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Fault Diagnosis of Industrial Gear Hobbing Machine

Himanshu Vasnani, Neeraj Kumar

***Abstract**: The aim of this paper is to develop a fault diagnosis algorithm by vibrational analysis for an industrial gear hobbing machine. Gear Hobbing is the most dominant and profitable process for manufacturing high quality gears. In order to sustain the market competition gear manufacturers, need to produce high quality gears with minimum possible cost. However, catastrophic failures do occur in gear hobbing process which causes unexpected machine down time and revenue loss. These failures can be avoided by using condition monitoring approaches. In the proposed approach vibration data during different faults such as lubrication error, excessive feed rate, loose bearing error is collected from an industrial gear hobbing machine using three axis MEMS accelerometer. The collected data is analyzed and classified with spectral kurtosis and Dynamic Time Warping algorithm. The efficiency of the proposed approach is 90 percent as determined by experimental results. The proposed approach can provide a low-cost solution for predictive maintenance for gear hobbing industries..*

***Keywords** : Gear Hobbing ,Vibration Analysis, Fault Diagnosis.*

I. INTRODUCTION

The manufacturing processes determines the quality of the gears. One of the most beneficial and efficient process for manufacturing gears is gear hobbing. Improving the precision of gear hobbing processes has remained a primary and ever evolving research focus. Extensive studies have been conducted for identifying various errors such as Position Independent Geometric Error (PIGE)[1].An algorithm for identifying and classifying different types of geometrical error is demonstrated in [2] and a compensation method is also presented. Another concept of geometric error measurement and identification using Double Ball Bar (DBB)is demonstrated in [3].The analysis of geometric errors using servo systems is shown in [4].A study which reveals relationship between geometric error and geometric precision of gears can be found in [5].

The most common errors geometric errors that may occur during gear hobbing are pitch deviation and profile deviation.

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* Correspondence Author

Mr. Himanshu Vasnani*, Scholar (PhD, Mechanical) in Mechanical Engineering Department, Suresh Gyan Vihar University, Jaipur, Rajasthan India.

Dr. Neeraj Kumar, Professor, Department, Mechanical Engineering, Suresh Gyan Vihar University, Jaipur, Rajasthan India.

In pitch deviation the pitch of gear is non uniform across different teeth. Whereas in profile deviation the generated gear shows irregular teeth surface. Both of these errors are fatal for productivity and if not identified in good time, the entire batch may become useless or waste. This is because gears are used in applications which demands high precision such as in automobile gearbox[6]. It can be observed that much research attention is focused towards identification of the geometric errors and very few researches investigate the causes and control of theses errors.

Different condition monitoring approaches [7] can be used for this purpose. Thermal analysis, vibration monitoring, noise analysis, electrical signature analysis are some examples of condition monitoring approaches. The inclusion of condition monitoring approaches leads to shift from scheduled maintenance to predictive maintenance. In scheduled maintenance machines are diagnosed for faults at a pre-defined time period, whereas predictive maintenance employs a close loop system for continuous monitoring. The aim of predictive maintenance is identifying faults at an early stage , before they lead to failure and machine down time. The heat transfer pattern in form of generated heat during high speed gear hobbing process is shown in [8]. An effective mechanism to identify and compensate thermal error during gear hobbing is presented in [9]. Enormous amount of literature can be found for domains such as simulation and analytical modeling of gear hobbing, determining undeformed chip geometry and tool wear. However, literature related to condition monitoring of gear hobbing process is relatively scarce.

It can be concluded that the gear hobbing process which accounts for nearly half of all the gear fabrication processes has not gained much from the advances in condition monitoring techniques. In contrast to other gear manufacturing process such as milling, gear hobbing shows high degree of complexity due to long strokes in both entry and exit sessions. Additionally, gear hobbing process is multi parametric. A careful observation reveals that vibration analysis is the most suitable condition monitoring approach for gear hobbing.

