Structure Health Diagnosis of Metro Rail Track by Using Vibration Mappings and Machine Learning

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Abstract. This abstract presents the methodology for the evaluation of metro rail tracks which can be used to produce a vibration map, also it is very fundamental for track maintenance, where we predict vehicle body vibration based on deep learning, which represents one of the newest areas in the Artificial Intelligence field. As we all know, in the entire world the evaluation of track quality had been through established track geometry standards. However, these types of standards may not be capable of detecting some abnormality of track geometry conditions that can cause vehicle body vibration. These vibrations also shake up nearby residents; measurements are carried out to evaluate the risk for structural integrity. With the help of SolidWorks software and structure, health diagnosis using Ansys software integration with experimental data for feature extraction used EEMD and for classification apply artificial neural network (ANN) where a model is proposed to make an accurate and point-wise prediction, due to which we can achieve optimal performance. This case study is based on the Delhi metro, for track health monitoring system was installed on several trains running on the green line in the underground which aims to improve the maintenance process. The early detection and surveillance of defects help to extend the service life of the tracks and it also reduced operating costs. A data acquisition system is used to analyze the continuously recorded measurements (vehicle body vibration), which consist of vertical bogie acceleration and surrounding noise, for example with a frequency of 22kHz. In particular, achieving optimal performance, and exploring the internal mechanism of the model, structural configuration, and inner states are mostly studied. However, ANN- LSTM can predict vertical vehicle-body vibration below 10Hz and lateral vehicle-body vibration below 1Hz. The above analysis shows that the performance of metro rail tracks by using the vehicle body vibration method acts as a performance-based model which evaluated the index of track quality.

Keywords: Track quality evaluation, track health diagnosis, vehicle-body vibration, Machine Learning, Artificial neural network (ANN), A. Ensemble Empirical Mode Decomposition (EEMD)

1 Introduction

India has one of "The Largest Rail Networks" in the World. The locomotive network is the catalyst for the Economic and Societal Growth of Cities, regions, And a Country. According to the survey, it has not reached the "Global Level" in terms of "Safety & Reliability". Railway Sleeper is a vital component of Rail Defects. In Railway/Metros Axle Bearing is a major primary defect that can affect operational efficiency or cause in-service failures, also damaging the track & its components. These cracks lead to derailments of tracks which may cause intense damage to the Life & Property of a developing region. Healthy bearings produce a certain level of Vibration And Noise. The undesirable locomotive Noise & Vibration include Rolling Noise, Impact Noise, Curve Noise, Mechanical Noise, Airborne Noise, Structure & Ground-Borne Noise.

We investigate the Bifurcation Phenomenon from Stick-Slip Vibration. Defects development 'Mapping the Underworld' (MTU).

The Dutch national calculation approach serves as the foundation for the railway noise impact models (SRM II). This approach uses source models of Dutch rolling stock that may be modified to simulate rolling stock from other nations. The propagation model comprises geometrical features and ground absorption. Most commercial software also enables calculating the affected population, the most important output criterion for strategic noise mapping.

What about rumbles? Local, regional, and national governments are now concerned about vibrations caused by railroads (see Figure 1). However, there is no standard methodology, and various national and regional laws result in various vibration level indicators, as well as various vibration restrictions. Action plans and strategic vibration maps are not discussed. Why are railroad vibrations a problem?

Due to the interaction of numerous variables along the wave propagation paths, such as the load generation mechanism of the train-track system, the geometry and location of the tunnel structure, the irregularity of soil layers, etc., the ground vibration caused by underground moving trains is a challenging dynamic problem. Previously, field measurement and empirical or semiempirical prediction models were used to undertake several research studies on ground-borne vibrations caused by subway trains. These studies offer useful guidance for resolving similar issues.

However, because most of these investigations were carried out for a particular illness, they lacked universality. On the other hand, when it comes to simulation techniques, the majority of earlier efforts have relied on 2D models, which are two-dimensional. Although designers typically employ 2D models, the results they produce are approximate and qualitative in nature. The influence of train speeds was not taken into account in the 2D models, which is a negative.

Researchers also employed three-dimensional 3D simulation methods, which were improved by the development of high-performance computers. Consequently, there is a tendency to use the 2D profile to generate the 3D response because of its relative precision and efficiency, as well as the geometry's periodicity or invariance along the load-moving direction. However, none of this research has completed a parametric investigation; instead, the majority of them were conducted for a particular example.

