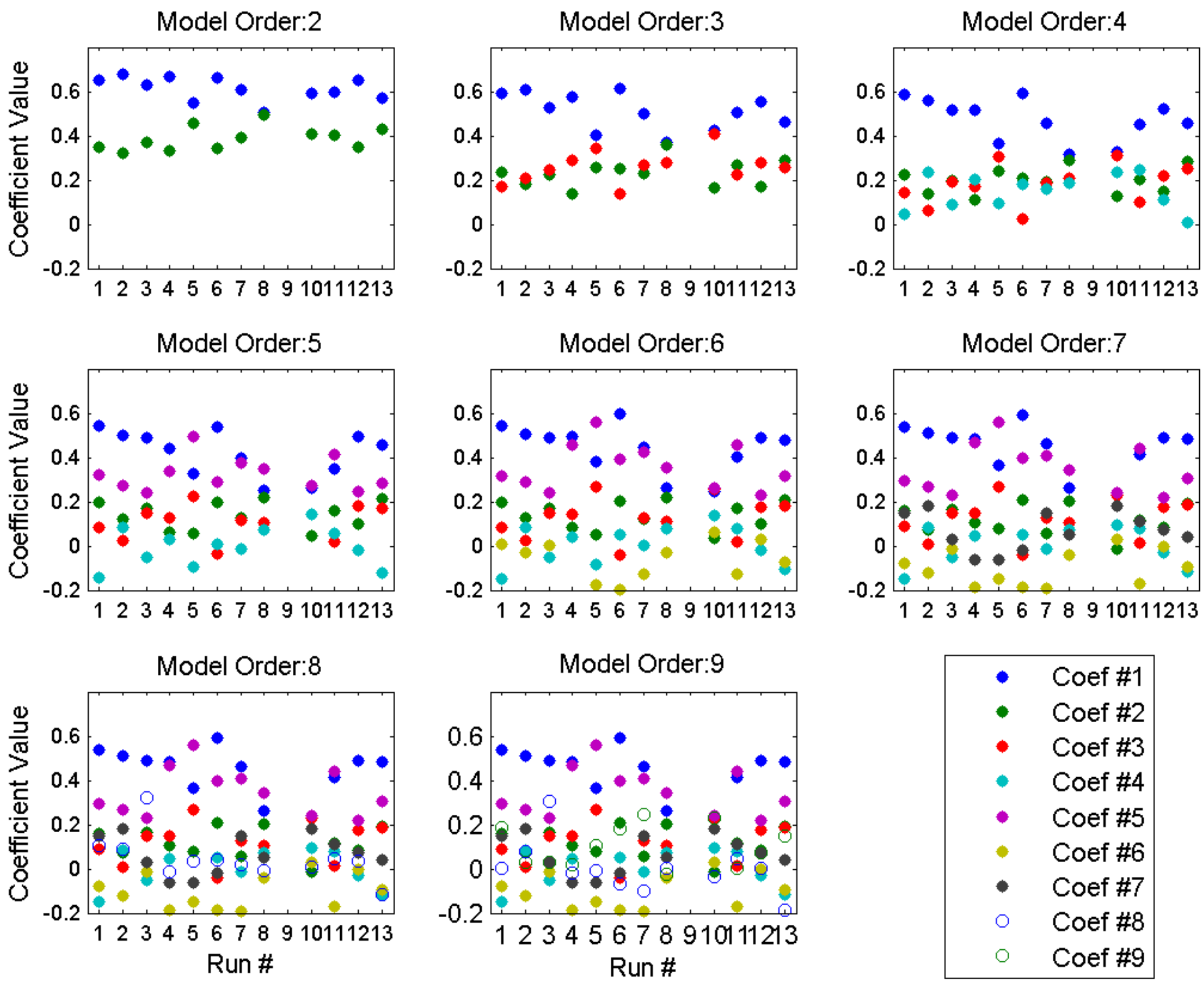


Figure 28: Mean Torque AR Model Coefficients

The twelve 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 as shown in Figure 29. 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 twelve calculated coefficients into a single value for the AR model. These averaged coefficients for each order of model are shown in Figure 30. The same process was carried out for the maximum axial force with very similar results. The value of the coefficients doesn't change significantly 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 Figure 31.

