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# On-Line Drill Wear State Monitoring in Machining of Stainless Steel using Virtual Instrumentation

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**Abstract:** In this paper development of an on-line drill wear state monitoring and effective tool replacement technique based on cutting current signals in drilling of stainless steel. The effective drill wear models are established based on the relationship between cutting current signals and the varying cutting parameters (cutting speed, feed and drill diameter) analyzed under different drill wear states. To prevent tool breakage caused by excessive wear and to extend tool life to its optimum level, the changes in the tools are enabled when they are worn, the cutting tool status is continuously monitored and the degree of drill wear is displayed as a percentage of the maximum permissible wear. The standard data acquisition software LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench), in the application of virtual instrumentation is used for the purpose of data collection, signal analysis and decision making. The software facilitates defective tool replacement at the proper time based on drill wear states in the automated manufacturing environment.

**Key words:** Stainless steel · Drilling · Wear · Cutting current signal · Varying cutting conditions · Virtual instrumentation

## INTRODUCTION

Drilling operation is frequently used as a preliminary step for many operations like boring, reaming and tapping; however, the operation itself is complex and demanding. The actual cutting ability of the drill is reduced with increased wear, resulting in poor surface finish, over-size holes, built up edges along the lips, noise etc., also if the resharpening is delayed, more material has to be ground off. So, online prediction of drill wear plays a very significant role in machining process. Monitoring of drill wear is an important issue, since wear on drill affect the quality of the hole and tool life of the drill. The drill wear monitoring methods can be classified into two categories, i.e. direct and indirect methods. With direct methods it is possible to determine tool wear directly, which means that these methods really measure tool wear as such. In spite of the many attempts direct methods such as visual inspection or computer vision etc. have not yet proven to be very attractive either economically or technically. Hence indirect methods using sensory feed back during machining has been used to assess the wear of the drill. In indirect monitoring methods, the wear is identified by measuring the parameters such as torque, force, vibration, sound and cutting current etc. Most of the indirect approaches have been developed for fixed cutting conditions in practical applications; however the cutting conditions are not fixed therefore a wear estimation strategy that operates under varying cutting conditions is much needed for dictating the dimensional accuracy of the workpiece and guaranteeing an automatic cutting process.

[1] Concerns with the development of a tool wear condition monitoring technique based on a two-stage fuzzy logic scheme. In the first stage of the proposed scheme, statistical parameters derived from thrust force, machine sound (acquired via a very sensitive microphone) and vibration signals acquired from various sensors were used as inputs to fuzzy process; and the crisp output values of this process were then taken as the input parameters of the second stage. Conclusively, outputs of this stage were taken into a threshold function, the output of which is used to assess the condition of the tool. Ertunc and Loparo [2] experimented on methods using

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Hidden Markov models, as well as a decision fusion center algorithm (DFCA). The proposed algorithm combines the outputs of the individual methods to make a global decision about the wear status of the drill with the use of force and power in drilling. New techniques are proposed in Ertunc and Oysu [3], for real time identification of tool wear status based on cutting force and torque measurements from dynamometer during drilling by using hidden Markov models (HMM), phase plane method, transient time method and mechanistic approach.

