during grinding. Its severity increases with mill speed. Fifth octave problems can be solved by

A good amount of work has been done for chatter detection in rolling processes. In reference [1] T. Farley explains the phenomenon of third octave and fifth octave chatter observed in cold rolling mills and their causes. Some authors used theoretical approach to study chatter using simulations. The objective of these simulations is to find effects of various rolling parameters on the stable rolling limit. In [2] J. Tlusty explained third octave chatter in detail. Tandem mill was simulated to study the effect of rolling speed, strip width, friction coefficient, and tuned dampers on third octave chatter. Similarly, in [3] electric drive & control system parameter was investigated to find a stable rolling region in domain of electrical drive parameters.

According to some authors rolls, gears and other mill part vibration kinematics frequencies are a source of chatter generation. They stated that chatter marks on the roll and strip surface are the result of resonance in the mill due to an integer number of defect wavelength along the roll circumference. These models are represented in references [4, 5, 6]. In references [7, 8] contact friction and emulsion instability is considered as a source of vibrations. During the emulsion breakdown heat generated in metallic deformation is not properly dissipated. This heat energy is dissipated in the form of large vertical vibration amplitudes of work rolls in mill stand. Some authors [9, 10, 11] successfully investigated the roll grinding process influence on the strip chatter marks and mill vibration. They showed the exact relation between usually invisible roll surface defects after grinding and chatter vibrations in the rolling mill. Some companies supply passive & active vibration dampers that can be installed in mill stands to dissipate vibrations [12]. As reported by designers such devices allow increasing mill speed by 25-30%. However, some structural modification in required in a mill which is not always feasible. Some authors have used vibration measurement & analysis for chatter detection. At Arcelor Mardyck cold rolling mill, online chatter detection system is developed for third octave using vibration measurement at mill stands [13]. In reference [14] time varying kurtosis of vibration measurement is used for chatter detection.

Principal Component Analysis (PCA) can be used for differentiating healthy and unhealthy conditions by capturing small differences in the data set for two conditions. PCA is used in fault detection using vibration data in reference [15, 16].In present paper PCA is applied in vibration measurement for chatter detection.

2. PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a statistical tool for variables reduction and analysis. identifying faulty equipment by doing vibration measurement and analysis.

It is used to obtain a smaller number of artificial variables from the large number of observed variables that will account for most of the variations in observed variables in the data set. The number of artificial variables called principal components are less than or equal to original observed variables. The first component extracted in a principal component analysis accounts for a maximal amount of total variance in the observed variables. Under typical conditions, the first component will be correlated with at least some of the observed variables. The second component extracted will have two important characteristics. First, this component will account for a maximal amount of variance in the data set that was not accounted for by the first component. Again, under typical conditions, second component will be correlated with some of the observed variables that did not display strong correlations with component 1. The second characteristic of the second component is that it will be uncorrelated with the first component i.e. orthogonal. The remaining components that are extracted in the analysis, display the same two characteristics: each component accounts for a maximal amount of variance in the observed variables that was not accounted for by the preceding components, and is uncorrelated with all of the preceding components. PCA capture variables which have the highest impact on variance within the data set and this forms the basis of chatter detection.

This paper involves the use of two methods for chatter detection. First method uses Fast Fourier Transform (FFT) data for chatter detection. PCA is applied to distinguish FFT pattern between chatter and non-chatter condition. In second method 10 statistical parameters are calculated using high frequency raw vibration data. PCA is applied to these 10 parameters to distinguish between chatter and non-chatter condition.

3. DATA ACQUISITION

Accelerometers are installed on mill housing on Operator Side (OS) in mill Stand #2, #3, #4, # 5 as shown in Fig. 2. As sensor installed on stand#2 was giving small vibration amplitude, a sensor on stand #1 was not installed. For chatter detection, vibration measurement in Stand#3, #4, #5 is important. The vibration measurement is done at a sampling frequency of 10 KHz. The raw vibration data from sensors on mill stand are transmitted through fibre optic cable to controller PC in the control room. In controller PC raw data is processed & data are saved in database in the workstation. Workstation is connected to the Centralised Condition Monitoring System (CCMS) on which HMI (Web Application) is hosted for online chatter monitoring. See Fig. 3 for complete system architecture of chatter detection system.

