A Review on Condition Monitoring Technologies for Railway Rolling Stock

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ABSTRACT

In recent years, considerable research has been carried out to improve the safety of the railways. Much of the research has been in the area of development of sensors to capture health of the railway equipment. So far, no comprehensive review of literature has been carried out for condition monitoring of the railways. Most of the accidents in the railways are due to wheel and bearing failures, which cause derailment of the train. The present paper gives a comprehensive review of the sensors available for assessing the health of these components. Wayside sensing technology is found to be more popular compared to the on-board sensing technology because of economic modeling of damage. Comparative analyses of various sensing technologies have been performed to understand their usefulness for estimation of a particular fault. The paper also summarizes different diagnostic tools used for fault identification of the component such as wheel and bearing. Case studies are included to show the usefulness of condition monitoring technologies for fault identification in railways.

1. INTRODUCTION

Railway is the largest man made transportation networks in the world and plays a vital role in driving economic growth of any country. With time rail transport in terms of passenger and freight is getting busier. Previously reported accidents show that the safety on the railway is still a matter of serious concern. According to the report of Ministry of Railways, Government of India (2012), in 2011, the derailment of Kalka mail caused the death of 71 passengers and injuries to 264 passengers. Figure 1 shows the number of casualties during 2006-2017 reported in India because of the rail accidents.

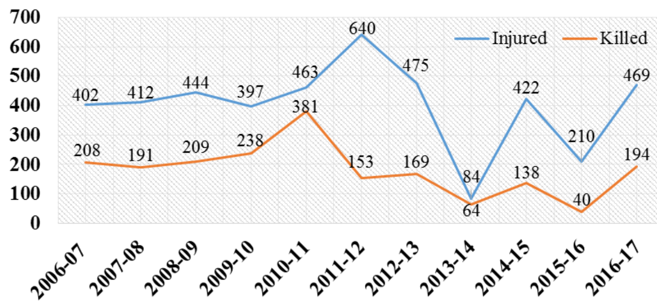


Figure 1. Number of casualties reported in railway accidents in India from 2006-2017 (the report (Ministry of Railways, Government of India, 2012); list of Indian rail accidents, 2018)

Globally, railways followed the preventive maintenance: equipment is opened at a fixed interval of time irrespective of component condition. Generally, non-destructive testing (NDT) based inspections are used which are costly, less efficient and time consumable. Sometimes they may not detect the defect, which may lead to catastrophic failures (Hong, Wang, Su, and Cheng, 2014). Another major drawback is that the train has to be stationary during the inspection. Nowadays, condition based maintenance (CBM) is preferred as it gives real time and in-service measurements of the railway components. With this technology, the faults can be detected while on the run. This procedure makes maintenance faster and increases the availability of the number of wagons/coaches for operation. It can identify the defect on any of the components, which otherwise would be opened during scheduled maintenance interval. For example, south-eastern railway replaced 160 bearings due to reported noise over a period of 2011-2013, while their service life had not expired (Symonds, Corni, Wood, Wasenczuk and Vincent et al., 2015). This shows the importance of CBM in railway where the fault was detected at an early stage and was repaired at the earliest opportunity (Zhang, 2011).

Many types of failure may take place during the train service but few of them only effect the train operation. Figure 2 shows the number of railway accidents reported across the 23 countries over the past few years. The data shows that 37% of the accidents are because of rolling stock. Out of these 37% accidents, almost 60% are because of wheel set failure.

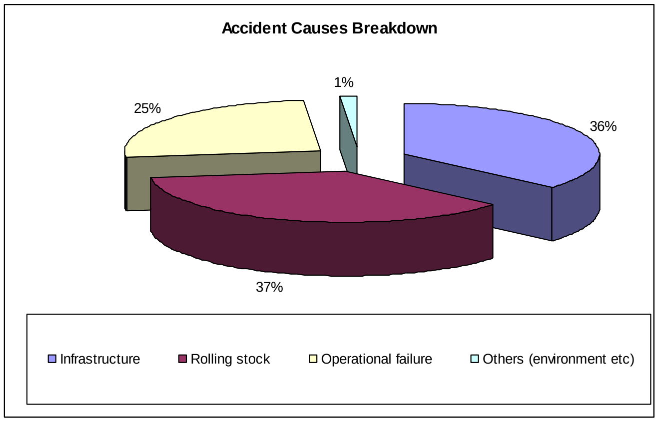


Figure 2. Railway accidents considered in the D-RAIL FP7 project by cause (Papaelias, Huang, Amini, Vallely, Day, Sharma, and Kerkyras, 2014; Andersen, 2011)

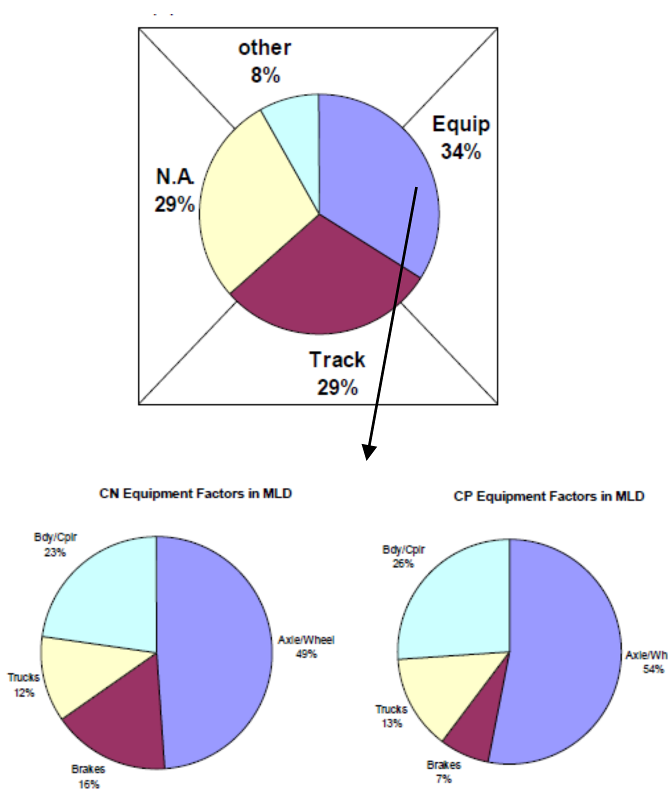


Figure 3. Canadian mainline derailments (MLD) by reported cause (Moynihan & English, 2007)

Figure 3 shows the reported number of accidents in Canada from 1999-2006. Majority of failures are because of axle/wheel (49 % out of 34% equipment failure in the overall in Canadian National (CN) Railway, and 54 % out of 34% equipment failure in the overall in Canadian Pacific (CP) Railway). Figure 4 shows the number of failures in Indian Railways during 2009-2014. Rolling stocks have a major impact on the train operations and are responsible for more than 35% of the total train failures. In Iran, 76.34 % of railway equipment failure was found because of the wheel set failure based on the failure history data from 2001-2004 provided by Raja train company of Iran (Rezvanizaniani, Barabady, Valibeigloo, Asghari, and Kumar, 2009).