[4] compares several architectures of the multi-layer feed-forward neural network with a back propagation training algorithm for tool condition monitoring (TCM) of twist drill wear. It was found that the frequency domain features, such as the averaged harmonic wavelet coefficients and the maximum entropy spectrum peaks, are more efficient in training the neural network than the time domain statistical moments. [5] explains the method for on-line wear state monitoring and tool replacement decision-making using spindle motor and feed motor current signals in drilling. The models on the relationship between the current signals and the cutting parameters are established under partial experimental design and regression analysis. A fuzzy classification method is used to classify the tool wear states. Lint and Ting [6] describes about identifying the tool wear conditions based on the thrust force and torque signal measured based on cumulative back-propagation algorithm. The accuracy of tool wear estimation has done by using the neural network. Fernandes and Cook [7] deals with the force and torque produced during drilling of carbon fiber using a 'one shot' drill bit and a mathematical model is developed to find maximum thrust force and torque. [8] discussed the correlation between Acoustic Emission (AE) parameters and torque measured during the drilling process. Torque was measured as a control parameter to follow the dynamic behavior of the drill bit. An alternative AE feature, called Mean Power (MP) showed a good correlation with torque when the moving average (MA) was computed. [9] compares different types of Artificial Neural Network (ANN) architectures, Back Propagation Neural Network (BPNN) and Radial Basis Function Network (RBFN). Its depends upon speed, feed rate, drill diameter and hence these parameters along with other derived parameters such as thrust force, torque and vibration have been used to predict flank wear using ANN. Li and Tso [10] presented on-line tool breakage detection of small diameter drills by monitoring the AC servo motor current. The continuous wavelet transform was used to decompose the spindle AC servo motor current signal and the discrete wavelet transform(DFT) was used to decompose the feed AC servo motor current signal in time–frequency domain.

In automated manufacturing systems, drill wear detection plays a critical role in dictating the dimensional accuracy of the workpiece and guaranteeing an automatic cutting process. It is therefore essential to develop simple, reliable and cost-effective on-line drill wear detection methodology. In order to accomplish the above objective the following works are carried out. a) To investigate outlet of stainless steel storage tank by secure joining through quality hole in chemical industries. b) To investigate quality of the holes (diameter, form, surface finish, etc.) for outlet is experimented thorough drilling c) A new on-line drill wear detection method is developed based on the cutting current signal of the spindle motor using virtual instrumentation. d) The drill wear model is developed using LabVIEW e) Based on the model cutting current signals are acquired using current sensor (current transformer) and the status of the wear is analyzed over a wide range of cutting condition (cutting speed v, feed rate f, drill diameter d and drill wear w). f) The defective tool replacement at the proper time is facilitated based on drill wear states.

**Industry Application:** Stainless steel material highly used various storage parts in chemical industries. Stainless steel storage tanks for meeting the process demands of chemical industry. Stainless steel storage tank used in many configurations depending upon functional requirements, these storage tanks are designed and constructed in accordance with all major codes and standards. The system should be large enough to contain the full potential volume of material in primary storage. Such containment areas should not have any major causes in outlets and should be made of proper joining with outlets. The Figure 1 shows the type of outlet in the stainless steel storage tank. In these industries, numbers of holes are drilled on the outlets, the great majority of which are fastener holes. The quality of the holes (diameter, form, surface finish, etc.) for outlet is important due to the high stresses and fatigue parts are subject to continuous load. The creation of holes (by drilling) on the storage parts is a complicated and complex process since many parameters affect the results. On-line drill wear state monitoring and instant tool replacement is an important issue in the above mentioned area. The proposed on-line drill wear state monitoring system using virtual instrumentation under varying cutting conditions is

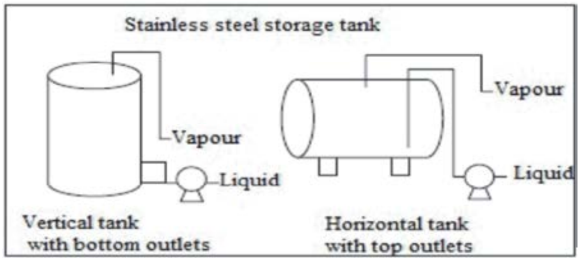


Fig. 1: Stainless steel storage tank with outlets

Table 1: Experimental conditions for On-line drill wear monitoring system

| S.No | Specifications | | | |
|---|---|---|---|---|
| 1 | Varying Cutting condition | Feed (0.1-0.3 mm/rev) | | |
| | | Cutting speed (500rpm-800rpm) | | |
| | | Drill diameter (Ø8mm, Ø10mm, Ø12mm) | | |
| 2 | Work piece | Material | Hardness | Tensile strength |
| | | Stainless steel | 420 BHN | 810 N/mm$^2$ |
| 3 | Tool | High speed steel (HSS) | | |
| 4 | Sample size | 200, during steady wear period of drill | | |
| 5 | Machine | Radial drilling machine | | |