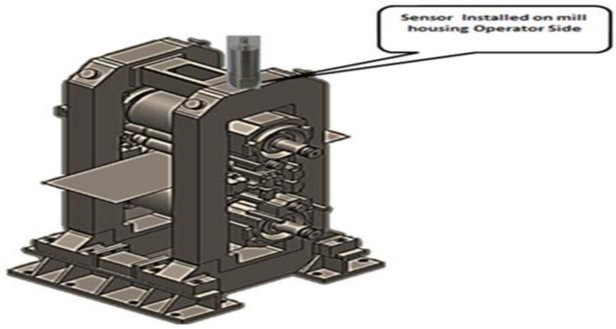

Fig. 2. Schematic diagram of sensor installation on mill stand

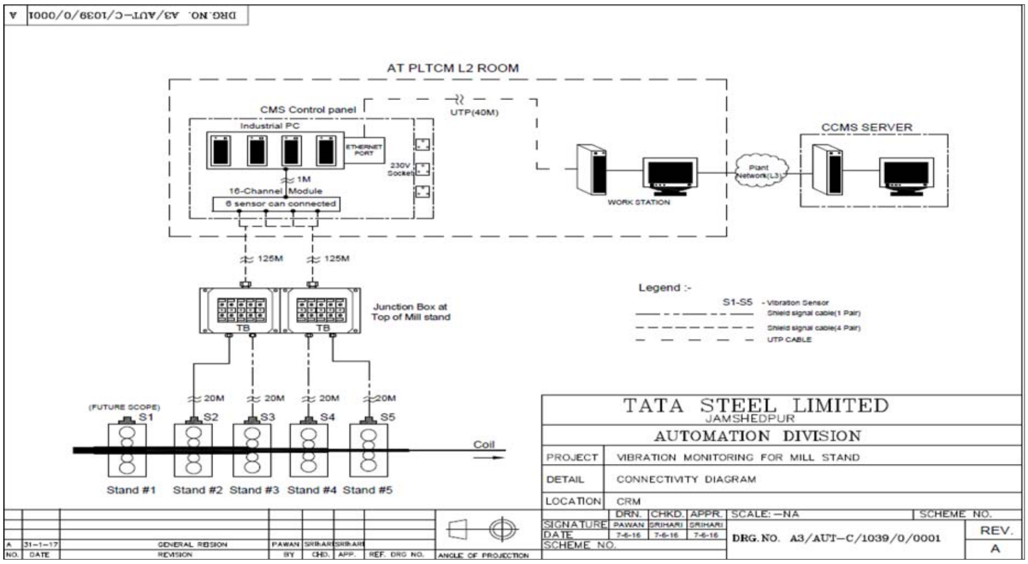

Fig. 3. Architecture of Chatter Detection System

4. CHATTER DETECTION

Two methods are used for chatter detection. First method uses FFT data for chatter detection while the second method uses 10 statistical parameters for chatter detection .PCA is used in both methods to distinguish between chatter and non-chatter condition. As chatter marks can come from any stand of mill each stand is investigated separately.

4.1. Chatter detection using FFT data

Raw vibration data is collected for 14 coils with chatter marks and 43 non-chatter coils for Stand#2, Stand#3, Stand#4, and Stand #5 at 10 KHz when the mill is running at constant speed. All the 57 coils are of similar grade and sections. FFT is performed on raw data using a Hanning window with frequency resolution of 1 Hz. Graph in Fig. 4 shows the frequency spectrum of chatter and non-chatter coil. Spikes with large amplitude are visible in range 0 – 20 Hz. Spikes are visible in different frequency ranges as shown in Fig. 4. No vibration is visible above 1300 Hz. Therefore, frequency range is limited from 0 Hz to 1300 Hz for analysis.

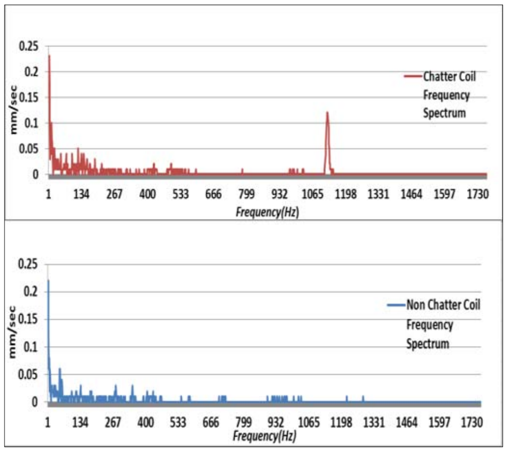

Fig. 4. Frequency spectrum of chatter and non- chatter coil

Applying PCA on 1300 variables gave a large number of Principal Components (PC). To simplify, 1300 variables are clubbed into 14 new variables by grouping based on frequency spectrum shown in Fig. 4. 14 new groups are formed by summing FFT amplitude in different frequency ranges as shown in Table 1. For example F20 is calculated by summing FFT amplitude in the frequency range 0 Hz to 20 Hz.