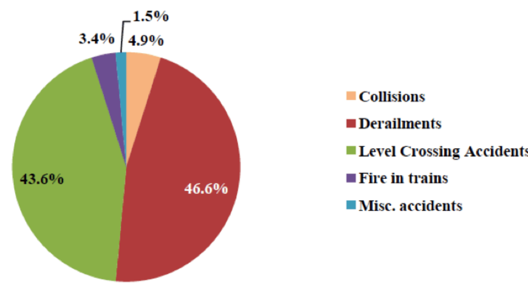


Figure 4. Percentages of railway accidents by type (India) (the report (Indian Railway Accidents Statistics, 2014))

Most of the accidents in the railways are due to rolling stock failure. The present paper also focuses on the causes of failure and available sensor's technologies for monitoring the failure of the rolling stock. Different types of failures reported in the rolling stock are shown in Figure 5.

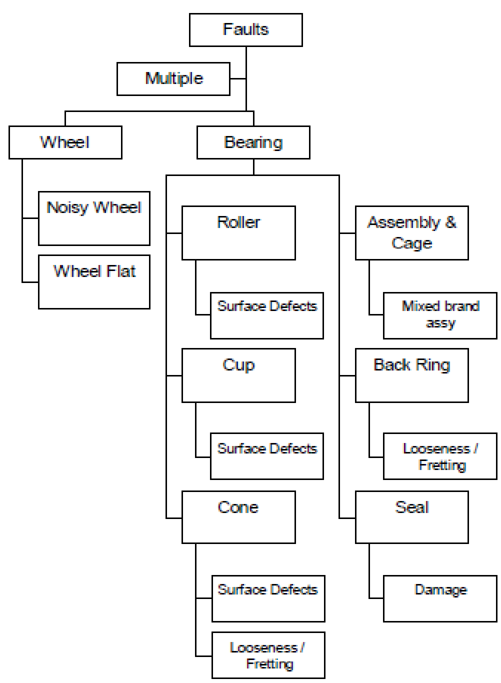


Figure 5. Bearing and wheel fault hierarchy (Southern, Rennison, and Kopke, 2004)

Table 1 shows the rolling stock related failure reported across the 23 countries over the past few years. Wheels account for 19 % failures while 41% are because of axle failures in which majority are caused due to faulty bearing (Papaelias et al., 2014; Andersen, 2011).

Table 1. Rolling stock related accidents in the D-RAIL FP7 project by cause.

Failure type	Failure frequency
Axles	41 %
Wheels	19 %
Bogie Suspension and Structure	22 %
Others and Unknown	18 %

Table 2 shows the rolling tock failure data from 2001-2004 provided by the Raja train company of Iran. In Iran also, 40.70 % failure was reported because of axle bearing and 19.56 % failure was reported because of wheels (Rezvanizaniani et al., 2009).

Table 2. Rolling stock related accidents in Iran from 2001-2004.

Failure type	Failure frequency
Axle Bearing	40.70 %
Wheels	19.56 %
Tyre Corrosion	16.08 %
Bogie Suspension and Structure	9.15 %
Others and Unknown	14.51 %

In order to reduce the unplanned failures, operation and maintenance costs, increase reliability and availability of the rail vehicles, the maintenance strategy is now shifting from preventive maintenance to predictive/condition based maintenance. Both wayside and onboard sensing technology are available for the rail vehicle components failure diagnosis. Different types of sensors such as temperature, vibration, acoustic, laser, ultrasonic, and force are used either wayside or onboard for diagnosing the axle bearing failure, wheel flatness, and wheel profile. The description of these sensing technologies and various diagnostic tools for the railway equipment fault identification is discussed in the section 2. Section 3 presents a comparison between available sensing technologies. Section 4 highlights the benefits of using CM technologies in railway. Finally, conclusions are presented in section 5 along with an overview of possible future research challenges.

2. SURVEY OF THE EXISTING ONLINE CONDITION MONITORING TOOLS

The condition based maintenance (CBM) program consists of three steps: data acquisition, data processing and maintenance decision-making (Jardin, Lin, and Banjevic, 2006). The maintenance decision can be made on-line based on the trend present in data. However, it is impossible to make the decision based on the trend every time, as the data obtained from the sensors are associated with noise. Advanced signal processing algorithms are used to process the data and extract the useful information. After suitable signal processing, diagnosis and prognosis algorithms are used for classifying and predicting the fault respectively. Diagnosis will detect the presence of the fault, whereas prognosis will predict when the fault is likely to occur. The next sub-section will discuss these aspects with case studies.

The sensors used in the condition monitoring of rail stock can be either wayside or on-board. Both the technologies have the unique advantages and disadvantages which are explained hereunder.

(a) Wayside sensing technology

The wayside monitoring system is installed in or next to the track. It is divided into two categories: reactive and predictive. Reactive systems detect faults on the railway vehicles and don't provide any trending information. Examples of such systems are the hot box and hot wheel detector and wheel impact load detectors (WILD). Predictive systems can predict the possible faults that may occur. It can measure, record and trend the ride performance of the specific components. Acoustic emission detectors and wheel profile detector are the examples of such kind of detectors (Papaelias et al., 2014; Lagnebäck, 2007). The benefit of Wayside technology is that once it is installed it will measure the health of all the trains passing over that rail. But in wayside technology, noise and various interferences also get recorded along with the data, thereby making fault estimation difficult. The use of advanced signal processing algorithm can overcome this problem.

(b) On-board sensing technology

In this technology, the CM sensors are mounted on the bogie. Their location depends on specific applications. This technology improves the quality and efficiency of the fault diagnosis because the sensor measurements are from the direct mechanical path. This eliminates the effect of surrounding noise and other environmental factors (Zhang, 2011). The major drawback of this technology is that sensors need to be installed on each wheel of the bogie, thus considerably increasing the cost of the system.