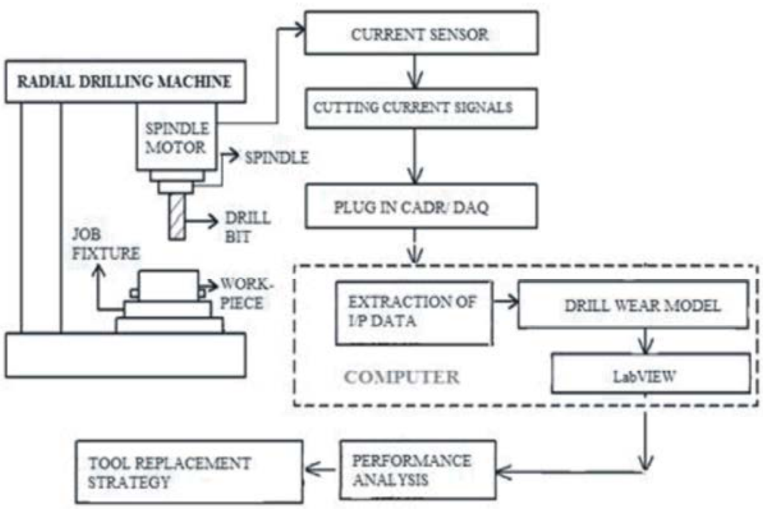


Fig. 2: On-Line drill wear monitoring system

Fig. 3: Current Transformer


Fig. 4: Data Acquisition card

simple, reliable and cost-effective. The developed on-line drill wear monitoring system will be helpful for industry people to get the idea of the secure joining of outlet (through quality hole) in storage tank, drill wear states and tool replacement control at proper time. Therefore it is essential to investigate and develop a best, simple, reliable and cost-effective on-line drill wear state monitoring system for instant tool replacement in joining outlet of stainless tank plate.

**Experimental Setup:** Proposed method measures the cutting current signals (e.g. spindle motor current signals) during drilling of stainless steel and identifies the wear states (Normal wear state, Moderate wear state and Ultimate wear state) from the measured process data. The identified wear states are used to decide the tool replacement at the proper time. Cutting tests were performed on a radial drilling machine. Figure 2 shows a schematic diagram of the experimental set-up. The spindle motor cutting current signals of the drilling machine are gathered and the reduced current from the high circuit current is produced by current transformer (CT) /sensor shown in Figure 3. Data Acquisition card (DAQ) is a core tool to understand the control and processes management in the system. Cutting parameter information i.e. cutting current signal gathered by sensor are converted into digital signals by DAQ which conditions, amplifies, measures, scales, processes, displays and stores the sensor signals. A common type of DAQ is plug-in card, which fits into the free expansion slot in the computer. NIcDAQ 9205 shown in Figure 4 is used in on-line drill wear monitoring system. Table 1 shows the experimental conditions for on-line drill wear monitoring system in machining of stainless material.

In these experiments, the flank wear is taken as a standard wear for evaluating drills wear condition. The average flank wear is computed by measuring the wear at each section and then taking the arithmetic average. i.e., Average Flank Wear = (A+B+C+D)/4. It is generally observed that the current amplitude increases as the drill wear increases, associated with the friction between tool and workpiece. The flank wear consists of following stages such as Initial stage, Normal wear stage, Moderate wear stage, Ultimate or end wear stage and Worn-out stage which are obtained from tool maker's microscope. Drill wear states can be classified into different wear stages as a function of tool life: Initial wear stage consists of up to 0.1 mm. Normal wear stage consists of wear rate between 0.1 to 0.2 mm this wear stage is the initial position of wear rate value. Hence it will not create any damage to the tool and machine. Moderate wear stage has wear rate value of 0.2 to 0.4 mm and this stage shows the Moderate wear rate value for a tool. Ultimate wear stage is the severe stage of wear. In this stage the wear range lies between 0.4 to 0.6 mm it shows the exact wear matter in the output graph. In ultimate wear stage the tool has to be replaced. Final wear stage is worn-out stage. According to the estimated drill wear state it is able to decide whether the tool should be replaced or not.