Vibration analysis differentiates between a healthy machine condition and a faulty machine condition based on the acquired vibration data. Every machining operation with given parameters has unique vibration signatures. The onset of errors such as process deviation leads to change in the vibration signature leading to error identification. Vibration analysis is used in fault diagnosis of many rotatory machining processes.

A use case of vibration analysis for identifying faults in a gearbox is found in [10]. The application of vibration analysis for rolling element bearing is found in [11].The authors in [12] reviewed time domain feature extraction for diagnosing small roller bearing defects. The previous approaches for vibration analysis do not separate the gaussian noise from the vibration signatures acquired during machining. This leads to implementation difficulties in practical situations. The aim of this paper is to develop a vibration analysis system for industrial gear hobbing machine by Using Micro Electro Mechanical Systems [MEMS] technology. Data is collected in real time from an industrial gear hobbing machine. The collected data is analyzed with spectral kurtosis and Dynamic Time Warping algorithm to eliminate the gaussian noise. The rest of the paper is organized as follows Section II depicts the proposed methodology and sequence of operations in detail. Experimental Results are presented in Section III.

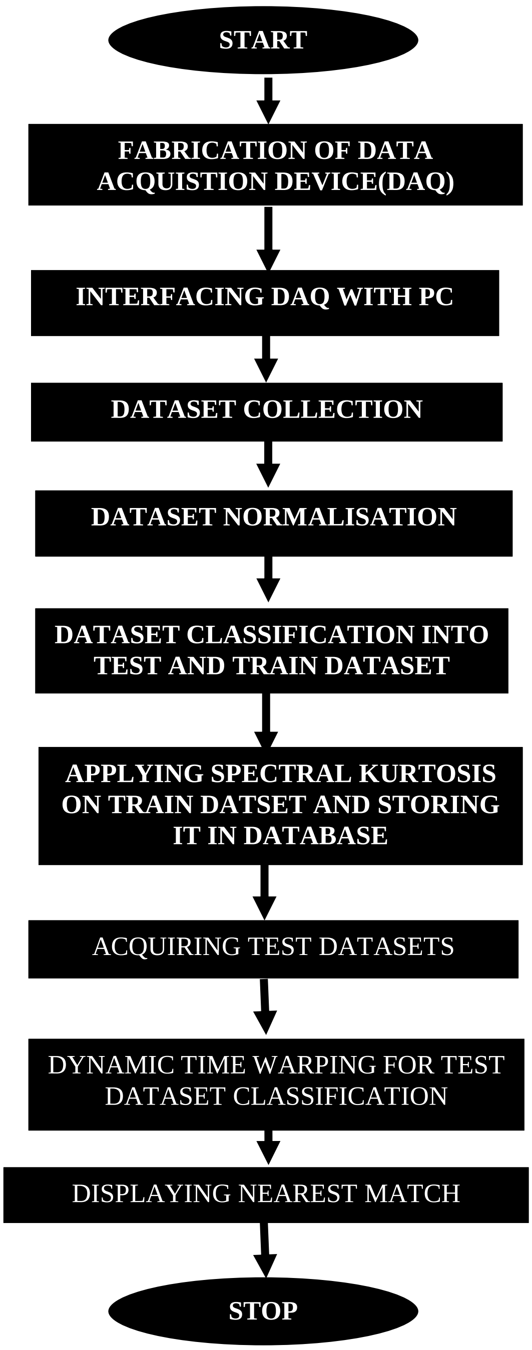

Fig 1:Process Flow for Fault Diagnosis of gear hobbing .

II. PROPOSED METHODOLOGY

The process flow is shown in Fig 1. Industrial problem related to gear hobbing process is identified as mentioned in section A. After problem identification a Data Acquisition Device (DAQ) is fabricated. The data collected by DAQ is analyzed by spectral kurtosis and Dynamic Time Warping Algorithms. A detailed description of these steps is mentioned in the following sub sections.

A.Problem Identification

Hob cutters are highly expensive due to their complex geometry. Thus, maximum utilization of hob tool's life is very essential. Capstan Meters, Jaipur reported recurring hob tool failures before fulfillment of expected life. The images of the failed hob tools are shown in Fig .2.