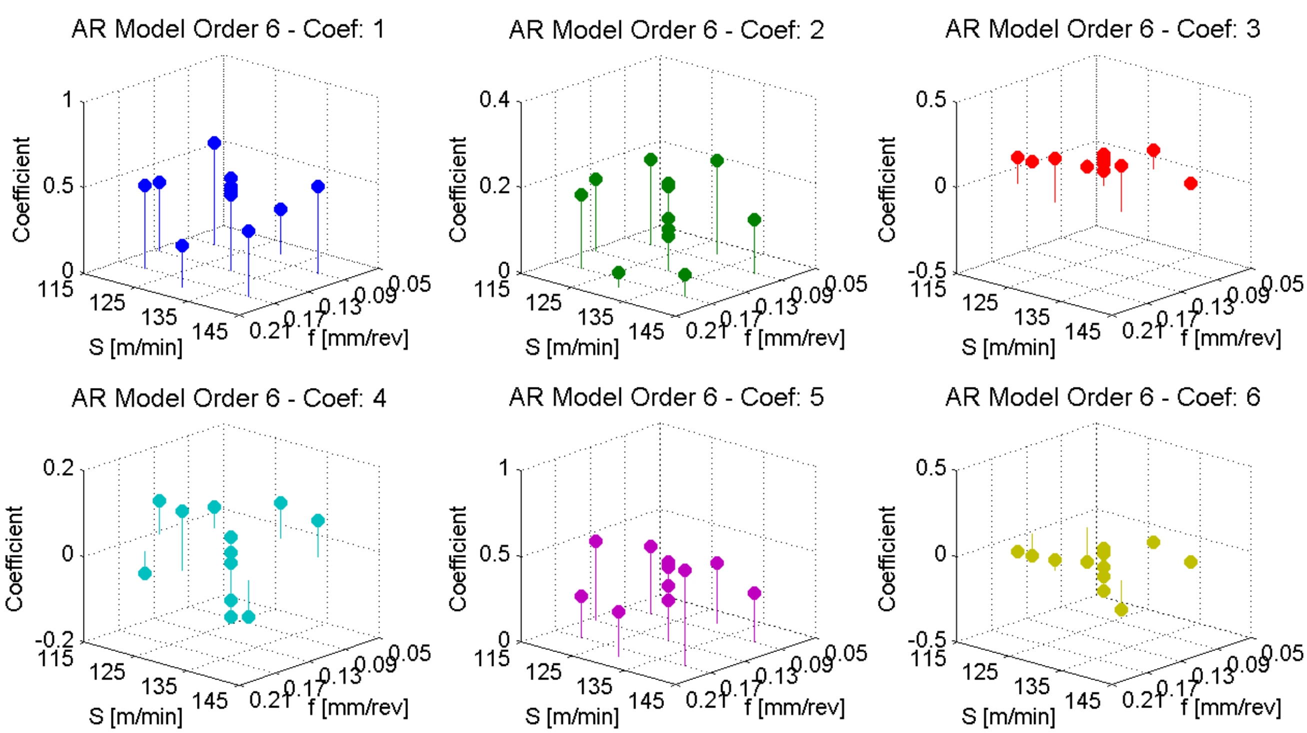


Figure 29: AR Coefficients for an Order 6 Model of the Mean Spindle Torque

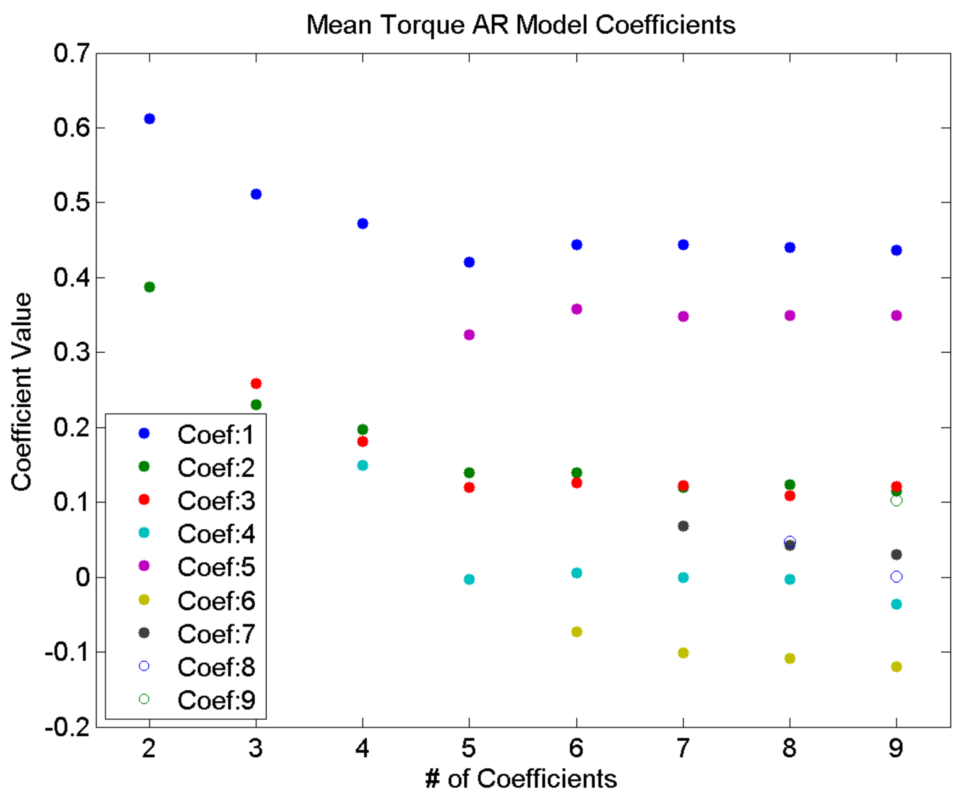


Figure 30: Summary of Mean AR Model Coefficients for Mean Spindle Torque

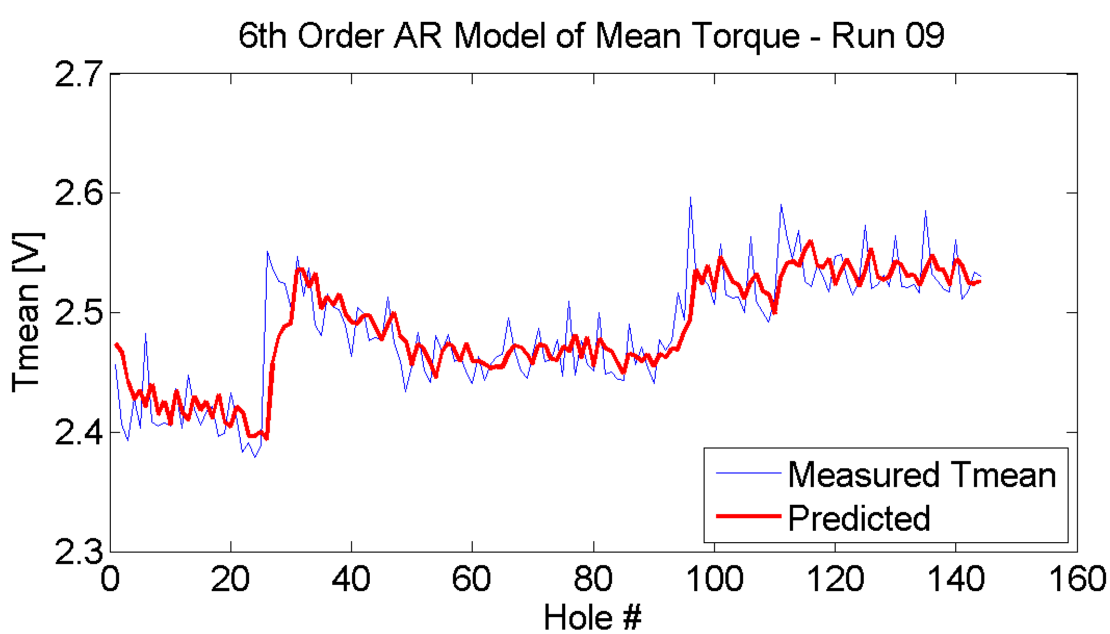


Figure 31: AR Model Results for Run 09 Mean Torque

5.2. Flank Wear Model

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. As discussed previously, a number of flank wear measurements were taken on each insert including an average wear based on 3 points taken across the flank of the insert, the maximum wear at the tip of the insert, and the overall maximum wear at any point on the insert. Each of these indications of the insert wear were 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. Since the wear measurements were only taken every 5 holes, only the values predicted for those holes were used in building the model. The best combination of inputs was found to be the feed rate and the maximum axial feed force. These input had the highest correlation with the overall maximum flank wear measurements. The final model is shown in equation (6). The data used to determine the model coefficients and the resulted model fit are shown in Figure 32 with a coefficient of determination for the model of 0.85. (The green vertical lines divide the data into sections based on the individual experimental runs.) The model validation using run 09 is shown in Figure 33 where the model reasonably follows matches the shape of the actual data.