Figure 6 shows the architecture for wayside and on-board health monitoring of the railway. Using both the sensing technologies, the signal from chosen components or systems is captured in real time. From the rail vehicle, the data will be transferred to the server room either by using GSM technique or wirelessly. From the sever room, through internet cloud, it can be sent to the control room for signal visualization. In the control room, an intelligent system can be installed which is capable of diagnose and predict the rail vehicle components life based on the approaches such as neural networks, fuzzy logic, expert systems, wavelet, empirical mode decomposition, etc. The intelligent installed in the control room should be programmed and capable of answer the questions such as in which component or systems faults exist, cause of failure, how much time component/system can survive based on the current condition of the component/system, consequences of the component failure, and recommended maintenance action (Marcus, 2003). Through the internet cloud, the control room can communicate with an alarm and display system installed in the driver cabin and also to the maintenance department. A failure threshold limit will be decided for each component based on the expert and system knowledge. If the signal level crosses the failure critical limit, an alarm will buzzer inside the train and simultaneously a message about the nature and severity of fault related to specific component can be sent to the maintenance department and railway driver. Based on subjective knowledge, the driver can make the decision regarding train stoppage. At the same time, maintenance personnel can get ready with necessary spare parts to repair the faulty component. It would save time and may avoid catastrophic failure.

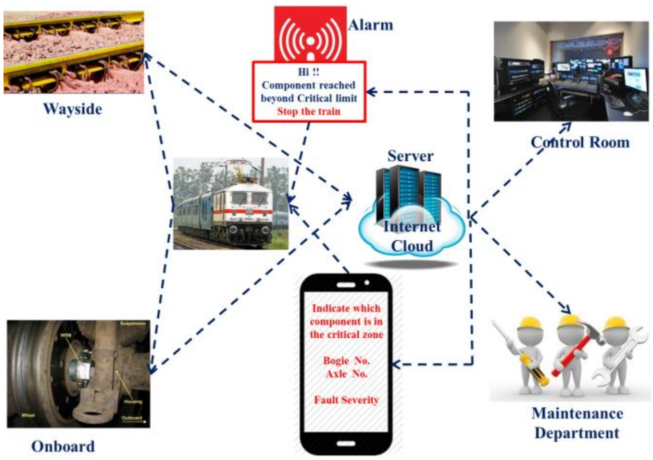


Figure 6. CBM architecture for railway

2.1. Types of sensing technology for railway vehicles

(a) Hotbox and hot/cold wheel detector

Hot box detectors (HBD) and hot/cold wheel detectors (HWD/CWD) are the oldest condition monitoring sensors. These are wayside sensors used for monitoring wheel, axle bearing and brake temperature. Infrared cameras are used for precisely measuring the temperature by digital processing of infrared images. The HBD is used for measuring the bearing temperature while hot/cold detector measures the wheel temperature. Hot wheel temperature indicates brakes are not fully released when the vehicle is moving, causing damage because of built up stresses in a locked wheel. Cold wheel temperature indicates the inadequate performance of the braking system (Papaelias et al., 2014; Moynihan & English, 2007; Lagnebäck, 2007). With these sensors, fault is identified in the bearing or wheel when these are in full failure mode, requiring immediate stoppage of train causing disruptions in traffic. Because of this critical disadvantage; these detectors are likely to be phased out in next 10-15 years, generating a need to develop new diagnostics tools (Symonds et al., 2015).

(b) Wheel profile or tread monitoring

Wheel profile technologies generally use high-speed CCD cameras and a laser diode installed wayside to measure wheel and rail head profiles when the train is moving at a normal speed (Moynihan & English, 2007; Lagnebäck, 2007; Attivissimo, Danese, Giaquinto, and Sforza, 2007). Wheel images are captured by lasers and then compared with the new wheel profile by using digital image processing techniques. The captured image can be analyzed in near real time by making key measurements including wheel treads, flange height, flange thickness and rim thickness (Moynihan & English, 2007; Attivissimo et al., 2007).

Cavuto, Martarelli, Pandarese, Revel, and Tomasini (2016) used an air-coupled ultrasonic method for measurement of the radial and circumferential wheel defect. It is an on-board sensing technology installed in the proximity of the wheel directly on the bogie. As shown in figure 7, an encoder is used for measuring the angular position of the wheel. Ultrasonic waves generated using laser were detected by the air-coupled ultrasonic probes which are installed on a frame and can move along the wheel axial and radial direction. This technique works on the low energy waves and is beneficial over conventional laser-ultrasonic systems operating under the ablative regime. A collimated laser beam of the diameter of 4 mm keeps the ultrasonic waves in between ablative and thermo-elastic regime. Since coupling medium is air, there is no need for probes to be in contact with the investigated object. On-board installation of this technique over each wheel can be costly because of the high cost of laser technology.

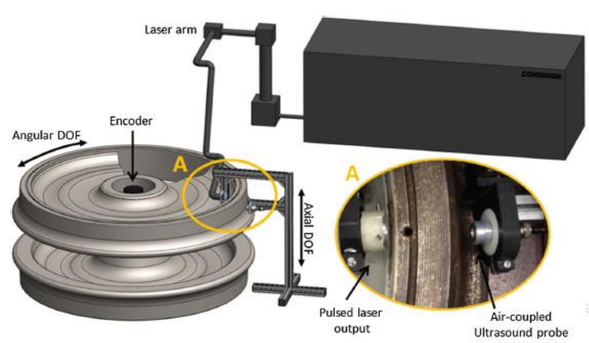


Figure 7. The laser-ultrasonic experimental set-up (Cavuto et al., 2016)

The shortcoming of the laser technology is its limited resolution. Also, laser source and camera require precise setup which may not be suitable in the railway environment. In addition, small irregularities or adherences on the surface may lead to false indications (Attivissimo et al., 2007; Brizuela, Fritsch, and Ibáñez, 2011).

To overcome the problems with the laser, Salzburger, Schuppmann, Wang, and Gao (2009) developed a new ultrasonic inspection system AUROPA III. This system detects crack-like defects in the tread of the railway wheels when the train is moving up to 15 km/h. The inspection principle of AUROPA III is shown in figure 8.

This system uses electromagnetic probes and generates magnetic field normal to the wheel surface. When a train is in close proximity to the sensor, a special sensor detects the arrival of the wheel and transmits Rayleigh waves or ultrasonic waves which travel around the rolling surface. The RF coil is used for generating and receiving the ultrasonic waves. The ultrasonic waves make several round trips around the tread of the wheel and echoes will occur if any discontinuity is present.