The supporting soils' stratum depth and damping ratio, the tunnel's depth and thickness, the trains' excitation frequency and speed, as well as other factors, must all be taken into account.

Fig. 1. Appearance of sleeper and track

2 The Vibration Problem associated with Metro Rail

As previously indicated, the principal noise impact indicators and the accompanying regulations consider the effect of dose. However, the generation of railway vibration is dependent on the ground vibration coupled behavior, the rolling stock, the wheel, and rail roughness profile, the rail, pad, sleeper, and under-sleeper pad. Additionally, the ground vibration mechanism is dependent on the extremely stochastic and statistical vibration propagation properties. Finally, because the majority of building vibration laws set restrictions inside structures, it is important to consider both the foundation-building coupling phenomena and the structural vibration behavior of buildings.

The majority of the mechanisms relating to the creation of railway vibrations, their transmission into buildings, and their propagation through the earth, include numerous complicated phenomena that are difficult to approach or quantify. In contrast, noise formation, transmission, and reception processes can be thought of as being very straightforward: A sequence of vertically distributed equivalent noise sources make up Dutch rolling stock noise models; the acoustic propagation medium is uniform, and reflection and absorption laws are well-known. Furthermore, while noise impact is often computed within the building wall, the acoustic isolation qualities of the building and the impact on human response are largely disregarded. If anticipated noise levels

are higher than allowed levels, acoustic screens can be used to effectively and cheaply lessen the impact.
However, the generation of railway vibration is dependent on the ground vibration coupled behavior, the rolling stock, the wheel, and rail roughness profile, the rail, pad, sleeper, and under-sleeper pad. Additionally, the ground vibration mechanism is dependent on the extremely stochastic and statistical vibration propagation properties. Finally, because the majority of building vibration laws set restrictions inside structures, it is important to consider both the foundation-building coupling phenomena and the structural vibration behavior of buildings. Several approaches have been put forth in this context for the prediction of vibration levels brought on by passing rolling stock.
Finally, there is a dearth of understanding of the effectiveness of vibration countermeasures. The coupled interaction between the rolling stock, rail, fastening system, and dirt heavily influence anti-vibratory solution behavior. When some crucial factors are changed, solutions with high vibration isolation properties for a rolling stock and soil combination may perform poorly. In contrast to the noise example, it is very expensive to change the vibration transmission impedance, and the efficiency that is attained depends heavily on the frequency. Given all of these details, it is vital to confront the issue of railway vibrations and find a solution.

2.1 Locomotive fault diagnosis of sleeper & track

A railroad tie or crosstie or railway sleeper is a rectangular support for the rails in railroad tracks. Generally laid perpendicular to the rails, ties transfer loads to the track ballast and subgrade, hold the rails upright and keep them spaced to the correct gauge.