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

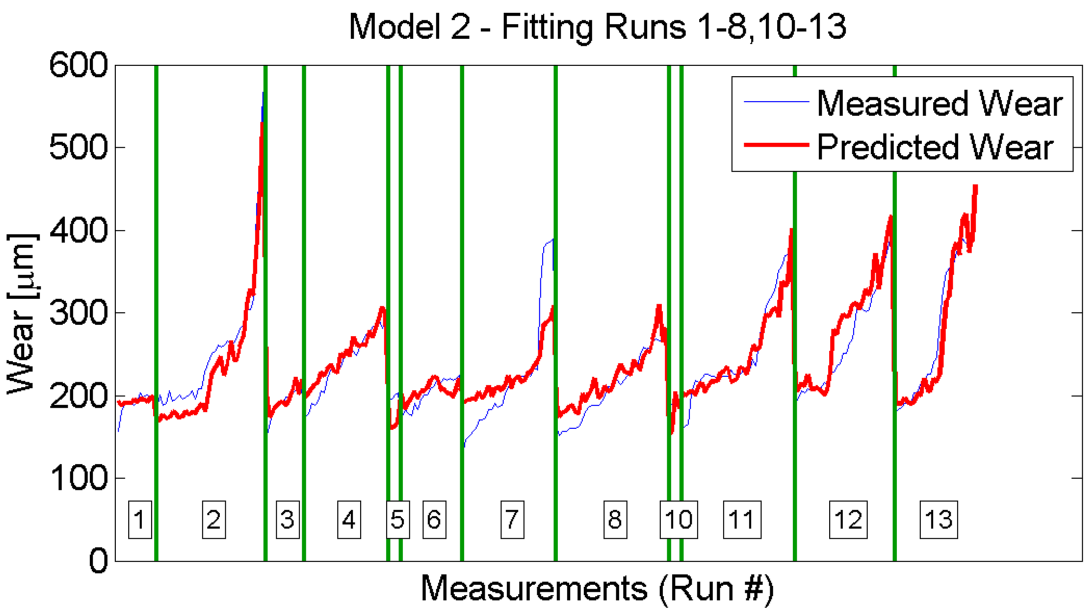


Figure 32: Model 2 - Flank Wear Model Fit

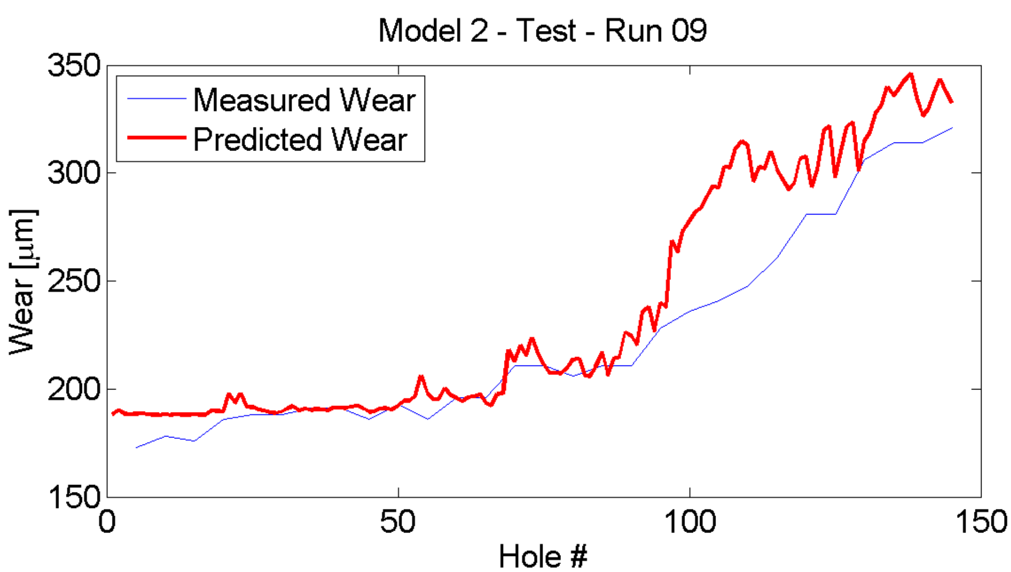


Figure 33: Model 2 - Flank Wear Model Validation

5.3. 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 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 development model. The best results obtained with the proposed inputs resulted in the model given by equation (7) with a coefficient of determination of 0.50. The data and the fitted model are shown in Figure 34 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 diameters. There are a number of reasons for this including variability in insert size or possibility of the insert not seating exactly in the pocket. Both of these problems would not cause a significant change in the axial feed force or the spindle torque so the model can't predict the hole size accurately but they would directly affect the hole diameter.

$$\hat{E}_D = 38.1 + 6.33 \times f + 0.0069 \times S - 0.47 \times f \times S - 0.0006 \times \hat{V}_b \tag{7}$$

If, instead of only using the machining parameters and the predicted wear values as inputs to this third model, the actual extracted features are used as well, an increase in the model accuracy can be achieved. The resulting model is more complex as is shown in equation (8) but is able to achieve a coefficient of determination of 0.57. The data and the fitted model are shown in Figure 35. The improved fit is visible but there are still areas where the fit deviates substantially from the data, again, Run 04 is a prime example.

$$\begin{aligned}\hat{E}_D &= 38.5 - 4.07 \times f - 0.0026 \times S - 0.19\hat{F}_{\max} + 1.41 \times \hat{T}_{mean} - 0.24 \times \hat{T}_{mean}^2 \\ &- 0.36 \times \hat{F}_{\max} \times \hat{T}_{mean} + 1.44 \times f \times \hat{F}_{\max} \times \hat{T}_{mean}\end{aligned} \tag{8}$$

Part of the improvement seen in the fit for (8) is due to the additional information contained in the mean spindle torque data as this information was not used in the wear model and was consequently not part of the input for the model in equation (7).