Table 1. Grouping of Variables

Variable Name	Range of Frequency
F20	0 Hz to 20 Hz
F100	21 Hz to 100 Hz
F200	101 Hz to 200 Hz
F300	201 Hz to 300 Hz
F400	301 Hz to 400 Hz
F500	401 Hz to 500 Hz
F600	501 Hz to 600 Hz
F700	601 Hz to 700 Hz
F800	701 Hz to 800 Hz
F900	801 Hz to 900 Hz
F1000	901 Hz to 1000 Hz
F1100	1001 Hz to 1100 Hz
F1200	1101 Hz to 1200 Hz
F1300	1201 Hz to 1300 Hz

After grouping FFT data of 43 non chatter coils in 14 variables, the data set is centered and PCA is applied. The Hotelling T^2 value is calculated using equation 1 to compare chatter and non-chatter coils.

$$T^2 = \frac{PC_1^{\ 2}}{\sigma_1^{\ 2}} + \frac{PC_2^{\ 2}}{\sigma_2^{\ 2}} + \frac{PC_3^{\ 2}}{\sigma_3^{\ 2}} \ldots\ldots + \frac{PC_n^{\ 2}}{\sigma_n^{\ 2}} \qquad (1)$$

where,
PC_1, PC_2, $PC_3 \ldots PC_n$ *are 1, 2, 3…n principal components respectively.*
σ_1, σ_2, σ_3 … σ_n *are standard deviation of 1,2,3..n principal components respectively.*

Table 2 shows 10 principal components (PC_1, PC_2, PC_3 , PC_4, PC_5, PC_6 , PC_7, PC_8, PC_9 ,PC_{10}) derived from 43 non-chatter coils FFT data for Stand#5.Variables F20, F100, F200 etc. are described in Table 1. Top 6 principal components are taken in Hoteling T^2 score calculations as it covers 90 % of the variance. The Hotelling T^2 score is calculated for each 43 non-chatter coils. For comparison data set of chatter coils is centered by subtracting each variable of every coil (14 chatter coils) by mean of the corresponding variable (F20, F100, F200...) of non–chatter coils. After this Hotelling T^2 scores for 14 chatter coils is calculated. The comparison is shown in Fig. 5 for non-chatter and chatter coils for Stand#5.In graph shown in Fig. 5 Coil1 to Coil43 are non -chatter coils (green diamonds), Coil44 to Coil57 (red squares) are chatter coils. For better visualization and comparison logarithmic scale is used. Similar comparison is shown in Fig. 6 for Stand#4.

The graph is Fig. 5 clearly distinguishes between chatter and non-chatter coils for Stand#5.For Stand#4 in Fig. 6 there in no such distinction between chatter and non-chatter coils. For Stand#3 and Stand#2 results are similar to Stand#4 and not shown here. Generally in PLTCM, chatter comes from Stand#4 or Stand#5.This shows that for these 14 coils chatter marks are generated in Stand#5.

Table 2. PC of Non-Chatter coils for Stand#5 derived from FFT data

Principal Components	Description
PC_1	0.353*(F100)+0.324*(F600)+0.314*(F200)+ 0.304*(F1300)+0.299*(F300)
PC_2	-0.491*(F1100) - 0.433*(F500) + 0.415 * (F800) - 0.343*(F1200) + 0.336*(F700)
PC_3	0.496*(F900)+0.446*(F400)+0.376*(F200) - 0.371*(F1200)-0.345*(F700)
PC_4	0.561*(F1000)+0.423*(F800)-0.403*(F600) - 0.315*(F900)-0.256*(F1300)
PC_5	-0.573*(F900)-0.483*(F1000) + 0.349* (F1100) - 0.343*(F1200)+ 0.288*(F1300)
PC_6	0.616*(F1100)-0.442*(F300) + 0.345 * (F900) - 0.338 *(F20) - 0.275*(F200)
PC_7	0.723*(F20)-0.401*(F1200)-0.295*(F200)- 0.266*(F400)+0.228*(F1100)
PC_8	-0.515*(F1200)+0.467*(F1000)-0.46*(F20) +0.327*(F300) - 0.26*(F400)
PC_9	-0.542*(F1300)-0.504*(F500)+ 0.368* (F700) + 0.362*(F200) + 0.221* (F1100)
PC_{10}	-0.622*(F100)+0.4*(F1300)+ 0.356*(F200) +0.338*(F700)-0.338*F600