**Virtual Instrumentation (VI):** Virtual instrumentation is defined as combining hardware and software with industry-standard computer technologies to create user-defined instrumentation solutions. It specializes in developing plug-in hardware and driver software for data acquisition (DAQ). The driver software is the programming interface to the hardware and is consistent across a wide range of platforms.

**Parts of Virtual Instrumentation:** Each VI contains three main parts: Front Panel (How the user interacts with the VI), Block Diagram (The code that controls the program) and Icon/Connector (Means of connecting a VI to other VIs). The Front Panel is used to interact with the user when the program is running. Users can control the program, change inputs and data updated in real time. Controls are used for inputs- adjusting a slide control to set an alarm value, turning a switch on or off, or stopping a program. Indicators are used as outputs. Every front panel control or indicator has a corresponding terminal on the block diagram. The block diagram (back panel) contains this graphical source code. Front panel objects appear as terminals on the block diagram. The block diagram contains functions and structures from built-in Lab VIEW virtual instrumentation libraries. Wires connect each of the nodes in the block diagram including control terminals, indicator terminals, functions and structures. Every VIs displays an icon in the upper right corner of the front panel and block diagram windows. An icon is a graphical representation of a VI. It contains text, images, or combination of both. SubVI's are also used for a VI. The icon indicates the subVI on the block diagram of the VI. The connector shows the terminals available for transfer data to and from the sub VI. Application software such as LabVIEW, LabWindows/CVI, Component Works and Measure deliver sophisticated display and analysis capabilities required for virtual instrumentation.

**LabVIEW:** LabVIEW (Laboratory Virtual Instrumentation Engineering Workbench) is a platform and development environment for a visual programming language from National Instruments. LabVIEW is a graphical programming language that uses icons instead of lines of text to create applications. In contrast to text-based programming languages, where instructions determine program execution, LabVIEW uses dataflow programming, where the flow of data determines execution. LabVIEW gives you the flexibility of a powerful programming language without the complexity of traditional development environments. LabVIEW is a graphical development environment with built-in functionality for simulation, data acquisition, instrument control, measurement analysis and data presentation.

**Drill Wear Model for Stainless Steel:** The drill wear model is developed based on cutting current signals using LabVIEW under varying cutting conditions in machining of stainless steel. The drill wear model consists of five stages. They are Analog pre processing, Digital pre processing, Feature extraction, Wear modeling and Decision integration. Analog pre-processing refers to process the raw data for digitization. It is a stage mainly determined by hardware applied to data collection. Digital pre-processing refers to filtering the screen out noise and other unwanted signals contained in digitized data and also to apply the analytical models to normalize the digitized data with regarding to varying cutting parameters. Feature extraction refers to extracting the meaningful information from digitized data which is used in subsequent wear modeling stage throughout the application. It also describe the total power level of a current signal in a given time interval at varying cutting conditions. Wear modeling refers to establish the dependency between extracted features and drill wear conditions through LabVIEW. The analog signals stored in appropriate format given in the drill wear model, the signal variation and tool replacement control are exposed through the selected format of graph in the drill wear model. Decision integration refers to integrate the outputs from drill wear models to reach a final decision regarding the tool condition. Figure 5a. is the part of the drill wear model. The nodes A and B are the connectors to the diagram given in Figure 5b.

The drill wear model shown in Figure 5b controls the drill wear monitoring system. The indicators on the front panel allow an operator to input data into or extract data from a running VI in drill wear monitoring system. Figure 5c. is also the part of the drill wear model. The nodes C and D are the connectors to the diagram given in Figure 5b. The indicators in Figure 5c used to measure and control the cutting current signals and to display.