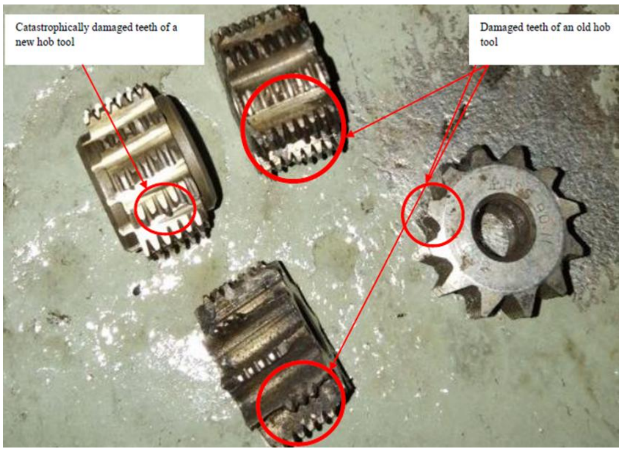

Fig 2: Images of the failed hob tools
[Source: Capstan Meters Pvt Ltd, Jaipur]

Fig 3: Industrial gear hobbing machine at Capstan Meters Pvt Ltd

Fig 4: Vibration Dataset Acquisition

B. Dataset Collection

Vibration data was collected from an industrial gear hobbling machine, present at Capstan Meters Pvt Ltd. The vibration data was collected by a fabricated device, which consisted of MEMS accelerometer and Arduino and is referred as Data Acquisition Device. The Data acquisition device was place at an appropriate position on machine as shown in Fig 3. The data was collected for normal and abnormal conditions and stored in computer. The normal conditions signified the ideal parameters required for machining whereas abnormal conditions included dataset obtained in case of presence of less lubrication error, Eccentricity of Work Piece shaft error, True Brinelling Error. The acquired data is stored in a computer for further analysis as shown in Fig 4. Fig 5 shows acquired dataset for a normal machining condition, machining with lubrication error and machining with Eccentricity of Work Piece shaft error. Fig 6-8 represents the vibration signatures for normal machining and machining with lubrication error in x, y and z axis.

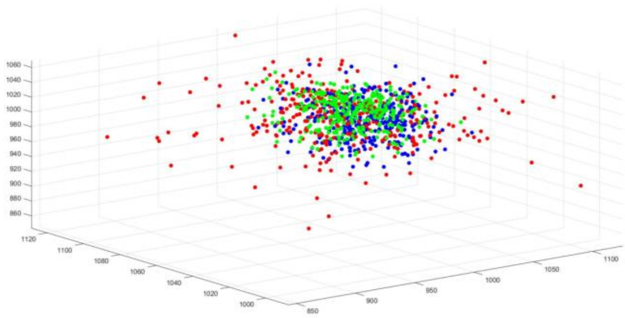

Fig 5: Acquired dataset for normal machining(blue), machining with lubrication error(green), Eccentricity of Work Piece shaft error(red)

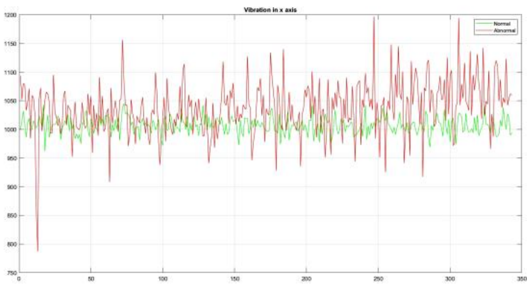

Fig 6: Vibration signatures for normal machining(green) and machining with lubrication error(red) in x axis

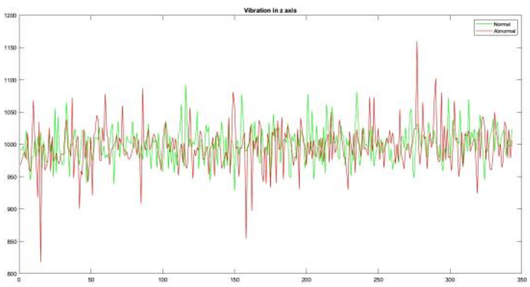

Fig 7: Vibration signatures for normal machining(green) and machining with lubrication error(red) in y axis