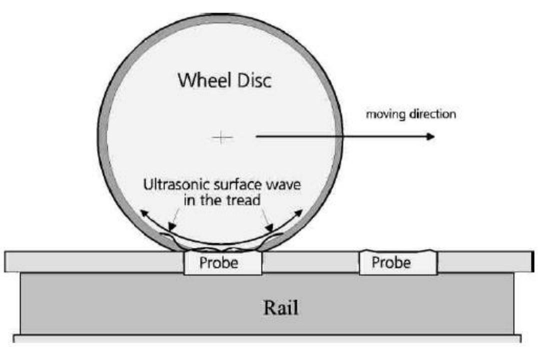


Figure 8. In-motion wheel inspection principle (Salzburger et al., 2009)

The disadvantage of this technique is that it cannot detect the rounded defects because their smooth edge produces small or no echoes (Brizuela et al., 2011).

(c) Wheel flatness

The wheel can fail because of polygonization, out of roundness, cracks and flatness in the tread. Flatness is most important because a wheel sliding for 200 or 300 meters produce a large wheel flat instead other needs thousands of kilometre to grow (Bracciali, Lionetti, and Pieralli, 1997). It happens during the braking process when the wheel gets locked and consequently slides along the rail. Low wheel-rail adhesion because of environmental conditions (rain, snows, leaves, etc.) also causes the wheel flatness (Brizuela et al., 2011).

Wheel impact load detector (WILD) is generally used for measuring the wheel flatness. Large numbers of strain gauges, load cells or accelerometers are used in WILD system for measuring the generated impact load when the defective portion of the wheel is moving on the rail head (Brizuela, Fritsch, and Ibáñez, 2011). This system detects the defect at very early stage and helps in avoiding derailment and catastrophic failures (Papaelias et al., 2014; Moynihan & English, 2007; Bracciali et al., 1997; Stratman, Liu, and Mahadevan, 2007). The WILD can also measure the out of roundness, overloaded axles, defect in suspension systems and misalignment of bogies. Recently WILD system developed by Research Design and Standards Organisation (RDSO) unit of Indian Railway in collaboration with IIT Kanpur is installed at 15 different locations on the wayside of the track. Based on the data gathered from the users it was found that 48 % of the wheel failures were detected by using this technology (the report (RDSO, Indian Railways, 2012); the report (RDSO, Indian Railways, 2014)). The drawback of WILD is that it requires a large number of strain gauges or accelerometers placed along the rails and hence a low reliability and high cost. In addition, it is affected by the dirty railway environment and can make false detection (Bracciali et al., 1997).

To overcome these disadvantages, wheel force detector (WFD) is developed by GE transportation in collaboration with University of Florence. This sensor has high performance to cost ratio and gives better results compared to the WILD system. Piezocable is used as a sensing element, which is sensitive to vibrations in all directions and less damped with the distance and hence defects detectability increased. These short length piezoelectric cables are mounted on a small aluminum block preloaded by special leaf spring and detect the wheel force (Bracciali et al., 1997).

Li, Liu, and Wang (2016), Belotti, Crenna, Michelini, and Rossi (2006) and Skarlatos, Karakasis, and Trochidis (2004) shows that many time use of only one accelerometer is enough for wheel flat measurement. In addition, accelerometer sensor doesn't have any train speed restriction during signal collection. The vibration signals are always contaminated by various interferences and noise and hence it is difficult to extract the fault relevant characteristics from raw vibration signal. Advanced signal processing algorithms are required for fault identification (Li et al., 2016). Discrete Wavelet Transform was used by Belotti et al. (2006) for wheel flat estimation whereas, Skarlatos et al. (2004) used the fuzzy logic methodology.

In order to improve the quality and efficiency of the fault diagnosis, Li et al. (2016) developed a rolling stock field simulator in which sensors are installed on the axle box (Figure 9).

This simulator can examine and reveal the sign of the faults which are difficult to perform by test on tracks. The vehicle is set on rollers which act as a rail and motion to the roller is provided by the servo-hydraulic actuators. A defined waveform input or measured track irregularity can be given with the help of a digital controller. Instead of wavelet and short time Fourier transform (STFT), Empirical Mode Composition (EMD) method is used because the STFT and wavelet uses some basic function for approximation. Incorrect results may occur, when the basic function does not match with the characteristics of the raw signal. The benefit of this technique is that it can be used for extraction of non-linear and non-stationary characteristics of the vibration signal.

Figure 9. Rolling stock simulator (Li et al., 2016)

To avoid the electromagnetic inference by using of strain gauges and piezoelectric sensors, Roveri, Carcaterra, and Sestieri (2015), Wei, Xin, Chung, Liu, Tam, and Ho (2012), Liang, Iwnicki, Feng, Ball, Van Tung, and Cattley (2013) and Wei, Cai, Tam, Ho, and Xin (2012) used the Fibre Bragg Grating (FBG) sensor which measures the rail strain response under wheel-rail interaction. The sensor is multiplexed in a single electric cable and allow distributed sensing over significant areas with FBG compared to multiple sensors used in WILD (Roveri et al., 2015). The strain responses at the wheel-rail interaction are measured and a condition index is generated which directly reflects condition of the wheel (Wei et al., 2012). This sensor can monitor both rail and wheel defects. In Milan, 50 FBG sensors were installed along 1.5 kilometres of the track with a train moving at a speed of maximum 90 km/h. Schematic of FBG sensor is shown in figure 10.

This sensor used a distributed Bragg reflector, which reflects a particular wavelength and transmits all others. The reflected Bragg wavelength λ_B can be defined as (Roveri et al., 2015)

$$\lambda_B = 2n\alpha \quad (1)$$

where, n is the refractive index of the fibre and α is the index modulation. When the rail is deformed, n and α gets modified and frequency bandwidth of the reflected light is changed. The spectrum analyzer detects this variation. After suitable signal processing, the presence of the defect can be detected. Liang et al. (2013) used three time-frequency transform i.e., STFT, Wigner-Ville Transform (WVT) and Wavelet Transform (WT) to extract fault related information from the vibration signal and found them useful for detecting the rail surface defects as well as wheel flat. The sensor is glued on the rail and hence reliability and durability of FBG sensor is still under investigation (Wei et al., 2012; Liang et al., 2013).