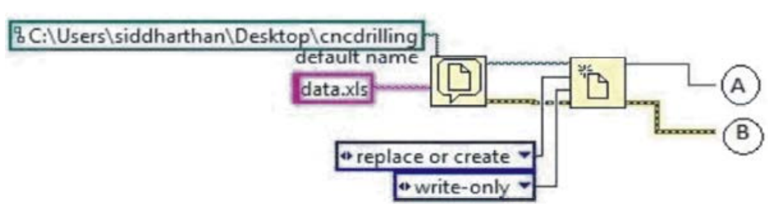


Fig. 5a: Part1 of Drill wear model for stainless steel

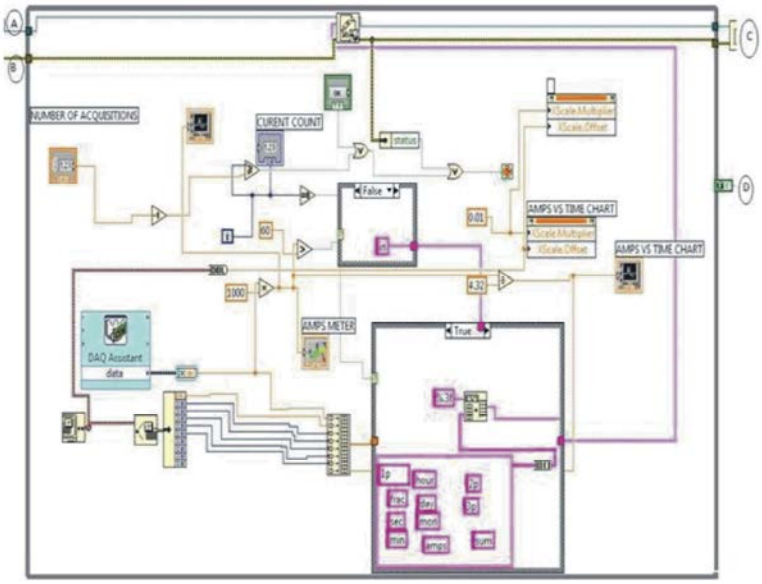

Fig. 5b: Part 2 of Drill wear model for stainless steel

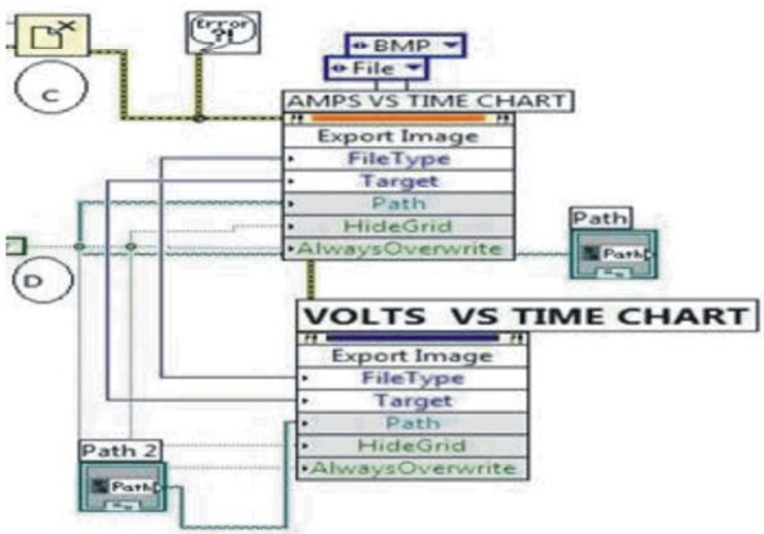


Fig. 5c: Part 3 of Drill wear model for stainless steel

**Experimental Results Analysis and Discussion:** A series of experiments carried out over a wide range of varying cutting conditions in machining of stainless steel by using conventional high speed steel tool are presented. Cutting tests were performed on a radial drilling machine. Initially, cutting parameter information (cutting current signal) is measured by a current sensor then it is changed to appropriate form which can be given as input into the data acquisition system. The current signals are measured as the AD converter output in mV and it is given to the on-line drill wear model. The modified output is given to drill wear model. The dynamic range signals are then modified as maximum accurate signals. It needs some preprocessing works such as removing unwanted signals, limiting the sensors spectrum etc. Additionally, analog signal processing (both linear and non linear) is used to alleviate the processing load in data acquisition system and the computer. The on-line drill wear model estimates the drill wear states from measured current signals and other varying cutting parameters. The results are obtained through drill wear model during machining of stainless steel which are developed in selected file form (digital values by table, analog values by graph) and displayed immediately. Table 2 shows the experimental