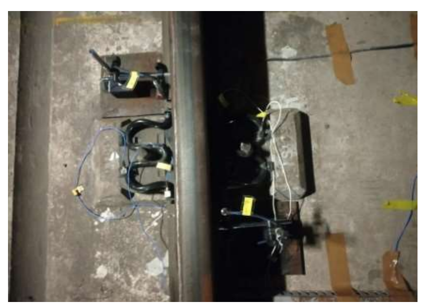


Fig. 2. Locomotive of sleeper and track reliability analysis

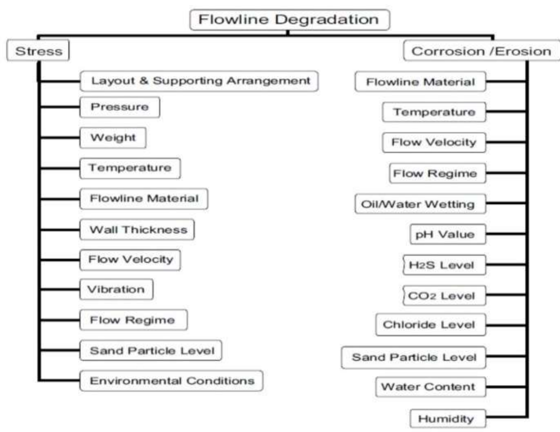


Fig. 3. Factors Affecting Flow line Degradation

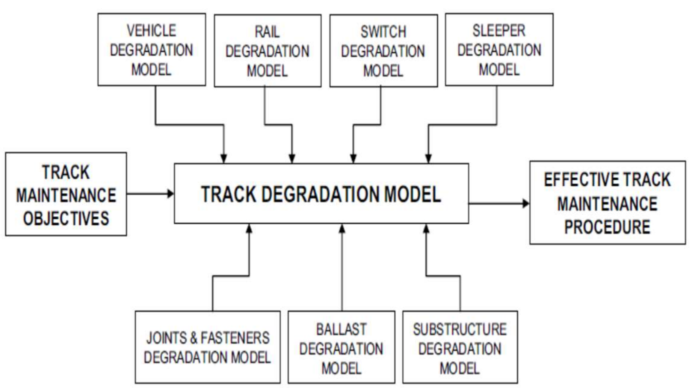
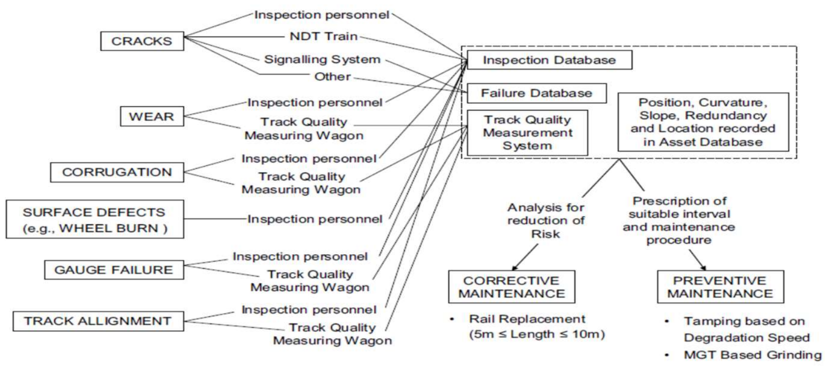


Fig. 4. Need for Effective Track degradation Model



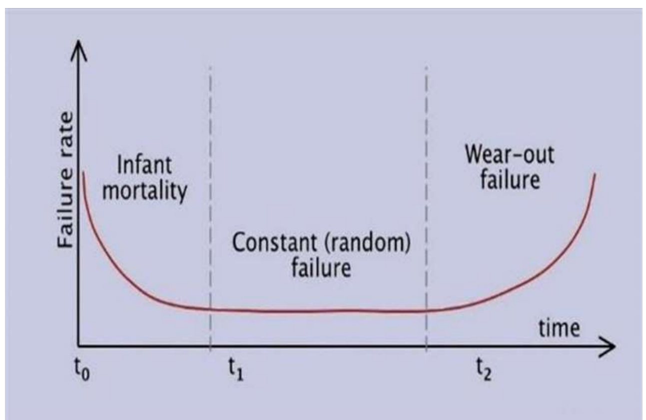
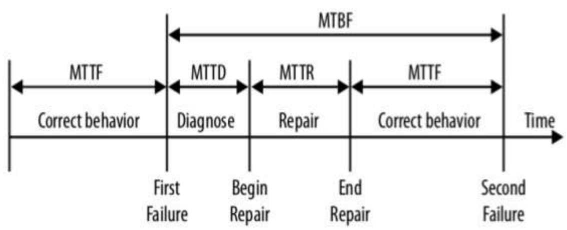


Fig. 5. Track Data Reporting & Analysis Procedure



$$\mathbf{A = MTTF / MTBF = MTTF / (MTTF + MTTD + MTTR)}$$

Fig. 6. Monitoring is critical for High Availability

2.2 Vibration Mapping

A user can analyze and assess the predictable values of vibration velocity from the source thanks to the phenomena known as vibration mapping, which involves calculating and presenting data about the areas that are inside the designated influenced or affected area. This can also be used to investigate the validity of existing buildings and models that include vibrations that could bother people or cause aesthetic harm.
Working on Raw Signals and comparing different train sets we came to know that axle bearing wear is also a key to vibration source which leads to vibration in tunnels and thus, leads to cracks & damages in existing buildings.