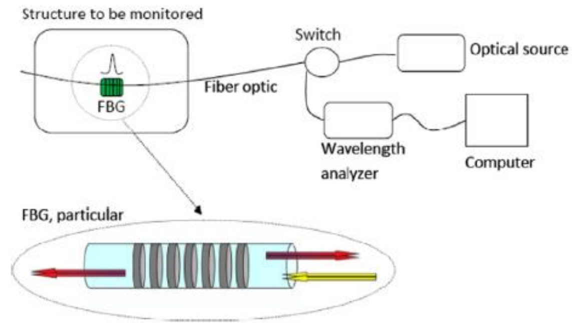


Figure 10. Schematic of the FBG sensor (Roveri et al., 2015)

The methodologies discussed so far WILD, WFD, piezoelectric and FBG detect the presence of flat. However, the size of the flatness is also important for decision making regarding train stoppage. Brizuela et al. (2011), Brizuela, Ibañez, and Fritsch (2010) and Brizuela, Ibañez, Nevado, and Fritsch (2010) used ultrasonic waves to detect the size of the wheel defect. Figure 11 shows a simplified model for the wheel flatness measurement, where, X_c is the height of the wheel center. The depth *'d'* and length *'L'* of the defect can be calculated as

$$d = R - R\cos\theta \quad (2)$$

$$L = 2R\sin\theta = 2R\sqrt{1-\cos^2\theta} \approx \sqrt{8dR} \quad (3)$$

Here, θ is the rotation angle and R is the radius of the wheel.

Figure 12 shows the prototype of a wheel flat detector which detects the size of the flat using Doppler Effect. Interrogating ultrasonic (Rayleigh) waves propagate when a wheel is moving on the measuring rail at a constant angular speed. Compared to conventional ultrasonic NDT transducers, which are based on the reflectivity of static flaws, here kinematics of the echo produced at the wheel-rail contact point is analyzed.

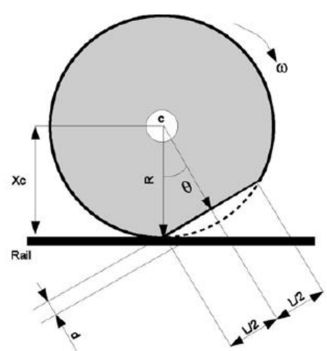


Figure 11. Simplified wheel flat measurement model (Brizuela et al., 2010)

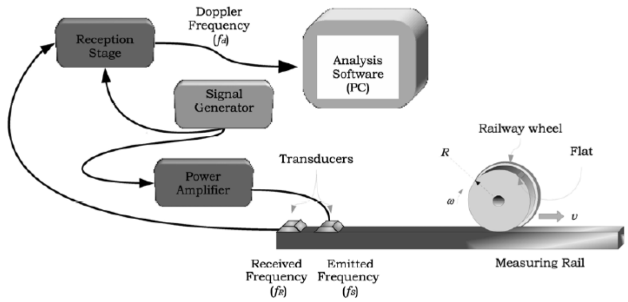


Figure 12. Wheel flat detector prototype (Brizuela et al., 2010)

Let us considered that rail-wheel contact is a mobile reflector point and moving at a constant angular speed ω over the measuring rail, f_s is the emitted frequency, c is the ultrasonic propagation velocity, and then received frequency f_d can be calculated as (Brizuela et al., 2010)

$$f_d = \frac{2\omega R}{c} f_s \tag{4}$$

When the wheel surface is irregular, this nominal Doppler frequency for a radius R will have a deviation given by

$$\Delta f_d = f_d(R) - f_d(R_{min.} \tag{5}$$

Now, depth of irregularities can be related to the Doppler shift frequency as follows

$$d = \frac{\Delta f_d}{f_d} R \tag{6}$$

The difference between emitted and received frequencies will change if defect is present on the wheel surface and thus resulting deviation in Doppler frequency gives depth of defect. The length of defect can be calculated from Eq. (3).

Brizuela et al. (2011) measured the wheel flatness by calculating round-trip time of flight (RTOF) of echo produced during the rail-wheel contact point. A mathematical relationship between the depth of flat *'d'*, wheel radius *'R'*, velocity *'v'* and RTOF is given. As wheel velocity and radius is constant, so variations in RTOF of the echo will be detected and quantify the wheel flat. The major limitation of these systems is that they will detect the defect size only when the train is moving at a slow speed (5-15 Km/h) (Brizuela et al., 2011; Brizuela et al., 2010). So, it is imperative to install these detectors near the station where train speed is low.

Restriction on the train moving speed is the biggest problem while using above mentioned sensors for measuring wheel flatness except with accelerometers. Acoustic emission (AE) sensors were tested by Bollas & Papasalouros (2010) for measuring the wheel flatness when the train is moving at a speed of 5 to 40 km/h. The sensors were mounted on the rail to monitor the AE transferred through the rail in real time. After signal processing and removing low frequency component from the signal; AE features such as RMS, absolute energy, etc. were extracted to measure the presence of the wheel flatness.

Wheel crack can also be detected using AE sensors if AE waves generated by growing crack are transmitted through the wheel to the rail (Amini, Entezami, Kerkyras, and Papaelias, 2013). One such attempt is made by Yilmazer, Amini, and Papaelias (2012) for continuous monitoring of the crack growth.

(d) Railway bearing health monitoring

Railway bearing allows the frictionless movement along the rail. Journal box holds the oil to keep the wheel bearing operation smooth. Any defect in the bearing causes the friction and heats up the journal box known as "hot box" which can be detected by hot box detector (HBD). The HBD detects defect in the advanced defect stage as explained earlier in section 2.1 (a). So there is a need for advanced technology, which can detect the defect at an early stage. For example, faulty bearing generally produces noisy rubbing sound and an acoustic emission (AE) sensor can be useful to detect the bearing health state. In addition, a defect in the bearing produces high level of vibration and accelerometer sensors are also used for bearing health monitoring. The data obtained from these sensors are contaminated with noise and interferences and hence the advanced level of signal processing is required for fault detection.

Association of American Railroads (AAR) used 12 wayside microphone arrays to measure the bearing noise. The microphone arrays were mounted horizontally and at the same height of centerline of roller bearings. Fault in the bearing was detected by acoustic signature frequencies generated because of defective bearing and envelope of the signal (the report (U.S. Department Federal Railroad Administration, 2003)).

The defect in inward bearing is difficult to detect using wayside acoustic arrays. Moreover, it may give false information about a defect or may fail to identify a defect. Amini et al. (2013), Choe, Wan, and Chan (1997) and Papaelias, Amini, Huang, Vallely, Dias, and Kerkyras (2014) installed AE sensor on the rail for bearing fault estimation. Physical coupling of the sensor on the rail gives much information about the fault in the bearing compared to microphone arrays. Amini et al. (2013) detected both wheel flat and axle bearing fault using AE sensors. Higher amplitude in the raw AE signal was observed for the faulty bearing.