Table 2: Experimental results for Stainless steel

| Power(w) | Fraction | Sec | Min | Hrs | Day | Mon(Fn) | Current (A) | Drill wear | Mode of Control |
|---|---|---|---|---|---|---|---|---|---|
| 0.022 | 0.21 | 51 | 36 | 2 | 9 | 2 | 2.37 | 0.13 | in |
| 0.027 | 0.74 | 03 | 37 | 2 | 9 | 2 | 2.51 | 0.17 | in |
| 0.032 | 0.65 | 12 | 37 | 2 | 9 | 2 | 3.11 | 0.25 | in |
| 0.036 | 0.50 | 21 | 37 | 2 | 9 | 2 | 3.45 | 0.33 | in |
| 0.041 | 0.65 | 29 | 38 | 2 | 9 | 2 | 4.09 | 0.37 | in |
| 0.047 | 0.32 | 36 | 38 | 2 | 9 | 2 | 4.31 | 0.42 | out |
| 0.053 | 0.39 | 42 | 38 | 2 | 9 | 2 | 4.64 | 0.46 | out |
| 0.059 | 0.43 | 54 | 39 | 2 | 9 | 2 | 5.29 | 0.51 | out |
| 0.065 | 0.61 | 01 | 39 | 2 | 9 | 2 | 5.63 | 0.55 | out |

Fig. 6: Stainless steel plate with drill

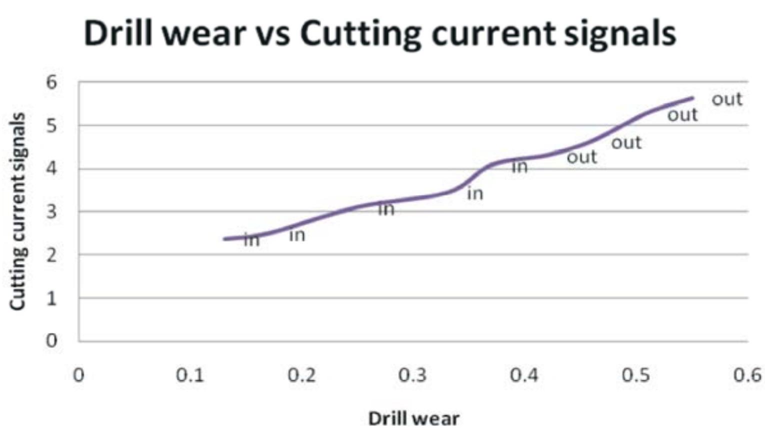


Fig. 7: Cutting current vs Drill wear

results of drill wear state for stainless steel under varying cutting conditions. The Figure 6 shows the sample holes were taken in stainless steel plate of storage tank. The values are taken during the steady state wear period. The time variables are given in the table since the drill wear model is for on-line. Based on the drill wear model the experimental result indicates the mode of control 'in' when the wear stage upto moderate. When the wear stage crosses the moderate it is specified as 'out'. Based on the mode of control the tool has to be replaced at the proper time.