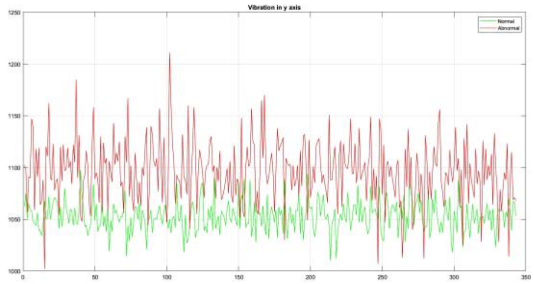

Fig 8: Vibration signatures for normal machining(green) and machining with lubrication error(red) in z axis

C. Dataset Normalization and classification

The acquired dataset is preprocessed and initial high vibration signatures are removed as they signify the starting of machine and is often accompanied by a sharp increase in vibration as shown in Fig 9. This may cause True Brinelling. The normalized data is split into training(60 percent) and testing dataset(40 percent).

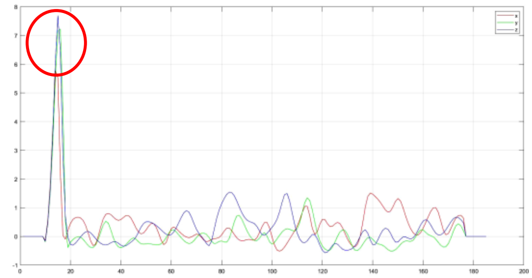

Fig9: Vibration peaks during machine start which may cause True Brinelling.

D. Spectral kurtosis

The conventional analysis techniques such as Power Spectrum Analysis are ineffective for fault identification during machining process. This is because Gaussian noise is always present in such processes and must not be confused with faults. To eliminate Gaussian nose from the normalized data Spectral Kurtosis is applied. The word 'Kurtosis' means ***peakedness***. Spectral Kurtosis is defined as a fourth-order spectral analysis tool for detecting and characterizing non stationarities in a signal. According to spectral kurtosis each signal is associated with an optimal frequency or frequency resolution at which maximum kurtosis is observed and the same must be detected.

The Spectral Kurtosis K(f) of a non-stationary process X(n),in presence of stationary additive noise b(n) is given in equation (1).

$$\boldsymbol{K_{x+b}(f) = \frac{K_{x+b}(f)}{1+p(f)^2}} \quad \text{.......................................(1)}$$

Where p(f) is noise-to-signal ratio. Thus, spectral kurtosis gives high value if noise to signal ratio is high. A detailed description of spectral kurtosis can be found in [13].Figure 10 and Figure 11 represents Spectral Kurtosis waveform for normal machining and machining with lubrication error in y and z axis.

When compared with Figure 7 and Figure 8 it can be observed that spectral kurtosis not only makes data analysis easier but also generates unique signature for each type of error.The spectral kurtosis of all training datasets is calculated and stored in database as unique signature.

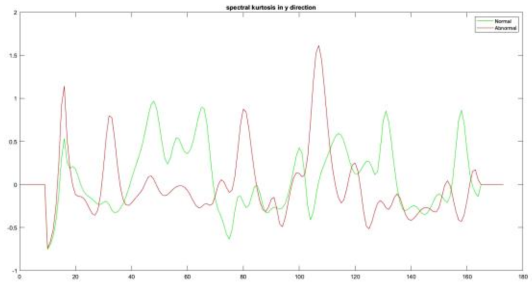

Fig10: Spectral Kurtosis waveform for normal machining(green) and machining with lubrication error(green) in y axis