Choe et al. (1997) used neural network approach for classifying different railway bearing defect with the help of AE signals. Four different transforms or features were extracted from the raw acoustic data: Fast Fourier Transform (FFT), Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) and Wavelet packet. Classification rate was calculated with individual feature and highly accurate results were found with all these features.

Papaelias et al. (2014) and Papaelias et al. (2014) installed both AE and accelerometer sensor on the wayside of the rail. Moving RMS extracted from AE and vibration signals was found to be useful for measuring the severity of the bearing fault and wheel flat respectively.

The results from AE sensors are quite impressive but obtained at a higher price (Choe et al., 1997). The major drawback with AE sensor is that attenuation of the signal is very severe and sensor needs to be placed close to the bearing. Secondly, interpreting and classifying the information from raw AE data is difficult (Cao, Fan, Zhou, and He, 2016).

The results obtained for the wheel flatness measurements with the accelerometer are quite good and hence accelerometer can be used as an alternative to the acoustic sensor for bearing condition monitoring.

Railway wheel bearing fault identification using vibration signal is carried out by several authors. Wayside accelerometers are used by Cao et al. (2016), Sneed & Smith (1998) and Donelson & Dicus (2002), whereas, on-board accelerometers are used by Symonds et al. (2015), Zhang (2011), Corni, Symonds, Wood, Wasenczuk, and Vincent (2014), Chen, Yan, and Chen (2014) and Chudzikiewicz, Bogacz, and Kostrzewski (2014). Different signal processing algorithms are used to process raw vibration signal because wheel/rail interface noise entered into the accelerometer with full strength. Cao et al. (2016) used empirical wavelet transform (EWT) for identifying the outer race fault, roller fault and the compound fault of the outer race and roller.

Keeping sensors on-board will give more accurate results because with the direct mechanical path the effects of the surrounding noises and other environmental parameters will be eliminated (Zhang, 2011). So on-board sensing is preferable as compared to the wayside.

Chen et al. (2014) developed a test rig to simulate the real wheel-bearings condition. The accelerometers were mounted on the surface of the outer race. Entropy, time spectral kurtosis (TSK) and support vector machine (SVM) based methodologies are used for bearing fault identification. Zhang (2011) used high-frequency envelope detection approach for fault identification. High frequency band-pass filter has been used to retain the high-frequency components and the fault was identified by calculating the power spectrum of the filtered signal.

Self-powered wireless sensor node was installed in the UK for monitoring the health of the bearing. This sensor works on the principle of vibration harvesting and can record the data in all three directions (Symonds et al., 2015; Corni et al., 2014). Features such as RMS_X , RMS_Y , RMS_Z , $Peak_X$, $Peak_Y$, $Peak_Z$ and vertical FFTs are calculated from the raw vibration signal. These features are combined and wirelessly sent to the cloud. Bearing health index (BHI) and wheel health index (WHI) values are calculated from these features which are available in real time and can be used for identifying the bearing and wheel issues (Corni et al., 2014). Similarly, Chudzikiewicz et al. (2014) placed the accelerometers over the axle box for health monitoring of the bearings of an EMU train.

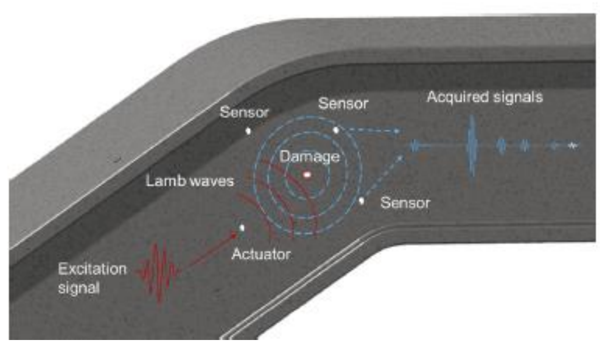
Vibroacoustic measurements were made by Bellaj, Pouzet, Mellet, Vionnet, and Chavance (2011) for fault detection in high speed train bearings. On-board measurements from accelerometer sensors show the increase in the vibration levels in the high-frequency region (beyond 2 kHz) for the damaged bearings. Trackside microphones were used for identifying the defective axle box. The signal noise level filtered in the 16 kHz octave band allows the discrimination between the healthy and faulty bearing. The fault detection capability from both the sensors was found better at higher train speed (greater than 60 km/h).

(e) Miscellaneous

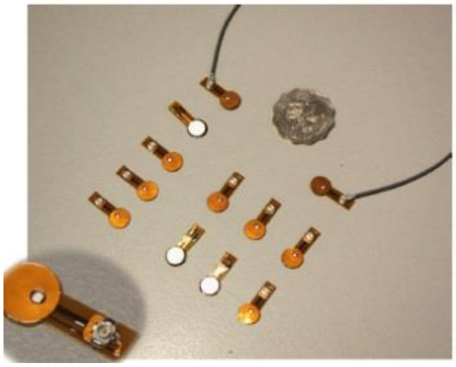
A guide wave (GW) based structure health monitoring technique is developed in China and experimented on Beijing-Shanghai high speed train. The piezoelectric lead zirconate titanate (PZT) sensor network was integrated into the bogie frames during final assembly (Figure 13).

The range of bogie-guided ultrasonic waves is generated and acquired by the PZT wafer. Numbers of linear and nonlinear GW features are extracted. Fusion of these features through a diagnostic imaging algorithm give various genres of damage index and estimates the overall health state of the bogie in a real-time (Hong et al., 2014).

In the USA, Transportation Technology Center Inc. (TTCI) developed a laser air-coupled hybrid ultrasonic technique (LAHUT) for automatic detection of cracks in axle (Moynihan & English, 2007). Ultrasonic surface waves were generated by a laser pulse travel from the mid-point of the axle outwards towards both the wheels. Two air-coupled ultrasonic transducers were installed for detection of the source pulse and any additional echo produced because of the surface crack.



(a)



(b)

Figure 13. (a) Principle of the proposed SHM technique for train bogie frames (b) standard PZT sensing units (Hong et al., 2014)

SKF developed multilog on-line system IMx-R for evaluating the condition of all bogie rotational components, i.e., motors, gearboxes, axle boxes, wheels and bearing (the report (Global Railway Review, 2014)). This system has inbuilt intelligent diagnostics capabilities.