Fig. 7. Investigation on Railway Track

Recent trends in vibration mapping

- Frequency characteristics- We present the characteristics of an indirect frequency measurement system based on off-axis digital holography (DH) for vibrating objects, which works on phase change characteristics of a medium where sound wave propagates. The sound field measurement method using off-axis DH already proposed by the author's group is applied to the measurement of vibration frequency of arbitrary sound sources.
- Autocorrelation analysis-In addition to spectral data computed from the time wave, it is possible to compute an Autocorrelation coefficient block of data. The autocorrelation Coefficient data has not been widely used as a tool for diagnostics in vibration analysis of rotating machinery.
- Sensitivity factor based on mutual- The relative sensitivity measured in this work can be used to obtain sensitivity and hence more accurate data from these low-cost accelerometers.
- Fusion method- It is necessary to monitor and diagnose these induction motors to prevent any sudden shutdowns caused by premature failures. Numerous fault detection and isolation techniques for the diagnosis of induction machines have been proposed over the past few decades.

2.3 Locomotive's vibration generates damage to buildings, humans & environment-

Noise and vibrations are transmitted through the physical medium and gradually disappear with distance. In practical engineering, noise and vibrations are inevitable. The research on noise and vibrations can be summarized into three parts: the source, the transmission path, and the receiver. Excessive noise and vibration are harmful to human health without a doubt, while the evaluation of their impacts can be subjective. The effects of noise and vibrations on human beings were discussed by studying different urban areas or different types of noise and vibration sources. Typical urban areas affected by noise and vibrations include schools.


Delhi Metro vibrations, noise shake up residents; experts roped in

DMRC is preparing guidelines to mitigate noise levels at its elevated stations and testing a new technology to reduce vibration at its underground ones.

A woman stands next to the cracks on the wall of a house due to the movement of Underground Metro Line, at Begumpur Village, in New Delhi. (Sanjeev Verma/HT PHOTO)

The ever-expanding Delhi Metro Rail Corporation (DMRC) has been plagued with a new problem —complaints regarding vibrations and noise caused due to its train movements.

To address the problem, the corporation is preparing guidelines to mitigate noise levels at its elevated stations and testing a new technology to reduce vibration at its underground ones.


15 OLD BUILDINGS IN BALEPET DEVELOP CRACKS DURING TUNNELLING WORK

6 November 2015 · by T&U Staff · in Asia, Damage, Metro, News, TBM, Tunnelling

Rate This

In Balepet, 15 buildings have turned out to be a bottleneck for the Metro tunnel-boring machine Kaveri after it damaged the buildings. The contractor of the Metro work has already issued notices to the occupants to evacuate the buildings. Once the machine burrows under these buildings, it will reach Metro intersect station in Majestic.

Chief PRO of the BMRCL Vasanth Rao said that the identified 15 buildings are old and are in poor condition. The occupants have to evacuate seven days before the machine approaches the buildings. After the reports of damage to the buildings, Kaveri is stalled for time being. After analysing the safety measures the machine will be operating again, the officials said. On Thursday, Metro workers were seen taking up repair works and grouting in the area.

"Everything is going well. The contractor is taking the most care in the process. There are various reasons why cracks have appeared on the walls of some of the buildings. The buildings are very old; some are even more than 60-year-old. Moreover, they do not have solid foundation and a number of

Fig. 8. Metro Vibrations Affects humans, the environment, and domestic buildings and crack generated during tunnel works

3 Methodology

In this paper, we are evaluating the metro rail track condition and also trying to solve with vibration mapping where ANN (Artificial Neural Network) is implanted through which a ROC plot is generated. Here we follow the mathematical model for monitoring where input-output ideas are done with the synaptic weights, threshold, and summing parameters considered.
There are different layers involved between input and output data to apply the ANN.
We made a matrix in reference to ANN (Artificial Neural Network), a confusion matrix where three types of data are combined tracing, training validation, testing, etc.
We can attain optimal performance by utilizing EEMD and applying an artificial neural network (ANN) for classification, where a model is proposed to generate an accurate and point-by-point prediction.

A. Shape Feature Learning On ANN

ANN is an Artificial Neural Network that was primarily developed to manage the complexity of two-dimensional (2D) shapes because of the properties of shift and scale invariance.

Several fully connected layers are usually followed by a stack of convolutional and pooling layers, which is the typical structure. Each convolutional layer has many kernels, and each kernel has a set of learnable weights. ANN performs 1D convolution with one-dimensional kernels on sequential data. Last but not least, fully-connected layers are employed as classifiers to categorize high-dimensional features by creating a complex decision surface. Geometric shape features in action. Local track geometry waveforms comprise the properties, which are correlated with vehicle-body vibration. Vehicle body vibration is typically sensitive for HSR vehicles. To categorize high-dimensional features, fully connected layers are utilized as classifiers. These layers provide a complex decision surface.