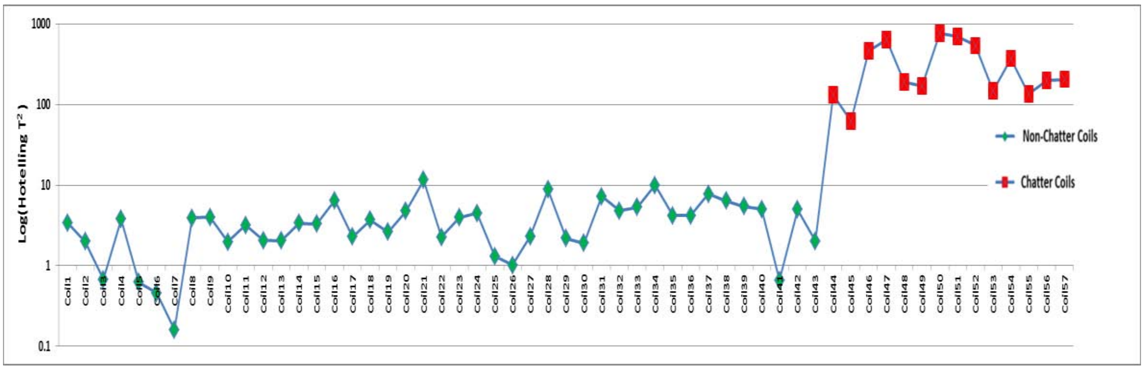

Fig. 5. Comparison between non-chatter and chatter coils for Stand#5 using FFT data

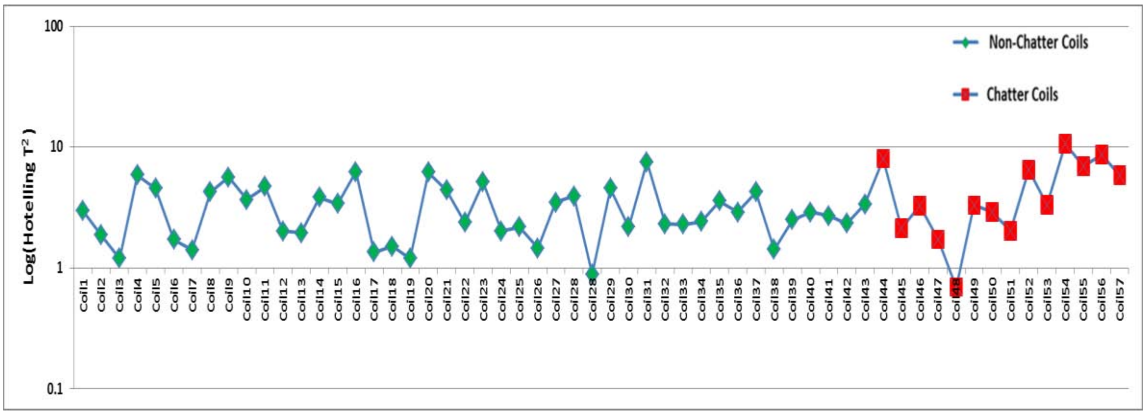

Fig. 6. Comparison between non-chatter and chatter coils for Stand#4 using FFT data

4.2 Chatter detection using Statistical Parameters

Raw vibration data is collected for 14 chatter coils and 43 non-chatter coils for Stand#2, Stand#3, Stand#4, and Stand #5 at 10 KHz when the mill is running at constant speed.The raw data is filtered using Butterworth fourth order low pass filter with cutoff frequency of 1300 Hz. One second raw vibration data is used to calculate 10 parameters, as given in Table 3. It is made sure that when the sample is taken mill is steady and running at top speed. This is done to capture steady state condition and avoid any transient.