3. COMPARISON OF VARIOUS CM SENSORS

Based on the above review, Figure 14 gives an overview of the available CM technologies for the bearing and wheel. Comparative analysis of various sensing technologies is given in Appendix.

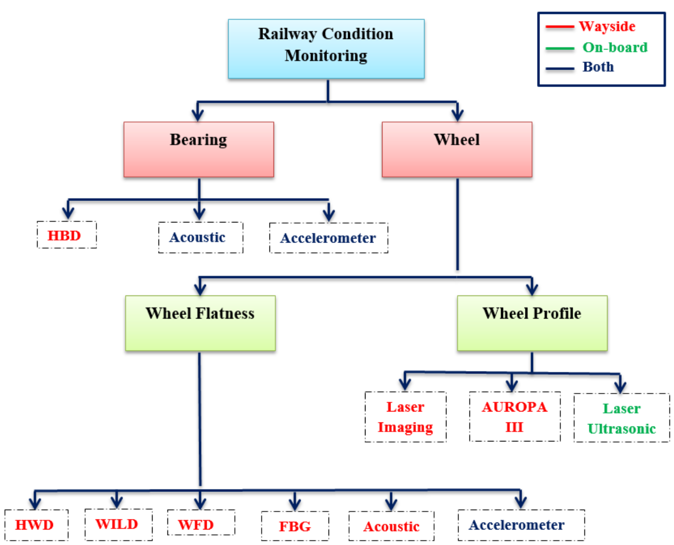


Figure 14. Overview of available CM technologies for railway bearing and wheel health monitoring

4. GLOBAL OVERVIEW

Globally, it is observed that implementation of the CBM technology in railway helps in reducing maintenance cost and accidents and life of the component are increased. From 2008 to 2012, Indian railway installed 15 WILD systems at different locations and detected early wheel failure 48% of the time (the report (RDSO, Indian Railways, 2012); the report (RDSO, Indian Railways, 2014)). In North America, more than 1000 HBD/HWD and 100 WILD were installed in last 20 years (Lagnebäck, 2007). Canada national railways had installed 452 of these wayside detection systems up to 2002. In 2003, Union Pacific railroad in the USA used the technology developed by the Canada national railway and installed around 1200 HBD in their railway network. In 2000, Great Britain introduced the WheelChex® in their railway network for detection of wheel flats and out-of-round wheels. Total 30 WILD sensors were installed and an 80% reduction in wheel failure over a span of 2 years was observed. The same trend was also observed in Spain, where the introduction of WheelChex® system reduced the wheel failure by 80% in 18 months. In the Netherlands, the introduction of GOTCHA (wheel flat detection and axle load measurement system) and QUO VADIS (weigh-in-motion system) system decreases the hot axles and spring failure by 90%. Both the systems were installed at 38 locations covered around 80% of the traffic movement.

An iron ore company BHP Billiton in Australia installed the different wayside condition monitoring systems such as HBD/HWD, WILD, weigh-in-motion, hunting detectors, track performance measurements and acoustic bearing detectors (Lagnebäck, 2007). Implementation of these technologies reduces the cost of railway transportation by 50% between 1990 and 1998 and vehicle service life of many major components, i.e., bogies, wheels and car bodies are increased by three times. Track life also increased five times by implementation of these technologies from 1972 to 2000.

Australia Rail Transport Corporation (ARTC) deployed railway bearing acoustic monitoring (RailBAM) system since December 2001 and found their system availability exceeding 97%. Approximately 1,30,000 bearings were analyzed per month by the RailBAM installed at different locations (Southern et al., 2004). Association of American Railroads (AAR) found that approximately 85% of the bearing faults were correctly identified by the acoustic bearing detector system (Choe et al., 1997). In the UK, on-board self-powered WSNs were installed in Southeastern Electrostar fleet (148 trains and 4944 wheels) (Corni et al., 2014).

Figure 15 shows the number of the derailments prevented by implementation of wayside technology installed in Cornrail. If a detector prevents one derailment, it pays more than for itself because each derailment costs a million dollars (Steets & Tse, 1998).

Figure 16 shows the cost associated because of derailments in 1996 and 1997 in Cornrail. As it evident from Figure 16, bearing and wheels failures are associated with very high costs, compared to costs associated with failure of other components. The wheel derailment cost is significantly reduced from 1996 to 1997 because Cornrail deployed wheel impact and sliding wheel detector system in their railway network.

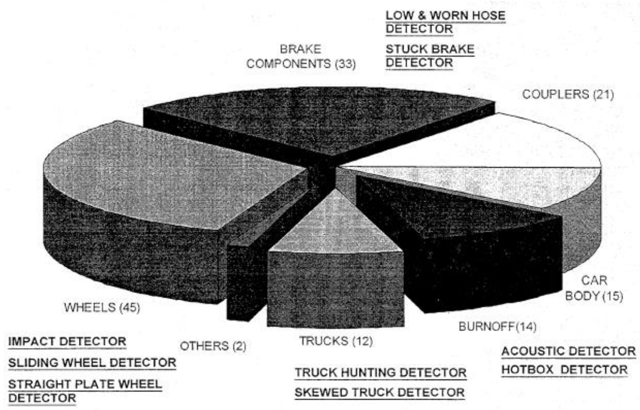


Figure 15. Number of derailment prevention using wayside detectors (Steets & Tse, 1998)

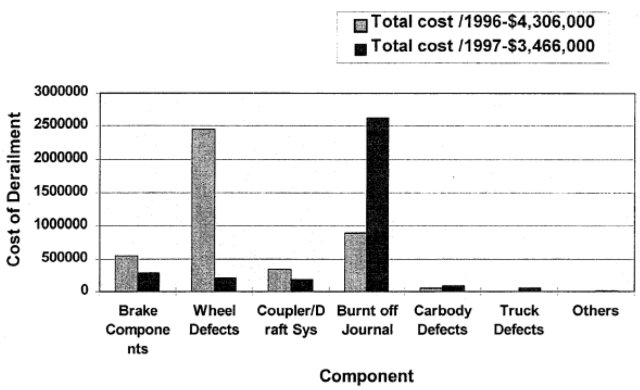


Figure 16. Cost of the freight car caused derailments (Steets & Tse, 1998)

Maintenance accounts for 30% of the life cycle costs, the highest cost factor in the high speed train (Palem, 2013; Lee, Lee, and Kim, 2016). Palem (2013) observed that the implementation of predictive maintenance program in the high speed railway can reduce maintenance cost 25% to 30%, elimination of breakdowns 70% to 75%, spare parts inventory reduced 20% to 30%, reduction in equipment downtime 35% to 45%, and asset life increased 20% to 40%. To reduce the life cycle costs of the rolling stock in Korea metro, Korea Railroad Research Institute implemented the condition based maintenance program since 2014. Based on the life cycle cost analysis, it is observed that the implementation of the predictive maintenance program in the Korea metro will reduce the total life cycle costs of more than 20% (Lee et al., 2016).