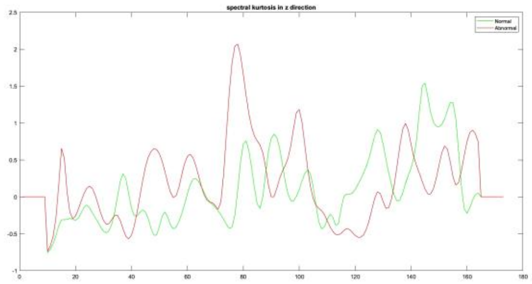

Fig11: Spectral Kurtosis waveform for normal machining(green) and machining with lubrication error(green) in z axis

E. Dynamic Time Warping

Dynamic Time Warping (DTW) Algorithm is used to calculate proximity between two vectors which vary either with time or speed. DTW is preferred over other algorithms such as Euclidian distance because DTW checks alignment between two signals by finding nearest match between the two vectors. Similar but out of phase signals produce large Euclidian distance but this problem is solved by DTW. The output of DTW between two vectors is the DTW distance which is calculated from Optimal Warping Path. A detailed description of DTW can be found in [14].

In our research the train vector is decided by the user. The acquired test vector during run time is compared with the train vectors present in the database. The length of both test and train vector is equal, m denotes this length. WP_x, WP_y, WP_z represents the Optimal Warping path with length K_x, K_y, K_z for spectral kurtosis signature x, y and z axis respectively between test and train vector. The Optimal Warping path denotes the best possible alignment between train and test vectors is evaluated by equations (2)-(4).

Here (g,f) represents any point within the accumulated distance matrix, ADM is Accumulated Distance Matrix of dimensions m*m. The ADM is formed by orchestrating test vector on top and train vector on left hand side of a m*m matrix.

For 0<=e<=K_x, 0<=e'<=K_y, 0<=e''<=K_z, e++, e'++, e''++.

$$WP_x\ (e) = \min\,[ADM_x\ (g,\ f), ADM_x\ (g,\ f\text{-}1),\ ADM_x\ (g\text{-}1,\ f), ADM_x\ (g\text{-}1,\ f\text{-}1)] \quad \ldots(2)$$

$$WP_y\ (e') = \min\,[ADM_y\ (g,\ f), ADM_y\ (g,\ f\text{-}1),\ ADM_y\ (g\text{-}1,\ f), ADM_y\ (g\text{-}1,\ f\text{-}1)] \quad \ldots\ (3)$$

$$WP_z\ (e'') = \min\,[ADM_z\ (g,\ f), ADM_z\ (g,\ f\text{-}1),\ ADM_z (g\text{-}1,\ f), ADM_z\ (g\text{-}1,\ f\text{-}1)] \quad \ldots\ (4)$$

III. EXPERIMENTAL RESULTS

The developed data analysis application is shown in Fig 12. The application is developed in MATLAB. The user can select any test case. Once the test case is selected the application calculates spectral kurtosis of the selected case and compares it with the signatures present in dataset by DTW. The identified case is the case with least DTW distance. The output window is shown in Figure 13 where abnormal signature 1 is correctly identified as Lubrication error. Table I represents the performance matrix by displaying error between actual case and identified case. The efficiency of the proposed approach is 90 percent.

