Preface

Catastrophic failure of mechanical systems due to faults occurring on different vibrating components is still a great challenge. Health Monitoring of such structures can be done as a preventive method to avoid huge financial losses by understanding the hidden messages in different type of signals emitted by them. Structural Health Monitoring (SHM) has three components; Detection, Diagnosis and Prognosis. Detection is a warning issued by SHM technique that some abnormality has occurred. Diagnosis notifies the type of fault, its location and its extent. Prognosis is for computation of the severity of the crack in terms of fracture mechanics parameters, and its Remaining Useful Life (RUL). Hence, the objective of structural health monitoring is four-fold task i.e. determination of damage existence, determination of damage's geometric location, quantification of damage severity and prediction of remaining useful life of structure.

Focused on especially the articles published after 2011, the present research work identified the following dimensions:

(1) Most of the signal analysis methods concentrate on the single point defects only and therefore, present study is focused towards the simultaneous detection of multiple faults i.e. compounded faults.

(2) There is a growing need of setting up signal processing methods, adaptive to the continuously changing defect conditions, during the bearing degradation phases.

3) There is a need of customized artificial intelligence techniques such as artificial neural networks, support vector machine, deep learning Convolution Neural Network (CNN) etc. for dealing with big data size of diagnosis and prognosis.

(4) If one intends to apply machine learning methods for structural health monitoring by using vibration signal, there has been no available criteria for the minimum size of data required for the diagnosis.

Based on the above gaps identified in the contemporary level of SHM techniques, present research work devised better tools for data processing, fault diagnosis and RUL prediction with special focus on Machine Learning (ML) and Artificial Intelligence (AI). In this research work, a new data processing method is proposed for the cases where machine learning methods fail due to smaller size of available data. This simple data enhancement technique is applied prior to machine learning. In this method the data is proposed to be just augmented by itself to its multiple number of sizes and tested on machine learning after each augmentation. The method is validated for fault diagnosis of a self-priming centrifugal pump.

Further, this research work deals with the diagnosis methods of multiple or compound faults of rolling bearings. Sudden failure of mechanical systems due to faults occurring on rolling bearing is still a serious challenge. These faults are of multiple type, and are compounded in nature. Analysis of vibration signals is one of the most effective techniques for the health monitoring of these bearings. A compound fault signal usually consists of multiple characteristic signals and strong confusion noise, which makes it a tough task to separate weak fault signals from them. We are proposing a new method based on use of Combined Mode Functions (CMF) for selecting the Intrinsic Mode Functions (IMFs) instead of the maximum cross correlation coefficient based Ensembled Empirical Mode Decomposition (EEMD) technique. Sandwiched with this, Convolution Neural Network (CNN), which is deep neural network, is used as fault classifier. This composite CNN-CMF-EEMD method overcomes the deficiencies of other approaches, such as the inability to learn the complex non-linear relationships in fault diagnosis issues and fine compound faults like those occurring on small rollers of the bearing. This study showed that the investigation of the nature and possible causes of bearing defects could be improved by using a CNN-CMF-EEMD approach, as it has exhibited its extraordinary capability of detecting roller faults, which were supposed to be most difficult-to-detect due to combined spin and the circular motion of rollers.

Further, this research work deals with the exploration of improved methods for prognosis i.e. prediction of the RUL with the help of vibration data. A novel method based on stacking ensemble of Gradient Boosted Trees (GBT) is proposed and validated for the case of engines which yields least amount of error as compared to other available methods. This data-driven prognostic uses pattern recognition and machine learning techniques to detect changes in system states. In this data-driven prognostics, the task is to learn a function from training data, mapping degradation patterns of time-series sensor data to engine's life ,and then use this model to predict the number of cycles a test system could run before failure, for a given time-series from initial state till an arbitrary point. After initial stages of data exploration and pre-processing, experiments are performed on the four run-to-failure C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) datasets. It concludes by presenting evaluations of five prediction models, i.e. MLP (Multi-Layer Perceptron), SVR (Support Vector Regression), CNN, gradient boosted trees (GBT) and proposed Stacking Ensemble method. The proposed method uses stacking ensemble of feed-forward neural networks and GBT, as first level learner, and a single-hidden layer- fully-connected neural network as the meta learner. This ensemble provides better results than any of the models alone or weighted average of their predictions. The proposed method outperforms MLP, SVR, CNN & GBT. Experiments are performed on the C-MAPSS datasets and the metric used for scoring models is Root Mean Square Error (RMSE). A comparison is performed with other methods for which RMSE scores are available for the C-MAPSS datasets. Results show the effectiveness of the proposed model.