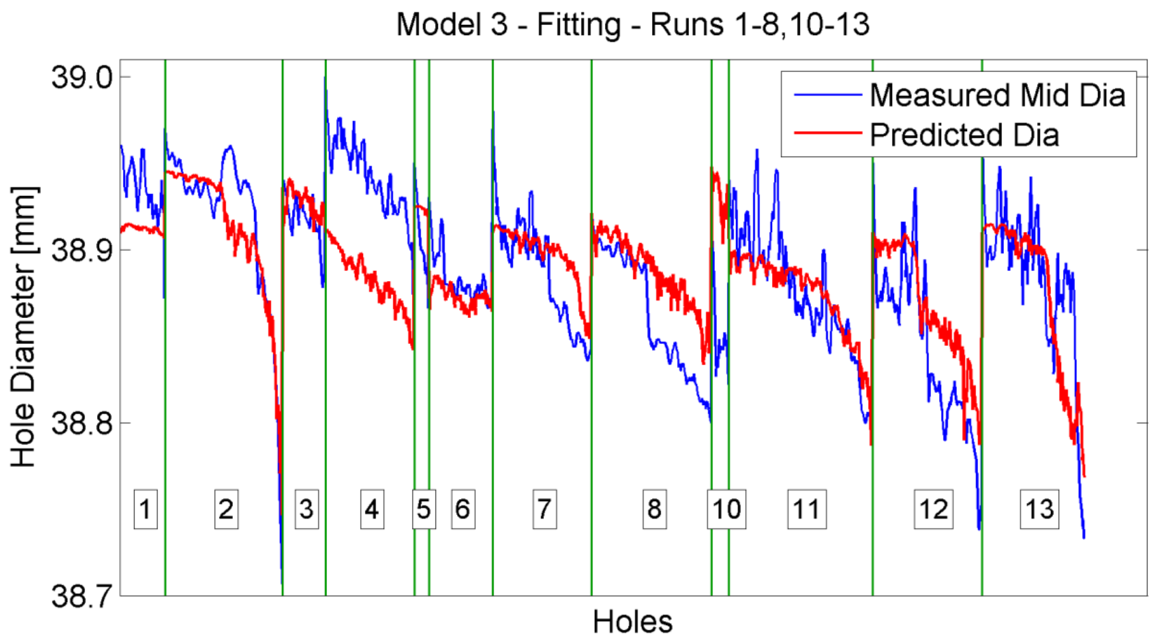


Figure 34: Model 3 - Hole Diameter Model Fit Using Predicted Wear Values

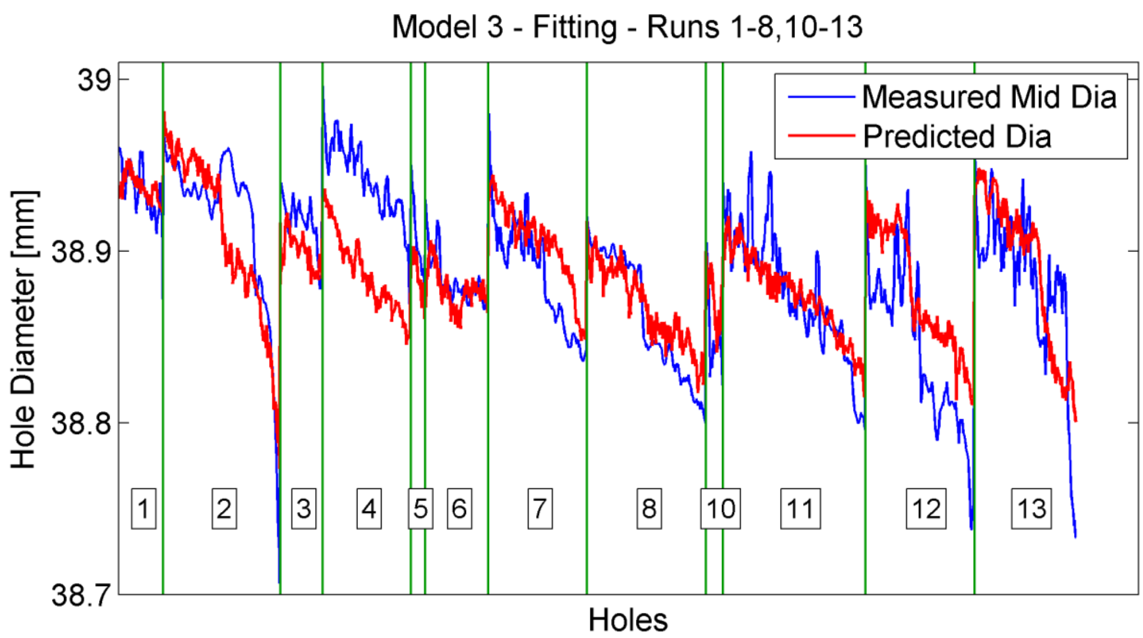


Figure 35: Model 3 – Hole Diameter Model Fit Using Extracted Features

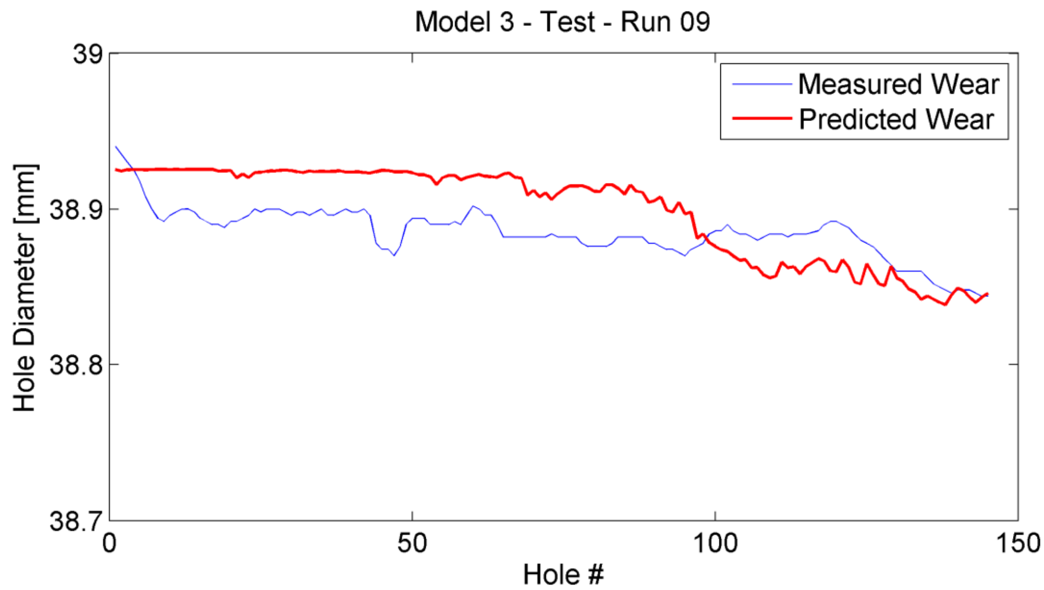


Figure 36: Model 3 – Hole Diameter Model Validation (Using Predicted Wear Values)

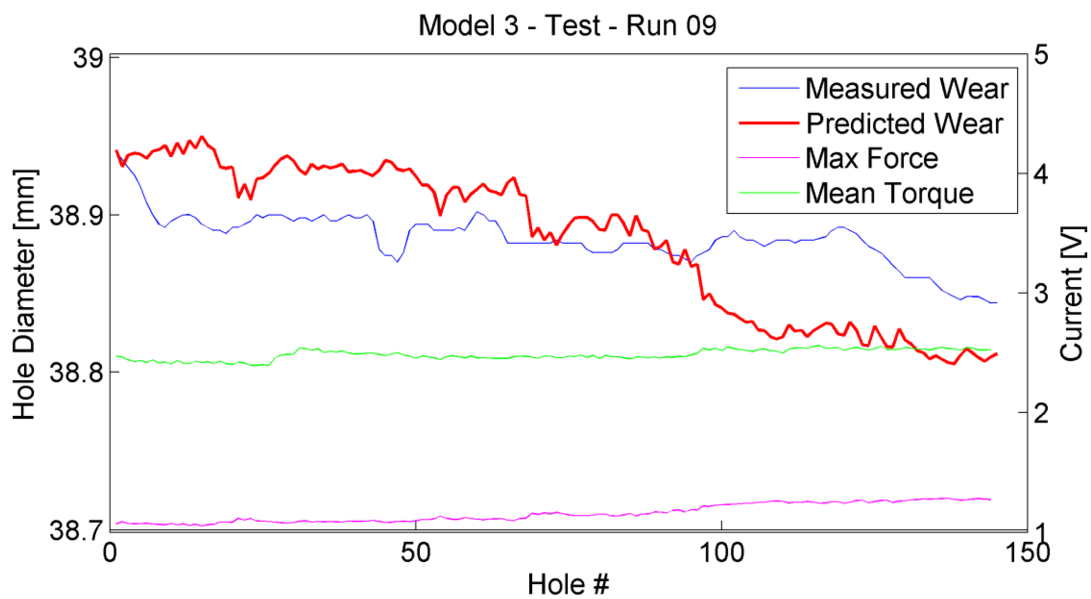


Figure 37: Model 3 – Hole Diameter Model Validation (Using Extracted Features)

The validation runs using the data from Run 09 for both models are shown in Figure 36 and Figure 37 and neither show the fit to be particularly good; however, they both predict the hole diameter within about 0.05mm with a downward trend as shown in the actual data. An item of interest that is shown by both of these plots can be seen around hole 100. Just before hole 100 both models predict 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 Figure 34 and

Figure 35 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 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. The images in Figure 38 show chips that were observed on the inside insert around hole 100 which are most likely the cause of the increase in diameter. Looking back at Figure 37 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.