Table 3. List of Statistical Parameters

S. No.	Parameter	Description
1	RMS	Root Mean Square
2	Kurt	Kurtosis
3	Skew	Skewness
4	Mean	Mean
5	Stdev	Standard Deviation
6	Var	Variance
7	Med	Median
8	Mod	Mode
9	P2RMS	Peak to RMS
10	P2P	Peak to Peak

PCA is applied to these 10 parameters for 43 non- chatter coils. Table 4 shows four principal components ((PC_1, PC_2, PC_3 , PC_4) derived for stand#5. Top 3 principal components (PC_1, PC_2, and PC_3) are taken in Hoteling T^2 score calculations as it covers 90 % of the variation. The Hotelling T^2 score is calculated for each 43 non- chatter coils. For comparison data set of chatter coils is centered by subtracting each variable of every coil (14 chatter coils) by mean of the corresponding variable (RMS, Kurt, Skew ...) of non–chatter coils. After this Hotelling T^2 scores for 14 chatter coils is calculated. Fig. 7 shows 3D plot of chatter and non-chatters along PC_1, PC_2, and PC_3 axis for Stand#5. Also Hotelling T^2 score comparison is shown in Fig. 8 for non-chatter and chatter coils for Stand#5. Similar comparison is shown in Fig. 9 for Stand#4.

The graph is Fig. 7 and Fig. 8 clearly differentiate between chatter and non-chatter coils for Stand#5. For Stand#4 there in no such distinction between chatter and non-chatter coils shown in Fig. 9. This shows that chatter in these 14 coils is generated in Stand #5. For Stand#3 and Stand#2 results are similar to Stand#4 and not shown here.

Table 4. PC of Non-Chatter coils for Stand#5 derived from Statistical Parameters

Parameter	Description
PC_1	0.398*Stdev + 0.398*RMS + 0.395*Mod + 0.393*P2P + 0.385*Var
PC_2	0.502*P2RMS + 0.489*Kurt+0.486*Med + 0.451*Mean- 0.158*Skew
PC_3	-0.519*Med -0.493*Mean + 0.471*Kurt + 0.435*P2RMS - 0.147*Var
PC_4	-0.916*Skew - 0.236*Mean - 0.136*Var- 0.131*Kurt

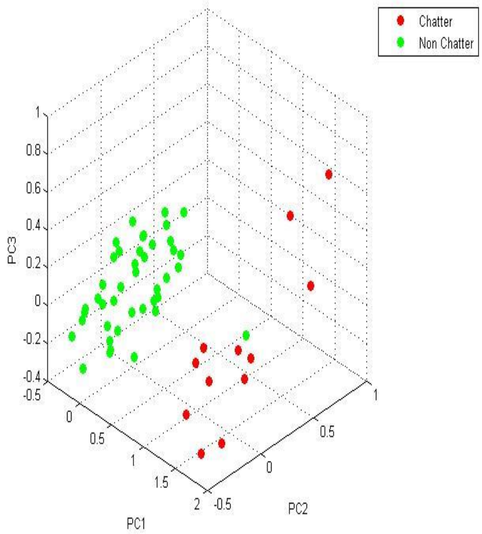

Fig. 7. 3D plot of chatter and non-chatter coils for Stand#5

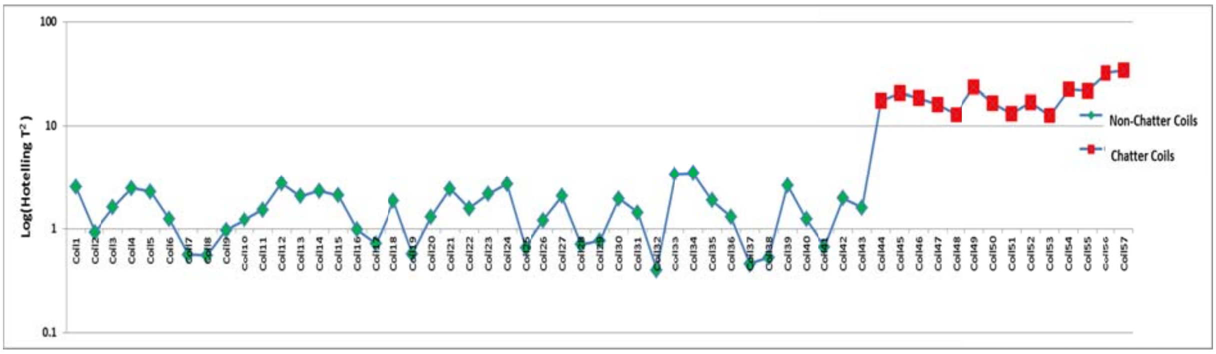

Fig. 8. Comparison between non-chatter and chatter coils for Stand#5 using statistical parameters