Figure 7 shows the relationship between cutting current signals and the drill wear. In drilling it is possible to monitor current signals during machining. It is generally observed that the current amplitude increases as the drill wear increases, associated with the friction between tool and workpiece. It is expected that the cutting current fluctuates when the tool gradually wears. It is generally known that cutting forces increase through current signals as tool wear increases. This is due to the increase of friction between tool and work piece. In drilling it is possible to monitor current signals during

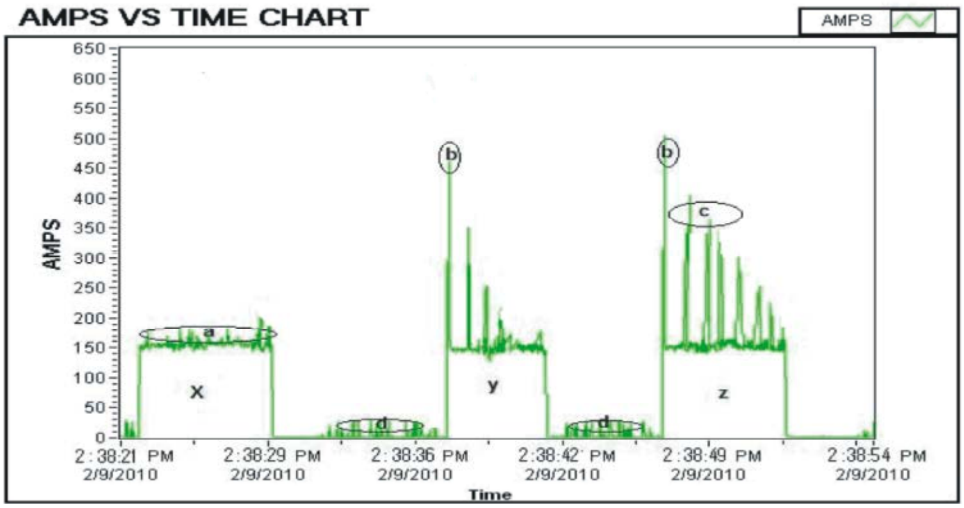


Fig. 8: Drill wear in HCHCr

machining. i.e., it is expected that the cutting current fluctuates when the tool gradually wears. Examining these results the following conclusions can be made: the drill wear states were estimated based on cutting current signals by using the virtual instrumentation method is on-line. This indicates that the method is very effective and simple for hole making industries. It is shown that the flank wear state can be more accurately estimated by using LabVIEW through cutting current signals than by using other indirect drill wear prediction methods (cutting force, vibration, torque, sound). So the new method of on-line drill wear state monitoring by virtual instrumentation provided more efficient than other methods in the field of manufacturing industries.

**Tool Replacement Control:** One of the main objectives of detecting the drill wear state is to obtain a basis for replacing tools. Based on the model, the drill wear states can be estimated from the knowledge of the cutting parameters and the cutting current signals. When the drill wear state is 'moderate', the alert has to be made and the state is 'ultimate', the tool has to be replaced. According to the wear state obtained, the decision about tool replacement can be made. Figure 8 shows the effect of drill wear on the sample by the spindle motor drive cutting current. The cutting current increases as drill wear increase with linear incremental relationship. The sample holes (X, Y, Z) are taken during the steady state wear period of stainless steel.

In Figure 8 'a' indicates minimal wear on the already drilled hole it also specifies some fluctuations of current signals and machine vibrations during machining. 'b' indicates initial thrust on the newly drilled hole and rest of the peaks in 'Y' indicates the moderate wear stages. 'd' indicates spindle rotation without producing any hole. 'c' indicates the maximum wear raise on the system so that the tool has to be replaced immediately.

## CONCLUSION

This paper describes a virtual instrumentation based model for an online drill wear monitoring system in a drilling of outlet in stainless steel storage tank. The effect of drill wear and varying cutting parameters are analyzed. The models regarding the relationship between the cutting current signals and drill wear for different drill wear stages are established through experimental study using virtual instrumentation with application of LabVIEW. The control of tool replacements requires the recognition of drill wear state associated with the cutting parameters including the cutting speed, feed and drill diameter. This work gives a simple and new method for on-line drill wear monitoring under the varying cutting conditions using virtual instrumentation. It is found that this method provides a convenient way to estimate the drill wear accurately using the cutting current signals. In On-line drill wear state monitoring, the different wear stages of stainless steel are exhibited effectively, so the defective tool has been replaced at the proper time in the automated manufacturing environment. Experimental results show that the method can be effectively employed in practice for manufacturing industries.

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