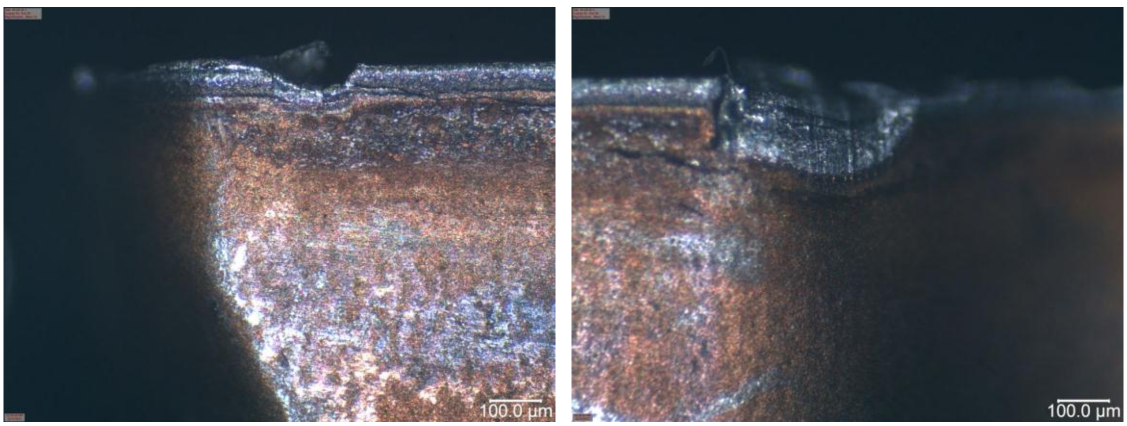


Figure 38: Wear on Inside Insert around Hole 100 of Run 09

Despite the fact that there are challenges in accurately predicting the true hole diameter, the models are able to capture the overall trend shown by the insert wear. This overall trend is key in designing an optimal tool replacement strategy which is discussed in the next section.

5.4. Tool Replacement Strategy

The final step in a TCM system is determining when the tool being used needs to be replaced. 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). A feature that was not implemented in this project but which could be implemented and would preclude the requirement for user input from the machine operator indicating the current machining parameters, would be to determine the machining parameters directly from the motor currents themselves as proposed by Li and Tso [6].
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 hole diameter for up to 6 holes ahead (a forecast of up to 6 holes ahead is possible since the AR models as part of Model 1 are both 6th order models), if any of the predicted hole diameters are outside of limits, stop drilling.
4. Drilling 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 step 3 & 4 for the first 5 holes (continue adjusting the limits based on the average of the first 5 holes).
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 Figure 39 with tight limits to minimize the risk of out of tolerance holes and maintain a tight tolerance of 38.925mm ±0.075mm. The following limits were set:

1. Minimum Diameter Tolerance – 38.85 mm
2. Upper Offset – 0.035 mm
3. Lower Offset – 0.037 mm

4. Absolute Upper Limit – 39.00 mm
5. Absolute Lower Limit – 38.868 mm

This figure illustrates how the TCM system can detect the changing hole diameter and stop drilling prior to drilling an out of tolerance hole. 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. The results of Run 01 shown in Figure 40 illustrate how an instantaneous tool failure, in this case the tip of the insert chipped off on the last hole drilled, 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 two experimental runs, Runs 1 and 3. Run 3 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. A summary of the results shown in Table 2 indicates that only a total of 6 holes out of 525 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, 61 holes were drilled per insert on average which is essentially equivalent to Hitachi's current 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. A small number of holes 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 is not usually allowed.

Figure 41 shows the results of applying the tool replacement algorithm to each run. This figure indicates at which hole the TCM system would have indicated that the cycle should be stopped and the drilling inserts be indexed, the diameters limits in the model, as well as the proposed minimum allowable diameter.