The cost is also very important while implementing the condition monitoring system. In literature, no specific data is found related to the implementation cost of the condition based maintenance program in railway. However, some cost analysis is presented here for CBM program implementation in the railway. The cost of the CBM program depends on the type of sensor used for health monitoring of the rolling stock. For example, the approximate cost of a vibration sensor is 50000 INR and the approximate cost of an acoustic emission sensor is 150000 INR. The approximate cost of data acquisition per sensor/channel is 60000 INR. The cost of developing the health monitoring software with display device can be considered as 1000000 INR. Each rail bogie has two wheel axles with four wheels and the sensor should be installed on each wheel of the bogie. A coach in which the passenger travel, including the two bogies and hence eight sensors should be required for health monitoring of wheel set of a coach. The overall implementation cost per coach can be calculated as

CBM program implementation cost per coach= Health monitoring software and display device cost + (Single sensor cost + Data acquisition cost per sensor) × Number of sensors per coach

$$= 1000000 + (50000 + 60000) \times 8 = 1880000 \quad \text{(for vibration sensor)}$$

or

$$= 1000000 + (150000 + 60000) \times 8 = 2680000 \quad \text{(for acoustic emission sensor)}$$

5. CONCLUSIONS

In this paper, an attempt has been made to summarize the recent developments in online condition monitoring of the railway equipment. The wheel stock failure is found to be the major cause of the overall system failure, which leads to the derailment of the train. Detailed explanations have been given about the wayside and on-board sensing technologies. Qualitative and quantitative benefits across the globe using CM technology in railway are also reviewed. The advantages and disadvantages of various sensing technologies have been enumerated, which would help in selection of sensors for a particular damage inspection. The observations made from this review are summarized below.

- The on-board sensing technology is superior because the direct mechanical path it provides between sensor and equipment eliminating the effect of the surrounding noise and interferences. However, deploying the sensors on-board increases the cost because the sensors are required to be installed on each wheel of the bogie. Development of cheap on-board sensors can be an important direction for further research. In this direction, Perpetuum Ltd. developed the on-board accelerometer which is working on the principle of vibration harvesting.
- The wayside sensing technology is found to be widely used because of its economical modeling of damage. There is a need for further research on wayside sensing technologies to increase their effectiveness for robust fault diagnosis and better decision making.

- In most of the cases, deviation of the captured signal from the reference signal is taken as an indication of damage. However, sometimes the signal obtained from the sensors doesn't show any trend because of the effect of noise and interferences. In that scenario, advanced signal processing algorithms are required for fault estimation.
- Most of the sensing technologies available for wheel profile and flatness have the restriction on the train moving speed during measurement. Sensors need to be developed which can measure the wheel condition at higher speeds.
- So far, no work has been reported on the prognosis of the railway components. Diagnosis provides information whether a fault has occurred or not, but the implementation of the prognosis algorithm would give an advanced alert of the failure and hence optimizes the life span of the component.
- Influence of operational parameters such as load and speed and external environmental conditions such as temperature needs to be considered in the fault diagnosis model for better damage detection capability.
- In summary, the review suggests that the further development of new CM sensing technology for better damage detection capability and integration of various sensing technologies and automation is required.

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APPENDIX

Comparison between railway health monitoring sensing technologies.

Sensor Name	Installation Location	Monitoring Object	Merits	Demerits	Fault Estimation Methodology
Hot Box Detector Hot/Cold Wheel Detector	Wayside	Bearing Wheel	- Cost is very less. - Simple to use.	- Identifies the fault when the component is in full failure mode.	Temperature trend analysis.
Laser Imaging	Wayside	Wheel Profile Monitoring	- Simple to use.	- Limited resolution. Small Irregularities on the surface may lead to false indication.	Compare the captured image with the reference image.
Air-coupled Ultrasonic	On-board		- No coupling medium is required.	- Because of high cost of laser, on-board installation is costly.	Echoes will generate if any fault is present.
AUROPA III	Wayside		- No coupling medium is required.	- Cannot detect rounded flats.	Echoes will generate if any defect is present.
WILD	Wayside	Wheel flatness	- Sensor accuracy is very high.	- Multiple sensors are required. - Electromagnetic Inferences.	Wheel impact trend analysis.
WFD	Wayside		- High performance to cost ratio.	- Electromagnetic Inferences.	Wheel impact trend analysis.
Accelerometer	Both		- A Single sensor is required.	- High level signal processing algorithms are required for fault estimation.	EMD (Li et al., 2016), Moving RMS (Papaelias et al., 2014; Papaelias et al., 2014), Fuzzy Logic (Skarlatos et al., 2004)
FBG	Wayside		- Avoid electromagnetic inferences. - No restriction on train moving speed.	- Sensors are glued on the rail, there reliability and durability need to be improved.	STFT, WVT, WT (Liang et al., 2013)
Ultrasonic	Wayside		- Give size of flatness.	- Restriction on the train moving speed	Doppler effect
Acoustic	Wayside		- No restriction on the train moving speed.	- Accuracy is not much high.	RMS (Amini et al., 2013; Bollas & Papasalouros, 2010), Energy (Bollas & Papasalouros, 2010)

Acoustic	Both		-Highly sensitive to bearing fault. -No restriction on the train moving speed	- Highly costly. - Interpreting and classify the information from raw AE data is very difficult	NN, FFT, CWT, DWT, WP (Choe et al., 1997), Moving RMS (Papaelias et al., 2014; Papaelias et al., 2014), RMS (Amini et al., 2013)
Accelerometer	Both	Bearing	- Vibration Signals are easily interpretable compared to AE signal. - No restriction on train moving speed.	- Accuracy is not better than acoustic.	EWT (Cao et al., 2016), TSK, SVM (Chen et al., 2014), HFED (Zhang, 2011), RMS, Peak, FFT (Symonds et al., 2015; Corni et al., 2014), Envelope Analysis (Bellaj et al., 2011)