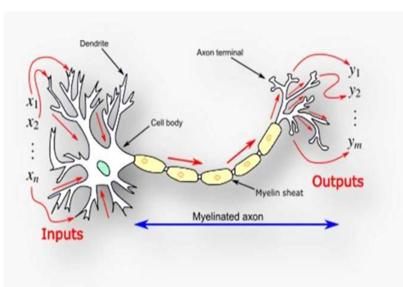


Fig. 9a. The structure of the Neuron

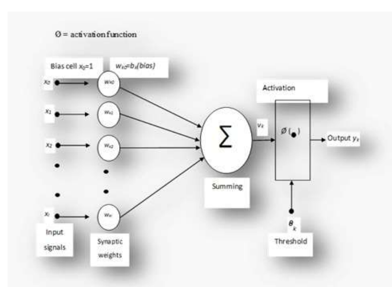


Fig. 9b. Mathematical Model of the Neural Network

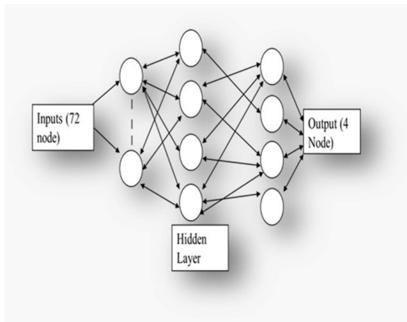


Fig. 9c. Application of ANN

Where,

y_k = Output of the network

w_{ki} = synaptic weight between input of neuron i and output of network k

$v_k = (\sum w_{ki} x_i)$ = net input of neuron i

Θ_k = threshold factor

$\emptyset$ = activation function

Fig. 9. Neural Network Model

B. Modifications to models

- *Confusion Matrix*

The confusion matrices for training, testing, and validation, as well as the three types of data, are depicted in the following figure. The network outputs are very accurate, as we can see by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The blue squares in the lower right corner show the overall accuracy.

In the training confusion matrix the 6 elements are correctly trained in class 1, again 6 elements are trained in class 2 then in class three 7 elements are trained but in class 4 only 5 are correctly trained and 2 elements are wrongly trained.

In the validation confusion matrix 2 elements were correctly classified for class 1, and for class 2 again 2 elements were correctly classified, in class 3 only 1 element was validated correctly and in class 4 none of the elements is validated. While from the Test Confusion Matrix plot we can see 1 element was correctly tested in class 1 giving a 100% test result, in class 2 again 1 element was correctly tested which also give 100% results in class 3 the same result is repeated as in classes 1 & 2. But in class 4, 1 element is correctly tested and 1 element was misclassified which gives the 50% result.

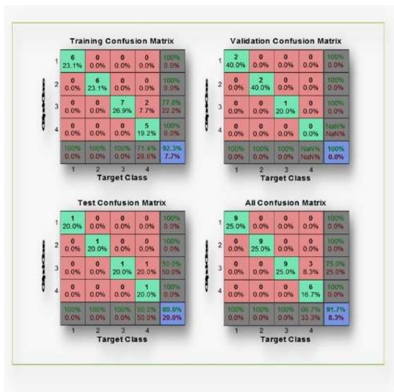


Fig. 10. Confusion Matrix

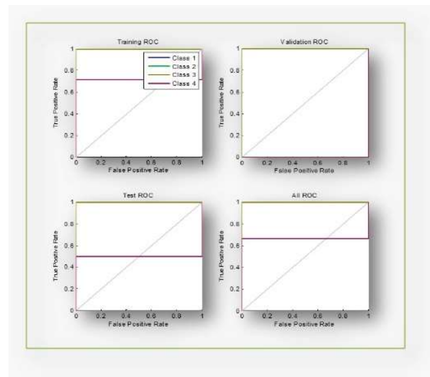


Fig. 10. ROC Plot

C. Ensemble Empirical Mode Decomposition (EEMD)

- Envelope construction- Cubic spline interpolation
- Sifting- Subtracting envelope means from the signal repeatedly
- Residue Extraction- Subtracting the intrinsic mode function (IMF) from the original signal
- Repeat (1)~(3)- Until the number of extrema of the residue ≤ 1