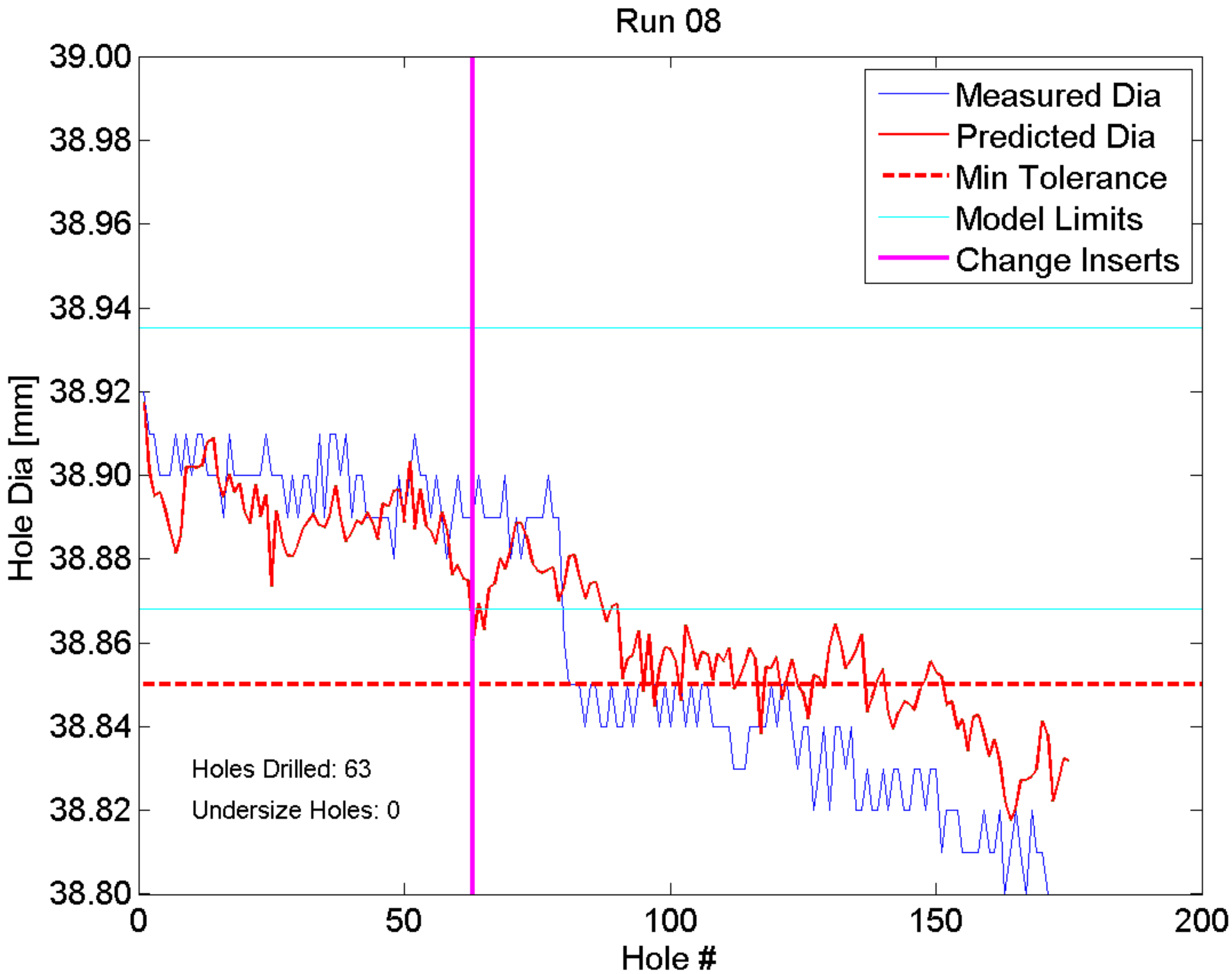


Figure 39: Tool Replacement Strategy

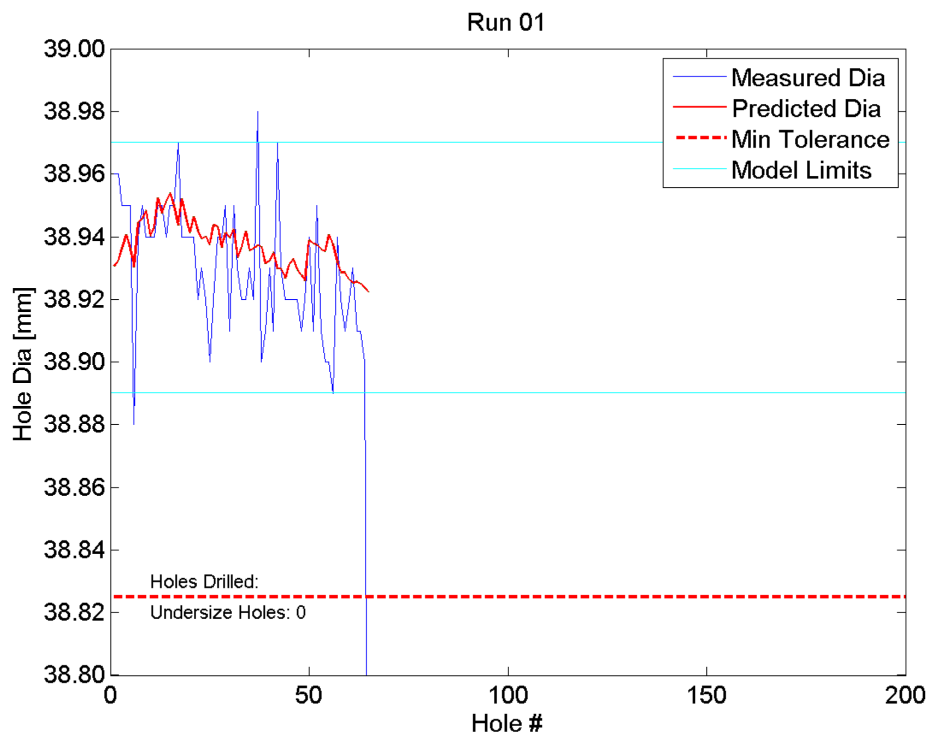


Figure 40: Tool Replacement Strategy Issue – Catastrophic Insert Failure

Table 2: Results of TCM Test 1

Run	# of Holes Drilled	# of Under Size Holes	# of Over Size Holes	Minimun Undersize Hole Dia
1	65	1	0	n/a
2	76	0	0	n/a
3	62	0	0	n/a
4	31	0	0	n/a
5	17	0	0	n/a
6	2	0	0	n/a
7	74	0	0	n/a
8	63	0	0	n/a
9	54	1	0	38.82
10	14	6	0	38.80
11	107	1	0	38.83
12	66	2	0	38.83
13	73	1	0	38.84
Totals	**704**	**6**	**0**	
Average	61.2	(Not including runs #5 and #10)		