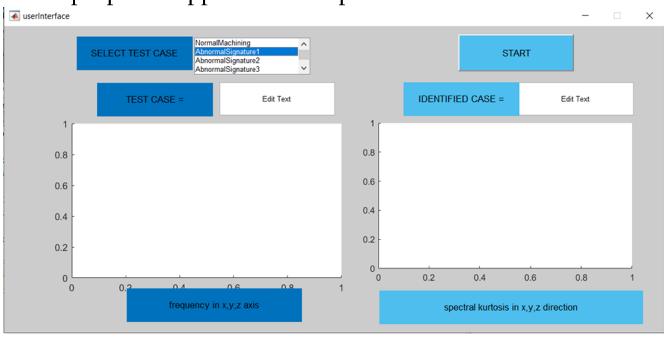

Fig12: Developed GUI in MATLAB

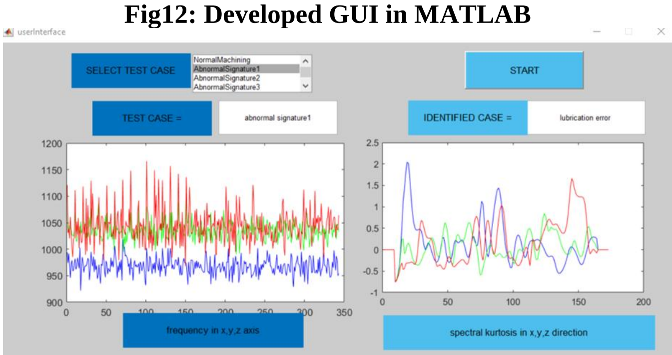

Fig13: Identification Result

Table I : Performance Matrix

SNO	TEST CASE	IDENTIFIED CASE	ACTUAL CASE
1	Normal Machining 1	Normal Machining	Normal Machining
2	Abnormal Signature 1	Lubrication error	Lubrication error
3	Abnormal Signature 2	Lubrication error	Lubrication error
4	Abnormal Signature 3	Lubrication error	Lubrication error

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5	Abnormal Signature 4	True Brinelling error	True Brinelling error
6	Normal Machining 3	Normal Machining	Normal Machining
7	Abnormal Signature 5	Eccentricity of Work Piece shaft error	Loose Bearing error
8	Abnormal Signature 6	Loose Bearing error	Eccentricity of Work Piece shaft error
9	Abnormal Signature 7	Excessive Feed Rate Error	Excessive Feed Rate Error
10	Normal Machining 4	Normal Machining	Normal Machining
11	Abnormal Signature 8	Eccentricity of Work Piece shaft error	Eccentricity of Work Piece shaft error
12	Abnormal Signature 1	True Brinelling error	True Brinelling error
13	Abnormal Signature 9	Lubrication error	Lubrication error
14	Abnormal Signature 10	Lubrication error	Lubrication error
15	Normal Machining 6	Normal Machining	Normal Machining
16	Abnormal Signature 7	Eccentricity of Work Piece shaft error	Eccentricity of Work Piece shaft error
17	Abnormal Signature 8	Eccentricity of Work Piece shaft error	Eccentricity of Work Piece shaft error
18	Abnormal Signature 9	Eccentricity of Work Piece shaft error	Eccentricity of Work Piece shaft error
19	Normal Machining1 0	Normal Machining	Normal Machining
20	Normal Machining 11	Normal Machining	Normal Machining

IV. CONCLUSION

Vibration analysis system for fault diagnosis for an industrial gear hobbing machine, using MEMS accelerometer is developed in this research. The vibration data is obtained by three axis MEMS accelerometer during normal and abnormal machining cases. The acquired data is firstly preprocessed by Spectral Kurtosis to remove noise and enhance peakedness of the acquired signal. The vibration signals are classified by Dynamic Time Warping algorithm. The developed system can identify different faults which may occur during gear hobbing process with 90 percent efficiency. The faults which can be identified using the presented approach are lubrication error and machining with Eccentricity of Work Piece shaft error.Spectral kurtosis and Dynamic Time Warping play a significant role in enhancing the efficiency of vibration data analysis. The efficiency can be further improved by advanced data analysis techniques such as machine learning.

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AUTHORS PROFILE

Mr. Himanshu Vasnani, Research Scholar (PhD, Mechanical) in Mechanical Engineering Department at Suresh Gyan Vihar University, Jaipur, Rajasthan India. He has interests in the field of Production Engineering and Dynamics of Machine. Total Number of Teaching Experience is approx 10 Years. He published one technical book and 12 research papers in various International and national Journals. email : himanshuvasnani1@gmail.com

Dr. Neeraj Kumar, he is presently working as Professor in Mechanical Engineering Department, Suresh Gyan Vihar University, Jaipur . His area of interest is Manufacturing System Engineering & Optimization Techniques. He has published 82 number of research papers inclusive 18 Scopus papers and has an experience of 15 years. email: Neeraj.kumar1@mygyanvihar.com