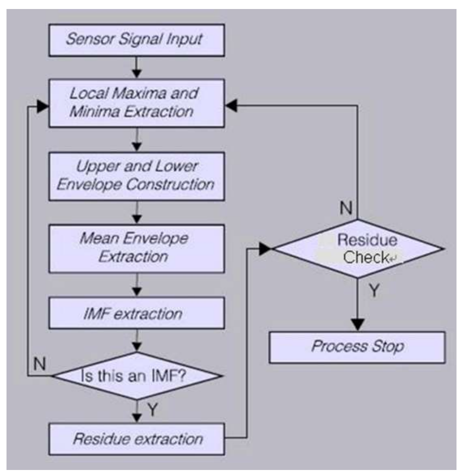


Fig. 11. Flow Chart of EEMD Process

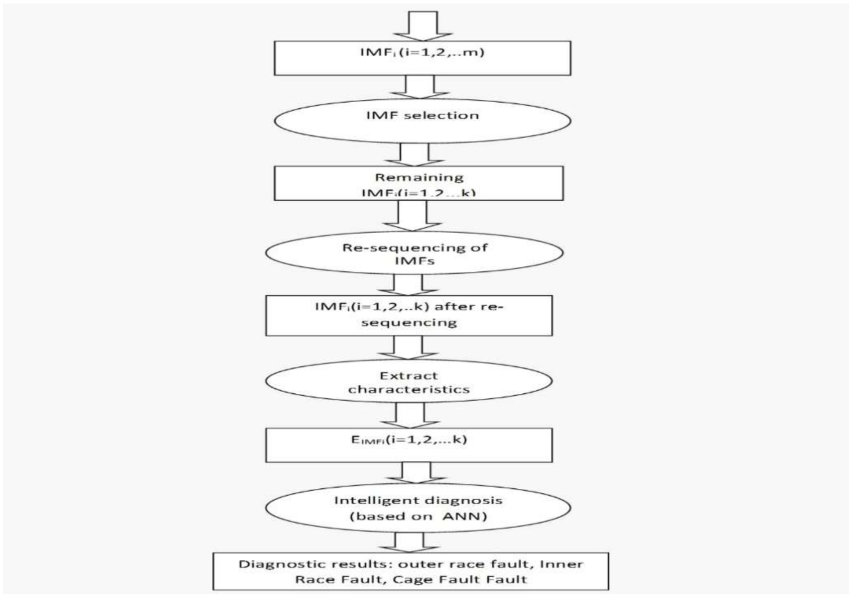


Fig. 12. Flow chart of bearing fault diagnosis using EEMD and Artificial Neural Network (ANN)

- *EEMD (Ensemble Empirical Mode Decomposition) – Intrinsic Mode Functions (IMF)*

Identify all the local maxima and then connect all of them by a cubic spline line as the upper envelope.
Identify all the local minima and connect them by a cubic spline line as the lower envelope. The data between the upper and lower envelopes should be covered by the upper and lower envelopes.
The mean of the upper and lower envelope value is designated as m1(t), and the difference between the signal x(t) and m1(t) is the first component h1(t). Ideally, if h1(t) is an IMF, then h1(t) is the first component of x(t).
If h1 (t) is not an IMF, it's treated as the original signal, and repeat steps 1, 2, and 3 to find the first IMF. After repeated up to k times, h1k(t) becomes an IMF, that is:

1k (1(k -1)) 1k h (t) =h (t)-m(t)(1)

Then, it is designated as c1(t)=h1(t) which is the first IMF.

4 Results and Discussion

A. Imagery Of Model Inner State

The activation and the hidden state of ANN and LSTM are extracted and shown to delve deeper into the black box characteristic of the proposed model. This is useful for learning more about how these deep learning models behave internally.

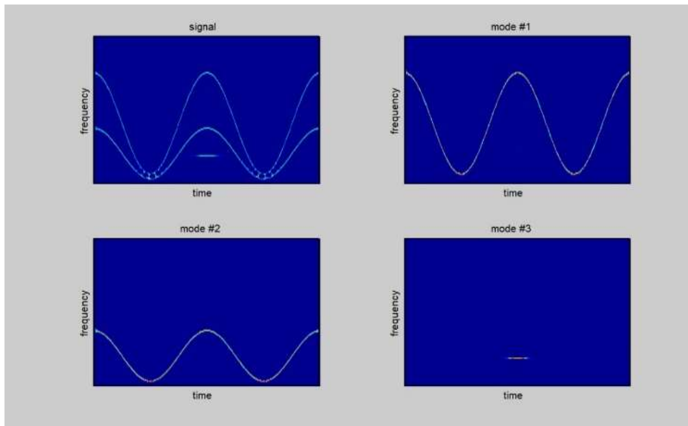


Fig. 13. Wavelet Transform or Time-Frequency Analysis

B. Non-Linear Oscillation- EEMD (Ensemble Empirical Mode Decomposition)

IMF ≠ Fourier mode and, in nonlinear situations, 1 IMF = many Fourier modes
example :- 1 HF triangle + 1 MF tone + 1 LF triangle