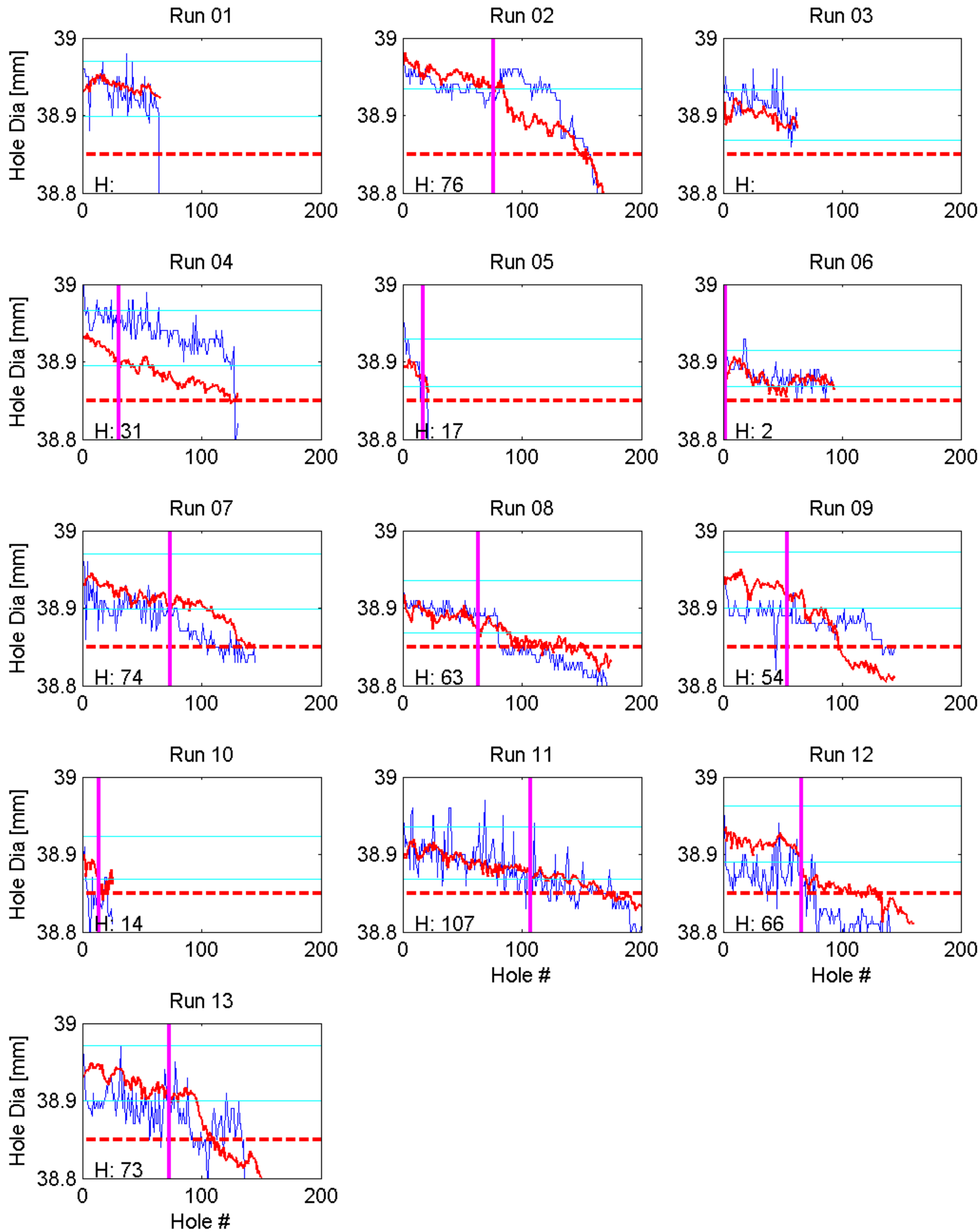


Figure 41: Summary of Results of TCM Test 1

To evaluate the potential for the TCM system to improve the tool life on average with slightly increased hole diameter tolerances, the process was repeated with slightly looser limits but still maintaining a tolerance of 38.925mm ±0.1mm. The limits were adjusted to:

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

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

Table 3: Results of TCM Test 2

Run	# of Holes Drilled	# of Under Size Holes	# of Over Size Holes	Minimun Undersize Hole Dia
1	65	1	0	n/a
2	85	0	0	n/a
3	62	0	0	n/a
4	46	0	0	n/a
5	21	0	0	n/a
6	93	0	0	n/a
7	111	0	0	n/a
8	91	0	0	n/a
9	69	1	0	38.82
10	17	2	0	38.8
11	165	0	0	n/a
12	67	0	0	n/a
13	97	0	0	n/a
Total	989	4	0	
Average	86.5	(Not including runs #5 and #10)		

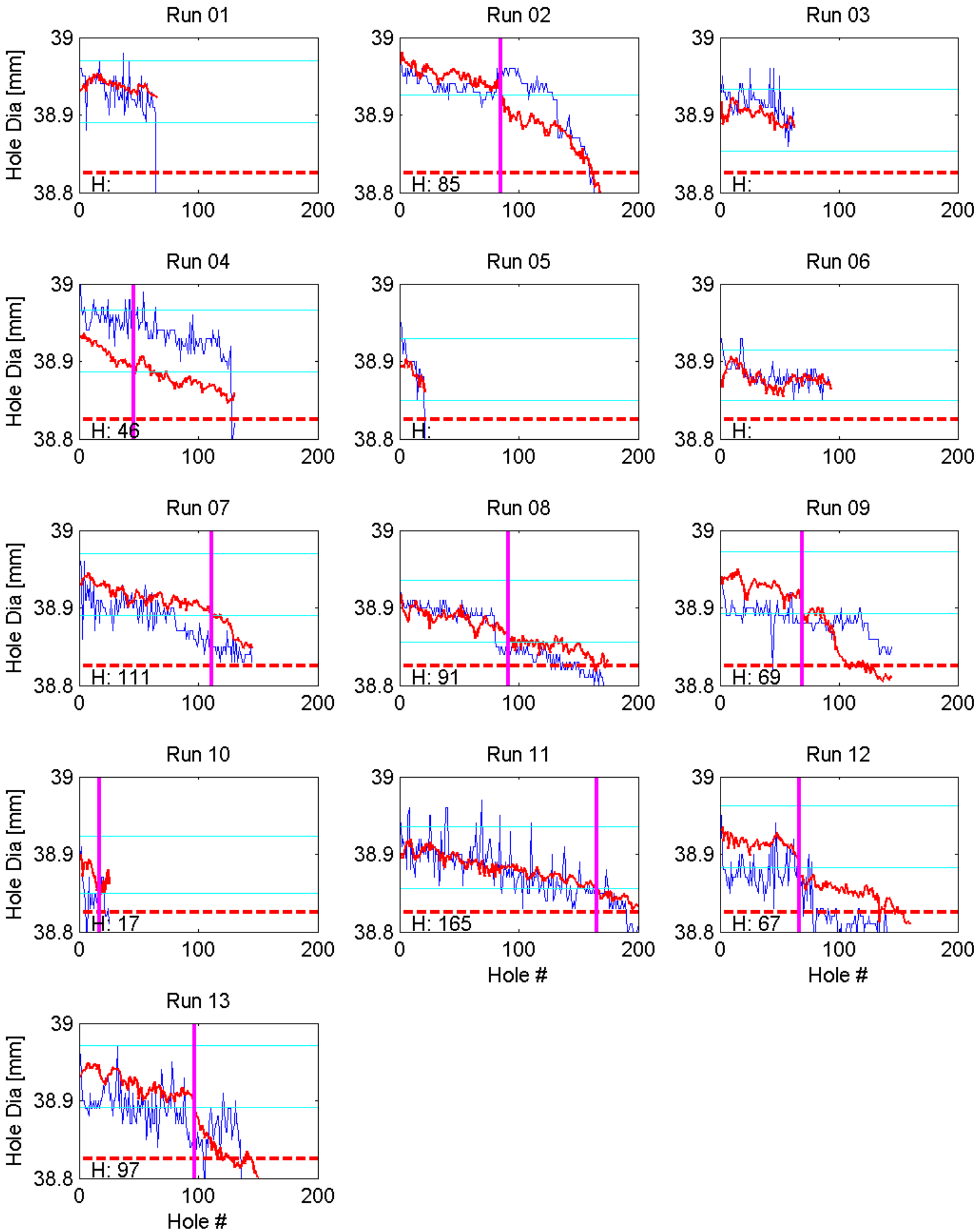


Figure 42: Summary of Results of TCM Test 2

6. Discussion of Results

The three model system proposed for a TCM system for monitoring the drilling of 39.0mm diameter holes in 2205 Duplex stainless steel was developed and tested using the experimental data obtained. The algorithms developed for both hole recognition and state determination were very robust and reliable. There were two slight issues with the algorithms, the first was related to the data capture being stopped prior to the spindle completely shutting down or being started after the spindle was spooling up. However, in a production environment where the hole recognition algorithm would be running in real time this would not be a problem. The second issue only occurred on Run 8 where the steady state drilling feed rate for the experiment was only slightly higher than the initial feed rate for the approach and start of drilling. The algorithm was able to determine the state accurately for over 95% of the holes. Since the drilling cycle is completely controlled by the CNC the timing is extremely repeatable. It would be a trivial task to modify the algorithm to monitor the drilling for a certain number of holes, determine the state for each hole, discard the state determination for any hole that is an outlier, average the times spent in each state per hole and then use time to divide up future holes at the same machining parameters instead of relying on the state determination algorithm.