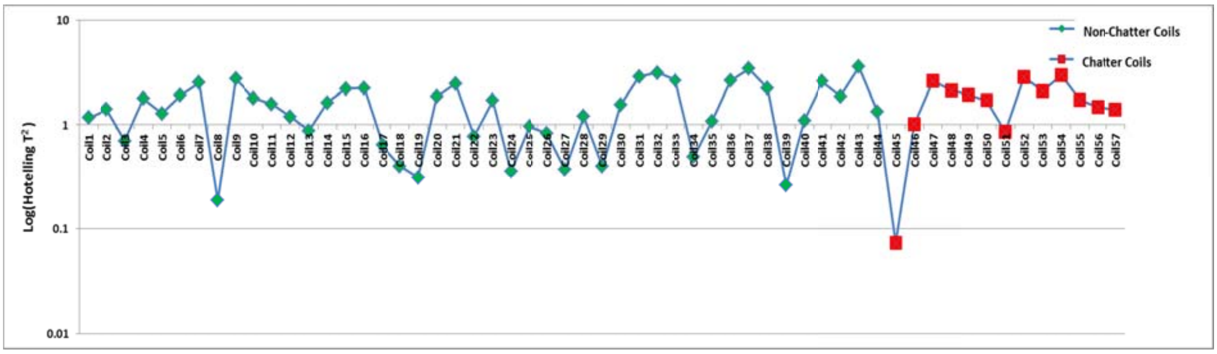

Fig. 9. Comparison between non-chatter and chatter coils for Stand#4 statistical parameters

10 parameters are separately checked for chatter detection for Stand#5. Out of these 10 parameters Root Mean Square (RMS), Standard Deviation, Variance, Peak to Peak is distinguishing between chatter and non-chatter coils as shown in Fig. 10.