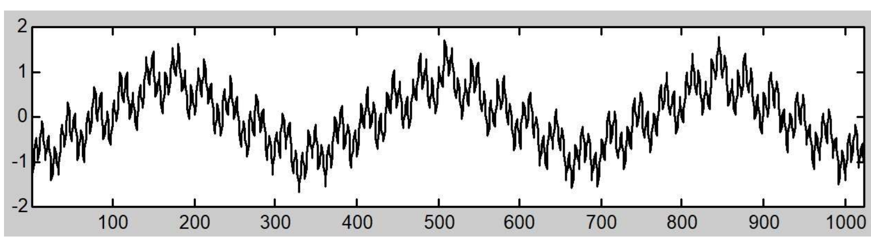


Fig. 14. Non Linearity wave in EEMD

C. Signals

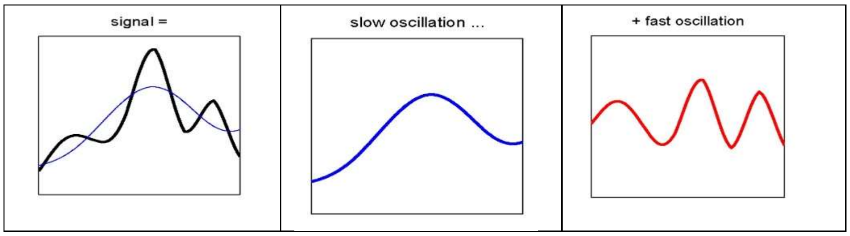
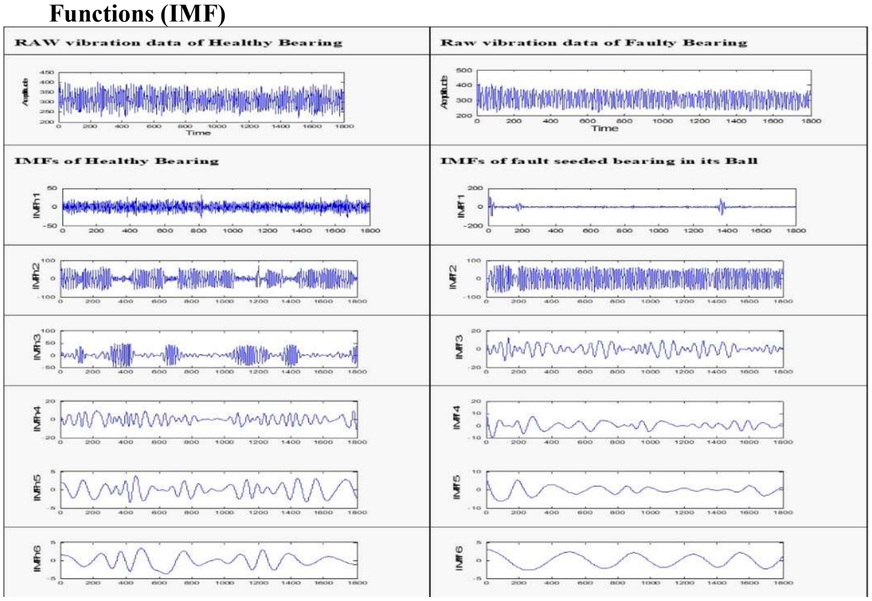