For this experiment a very large amount of data was acquired and saved for research purposes; however, if this TCM system was implemented into a production environment, the hole recognition and state determination algorithms would be performed online allowing the features to also be extracted online. 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 one hole 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 much lower than that for the 2nd model when the model was initially developed using only the machining parameters and the predicted flank wear as inputs; however, the accuracy of the model was improved somewhat by using the predicted features from the AR models instead of only the flank wear. A second benefit, in addition to the improved fit of the 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.

As discussed previously, 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.

This lack of fit doesn't have a large effect on the practicality of the TCM system. 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 ±0.1mm can be held reliably with a significant 40% increase in tool life and a non-trivial reduction in machine down time due to fewer tool changes. A tolerance zone of ±0.1mm 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 Figure 20.

As anticipated, a significant 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. This TCM system is capable of detecting and predicting the flank wear of the drilling inserts as well as the hole quality and the changes to these items as a result of gradual wear; however, an in order to detect instantaneous, catastrophic insert failure, an additional model needs to be developed that can respond quickly (within a fraction of a second) when an insert fails. If an insert chips upon the drill exiting the back of the plate at the end of a hole, the proposed TCM system would not detect anything until the entire next hole is drilled; but with a chipped insert the drill would be destroyed before completing the next hole. The combination of the proposed TCM system with another model to detect catastrophic insert failure would result in a robust and very useful TCM system for industrial applications.

7. Conclusions and Future Work

7.1. Summary and Conclusions

There were 3 main objectives to this research that were accomplished.

1. A data acquisition system was established in an industrial setting to capture the required data from the experiment for the analysis including the development of a visual user interface in Matlab to control the data capture. The spindle motor current and the axial feed motor current were measured and recorded for the entire experiment at a frequency of 100 kHz. Acoustic emission sensors were also implemented and tested to allow for future research although they were not utilized in this research.
2. A drilling experiment was designed and carried out to provide the data to determine the coefficients of the proposed models. A central composite design with a single replicate and total of 9 different level combinations and 5 center runs was used for the experiment. In total, 1654 holes were drilled over 13 separate runs. The data collected in the experiments was analyzed and a number of algorithms were created and optimized to reliably detect individual holes in the continuous data signals as well as to break each hole down into a series of distinct states. These algorithms and the subsequent models were implemented in an object oriented Matlab program that can be adapted to run on a standalone device for a production environment. The algorithms provided very reliable detection of the drilling state with only a slight reduction in reliability for one run (run 8) where the steady state drilling feed rate was only slightly higher than the initial feed rate for each hole. A series of models were developed to predict the measured current signals prior to drilling each hole and to accurately predict the insert flank wear and the actual hole diameter.
3. Finally, a tool replacement strategy was developed and tested showing that the TCM system developed shows significant promise in reducing risk of machining inaccuracies while at the same time improving productivity. A 44% increase in the tool life, with an associated increase in productivity resulting from fewer insert changes, and a significant reduction in the risk of out of tolerance holes was achieved over the standard process

where the inserts were changed every 60 holes in order to control the risk of out of tolerance holes.

In conclusion, the proposed 3-model TCM system shows promise in being able to significantly reduce the risk of drilling out of tolerance holes while at the same time increasing tool life and decreasing tool change time. The models are able to accurately predict the insert flank wear and as well as the actual hole diameter within the range to be expected based on the repeatability of the drills. The TCM system could be implemented in an online system with minimal revision to the algorithms. A few slight revisions are required to account for the fact that the algorithm testing for this research was all done after the completion of the actual drilling testing using saved data from the drilling process instead of being done online. The proposed algorithms can all be used in an online fashion with only minor modifications.

7.2. Limitations and Future Work

A significant limitation to the TCM system as proposed is that the models only update and allow decisions regarding the changing of inserts in between holes and not in the middle of drilling a hole. This means that catastrophic insert failure cannot be detected until it is too late and the drill would already be destroyed as well as potentially damaging the work piece.

The algorithm used to determine the different drill states in the proposed TCM system requires alpha-beta filtering and the calculation of two derivatives which are computationally intensive processes which could potentially be a limiting factor on the hardware that could be used to implement the TCM system in an industrial setting.

Another remaining challenge is the application of the proposed TCM system to different drills, either different sizes, a drill from a different manufacturer, or a different material. Any of these changes could affect the validity of the model and no testing was completed to determine the sensitivity of the models to these changes.

These limitations and challenges require further research related to the TCM system developed in this project.

1. An additional online model for detection of catastrophic insert failure is necessary to complement the wear models developed in this project. This additional model could potentially use the same motor current signals as inputs. The 3 models developed in this research essentially ignore the initial few seconds of drilling for each hole and are really only concerned with the steady state portion of the hole. It is these first few seconds that are crucial for detection of chipped inserts since experience has shown that the inserts typically chip as the drill exits the back of the plate and then if the operator is not paying close attention the next hole is drilled without an insert. Acoustic emission sensors were also commissioned as part of the data acquisition setup for this project and there is significant promise for their ability to detect catastrophic failure.
2. As mentioned in the previous chapter, the timing of the drilling cycle is very repeatable since the drilling is CNC controlled. This repeatability and the fact that the drilling parameters are not typically changed very often during the repetitive process of tubesheet and baffle drilling would allow the use of the proposed algorithm for determining the drill state to be used only during a training stage on a very limited number of holes (10-20 holes). The result of this training state could be used to determine the drill state based solely on timing which would preclude the need to use alpha-beta filtering and the calculation of derivatives on each and every hole.
3. The developed models need to be implemented on a standalone device that requires essentially no operator input to monitor continuous drilling operations for tubesheet and baffle applications. This implementation could also include automatic detection of the machining parameters using frequency analysis of the motor signals.
4. Automatic retraining of the models to account for different size drills or different materials would greatly improve the usability of the TCM system in an industrial setting. Further research on implementing an operator friendly training process that requires minimal user input and that would allow training on production work pieces could make this a possibility.

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Appendix 1

The following is the EIA/ISO CNC machine code for the cycle of drilling a single hole once the drill has be positioned in the correct X,Y location. In this code Z=0 is at the back of the plate (away from the machine) and Z positive is towards the drill/machine from the surface of the plate. Since 31.8mm plate was used for this project, Z=31.8mm is the front surface of the plate.

```
M03 S1061
G01 Z34.8 F4000.
G01 Z29.8 F65.
G01 Z3.0 F138
G01 Z-2. F55.
G01 Z140. F4000.
M99
```

CNC Code	Description
M03 S1089	Turn on spindle at an rpm of 1061
G01 Z34.8 F4000.	Feed to Z=34.8 at a feed rate of 4000 mm/min (3mm from the surface of the plate)
G01 Z29.8 F65.	Feed until the tip of the drill is 2mm into the plate at 65 mm/min
G01 Z3.0 F138	Feed until the tip of the drill is 3mm from the back of the plate at 138 mm/min
G01 Z-2. F55.	Feed until the tip of the drill is 2mm past the back of the plate at 55 mm/min
G01 Z140. F4000.	Retract the drill from the hole to a clearance of 108.2mm from the front surface of the plate at a rate of 4000 mm/min