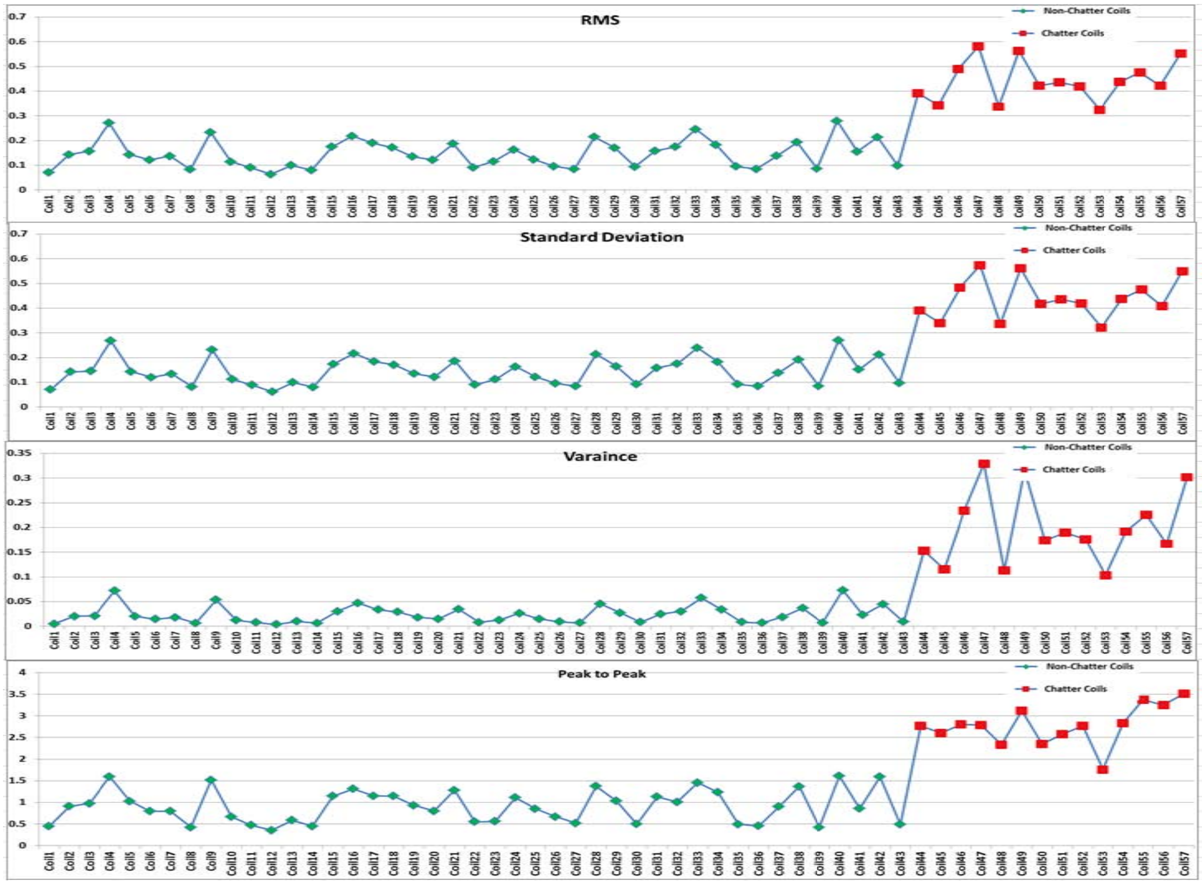

Fig. 10. Chatter detection using RMS, Standard Deviation, Variance, Peak to Peak

5. RESULTS & DISCUSSIONS

This work presents two algorithms using PCA for chatter detection in cold rolled coils. The graph is Fig. 5 clearly distinguishes between chatter and non-chatter coils for Stand#5 when PCA is applied to FFT data. Similarly, graph in Fig. 7 and Fig.8 clearly differentiate between chatter and non-chatter coils for Stand#5 when PCA is applied on 10 statistical parameters calculated from raw data. However, differentiation between chatter and non-chatter coils is better for FFT data method compared to the statistical parameter method.

Graph in Fig. 10 shows Root Mean Square (RMS), Standard Deviation, Variance, Peak to Peak is distinguishing between chatter and non-chatter coils. RMS is widely used in vibration monitoring. Author in reference [14] used kurtosis for chatter detection, but for these 57 coils kurtosis is not able to distinguish between chatter and non-chatter coils as shown in Fig. 11. Mean plot in Fig. 11 is close to zero and not zero as vibration is not purely sinusoidal.

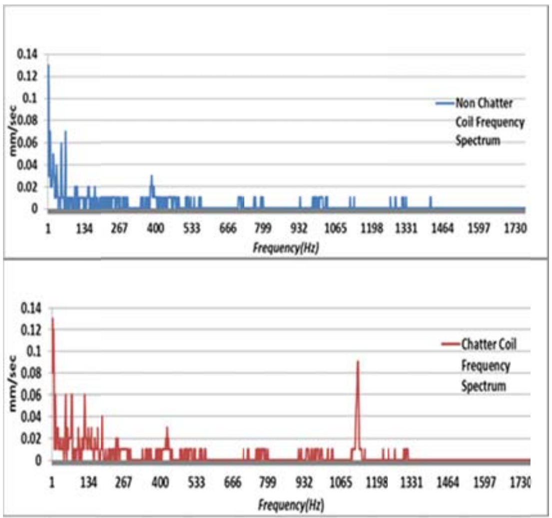

Fig. 12. Frequency spectrum of chatter and non-chatter coil for comparing results

Graph in Fig. 12 shows an example where these two methods are successful while RMS and kurtosis fails to detect chatter. Graph in Fig. 12 shows the frequency spectrum of non-chatter and chatter coils which are very similar. Table 5 shows the analysis results - Hotelling T^2 scores for FFT method, Hotelling T^2 scores for statistical parameter method, RMS, kurtosis for chatter and non-chatter coil. Two methods suggested in this paper are able to clearly distinguish between chatter and non-chatter coil. PCA captures small variations in data set for chatter and non-chatter coil. Appropriate filter range can be calculated and applied using chatter pitch length and mill speed before calculating RMS to catch chatter. However, determining threshold value of RMS for chatter start is difficult. Two methods suggested have an appreciable difference in Hotelling T^2 scores while RMS and kurtosis are nearly same for chatter and non-chatter case.

Table 5. Comparison of Results

Results	Chatter coil	Non-Chatter Coil
Hotelling T2 scores for FFT method	503.10	64.38
Hotelling T2 scores for Statistical Parameter method	15.65	3.88
RMS(mm/sec)	0.31	0.32
Kurtosis	2.95	2.90

6. CONCLUSIONS

This work proposes two approaches to detect chatter in cold rolling mill using a statistical technique called Principal Component Analysis (PCA). First method uses Fast Fourier Transform (FFT) data while the second method uses statistical parameters calculated from raw vibration data to detect chatter. PCA is applied to capture small variation in the data set during normal and chatter conditions. Both methods are able to capture chatter accurately and give better results than monitoring single statistical parameters like RMS, kurtosis etc. This will help in improving product quality and productivity of the mill.