Fig. 15. Signal Oscillating at a different speed

D. EEMD (Ensemble Empirical Mode Decomposition) – Intrinsic Mode Functions (IMF)



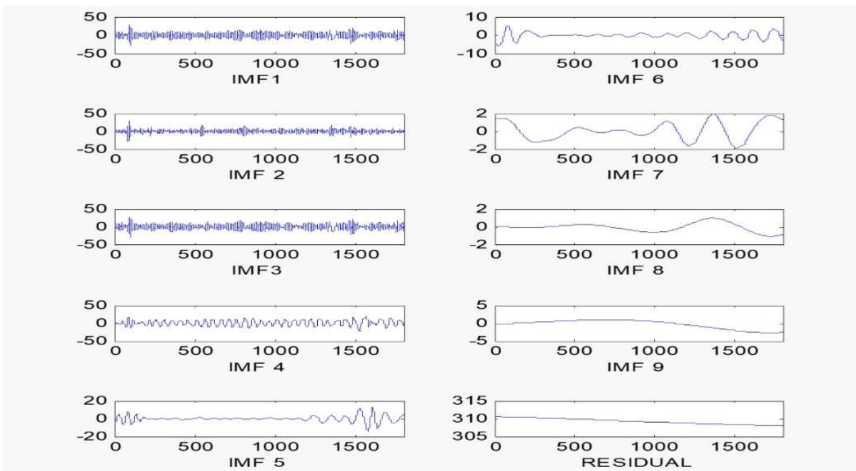


Fig. 16. Intrinsic Mode Functions wave formulation

E. ANN (Artificial Neural Network)

Bearing faults categorization by using ANN for these purposes 13 bearings are selected and vibration data is collected at every 3 minutes interval is recorded with 20 kHz sampling with a total number of records is 1800.

Four layers artificial neural network has been proposed, 13 nodes should be allotted to the input layer according to components of feature vectors, 20 nodes to be the first hidden layer, a second hidden layer with 18 nodes should be on the second layer, four nodes should be on the output layer. Each following layer inherits a weight from the preceding layer. Back-propagation (BP) is used and the algorithm and 1800 learning data, trained ANN can recognize as a whole average classification rate of 84.3 % are reached.

- *Receiver Operating Characteristics (ROC)*

The receiver operating characteristic is a statistic used to assess classifier quality.

Roc applies threshold values throughout the interval [0,1] to outputs for each class of a classifier.

The True Positive Ratio (the number of outputs greater or equal to the threshold divided by the number of one target) and the False Positive Ratio are determined for each threshold (The number of outputs less than the threshold, divided by the number of zero targets).The ROC plots for this work are shown below:

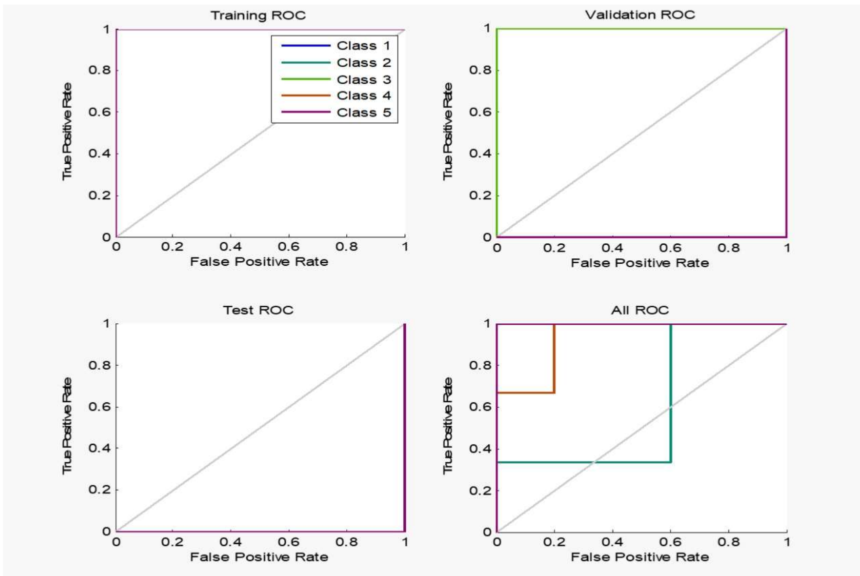


Fig. 9. ROC PLOTS

5 Conclusion

This work presents a new signal compression method based on the optimal Ensemble Empirical Mode Decomposition (EEMD) along with an artificial neural network (ANN) for fault detection. The various types of bearing fault data collected in the earlier work are used for feature extraction using EEMD. Appropriate EEMD parameters are selected for the vibration signal to be analyzed so that the significant feature signal of the faulty bearing can be extracted from the original vibration signal and separated from background noise and the other signal components that are low-correlated or irrelevant to bearing faults. These EEMD parameters are used as input to ANN for the classification of the bearing faults. By applying the back-propagation (BP) algorithm in MATLAB-GUI, the overall average classification rate of 84.6% is reached.

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