Acknowledgements

The authors acknowledge the help extended by Mr. Vinod Kumar & Mr U.S Patnaik of Tata Steel for the help in installing sensors in mill stands .We would like to thank the management of Tata Steel for their kind permission.

REFERENCES

1. Farley T, Rogers S, Nardini D. Understanding Mill Vibration Phenomena. Innoval Technology Limited, 2008.
2. Tlusty J, Chandra G, Critchley S, Paton D. Chatter in cold rolling. CIRP, 1982; 31(1):195-199.
3. Klepikov VB. On a frictional auto-vibrations in the electrical drives. Electricity Journal, 1986; 4: 54-62.
4. Gasparic JJ. Vibration analysis identifies the cause of mill chatter. AISE Year Book, 1991;1: 27–29.
5. Bollinger LA, Rapsinski TA. Winding reel involvement in temper mill chatter. Iron and Steel Eng., 1994; 71(12): 27-29.
6. Nesseler GL, Cory JF. Cause and solution of fifth octave backup roll chatter on 4-h cold mills and temper mills. Iron and Steel Eng., 1989; 10:23-27.
7. Pimenov VA. On the causes of non stable cold rolling. Izvestiya VUZov. Chornaia Metallurgy ,1990; 8: 36-38.
8. Yarita I, Furukawa K, Seino Y. An analysis of chattering in cold rolling for ultra-thin gauge steel strip. Trans. of the Iron and Steel Inst. of Japan, 1978; 18(1): 1-11.

9. Hardwick BR. Identification and solution of chatter vibration on roll grinding machine. Iron and Steel Eng., 1994; 71(7): 41-46.
10. Hardwick BR. A technique for the detection and measurement of chatter marks on rolls surfaces. Steel Technology, 2003; 4: 64-70.
11. Benhafsi Y. The use of vibration analysis tools to solve chatter problems on rolling mills and roll grinding machines. Proc. of Steel Rolling 2006, the 9th International and 4th European Conference, France, 2006.
12. Holl J, Schlacher K. Analysis and active rejection of chatter in rolling mills. Proc. App. Math. Mech., 2003; 3: 134-135.
13. Petit B, Decrequy D. Global approach of 3rd octave chatter vibrations at Arcelor Mardyck cold rolling mill and analysis of technological interactions. ATS International Steel Making Conference, Paris, December 9-10, 2004.
14. Shao Y, Deng X. Characteristic recognition of chatter mark vibration in a rolling mill based on the non-dimensional parameters of the vibration signal. Journal Of Mechanical Science And Technology, 2014; 28(6):2075-2080.
15. Ahmed M, Baqqar M, Gu F, Ball AD. Fault detection and diagnosis using Principal Component Analysis of vibration data from a reciprocating compressor. Proceedings of 2012 UKACC International Conference on Control, p.461-466. 10.1109/CONTROL.2012.6334674
16. Plante T, Stanley L, Nejadpak A, Yang CX. Rotating machine fault detection using principal component analysis of vibration signal. IEEE AUTOTESTCON, 2016, p.1-7. 10.1109/AUTEST.2016.7589634

Received 2017-10-29
Accepted 2018-01-02
Available online 2018-01-03

Najmul Islam USMANI has a Master's degree in Electrical Engineering. Presently working in Tata Steel as Senior Technologist. Works in area of cold rolling & continuous annealing. Area of interest includes mathematical model-ling, process optimization, data analytics, instrumentation and control.

Sanjeev KUMAR is presently working in Tata Steel as Principal Technologist. Works in area of hot strip mill and reheating furnace. Area of interest includes mathematical modelling, data analytics, instrumentation and control.

Srihari VELISATTI has a Master's degree in Electrical Engineering. Presently working in Tata Steel as Senior Technologist. Works in area of crane automation, sensor development, instru-mentation and control.

Prabhat Kumar TIWARI is presently working as Head System Integration group in Tata Steel. Area of interest includes robotics, sensor development, data analytics and digitalisation.

Susanta Kumar MISHRA is presently working as Head Mills group in Tata Steel. Area of interest includes mobile app development, software application development, and data analytics.

Uma Shankar PATNAIK is presently working as Head Process PLTCM in Tata Steel. Area of interest includes cold rolling process, digitalisation, and data analytics.