

# Vibration Based Condition Monitoring of a Hydraulic Brake System through Statistical Learning Approaches: A Review

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## Abstract

**Background/Objectives:** To study the recent development for monitoring the condition of a hydraulic brake system using statistical learning approaches. **Methods/Statistical Analysis:** Machine fault diagnosis is one of the condition monitoring approaches used to monitor the condition of machinery. For brake fault diagnosis, many conventional techniques have been reported in literature. In recent days, statistical learning approaches like, naïve bayes, decision tree, bayes net, best first tree, support vector machines, K Star have been successfully used for the fault diagnosis study. **Findings:** Keeping in mind the end goal to distinguish the most plausible deficiencies prompting to disappointment, numerous strategies in particular, like thermal image mapping, oil particle analysis, acoustic emission signal analysis, vibration analysis have been used for analyzing the data. Among these, vibration signal has been conveniently used for many fault diagnosis study. The same vibration signal can be used for the brake fault diagnosis study. Then these vibration data are processed using short-term Fourier transform, high-resolution spectral analysis, waveform analysis, wavelet analysis, wavelet transform, etc. The results of such analysis are used to analyze the causes of failures. Recent advancement is the application of statistical approach for analyzing the data. This study presents a brief review about the possibilities for implementing the recent statistical learning approaches for monitoring the condition of the brake system. **Application/Improvements:** Number of new statistical learning approaches like nested dichotomy, clonal selection classification algorithm, Artificial Immune Recognition System (AIRS) algorithm can be used for the brake fault diagnosis study.

**Keywords:** Brake System, Condition Monitoring, Fault Diagnosis, Statistical Learning, Vibration Signal

## 1. Introduction

Brakes are a standout amongst the most vital control segments which convey the vehicle to rest inside a sensible separation. The slowing mechanism ought to advance the most astounding level of security out and about. The slowing mechanism may get flawed because of wear, air spill, blur, and so forth. At the point when such things happen, the viability of the brake decreases bringing about mis-chances. Henceforth, it is inescapable that they ought to be observed constantly and analyzed when deficiencies happen. There are numerous procedures, for example, stun beat technique, wear garbage examination,

acoustic emanation, vibration investigation is accessible for the blame finding issue. The audit around one such examination procedures is talked about in the accompanying areas.

The stun beat strategy is essentially a vibration-observing procedure. The effects brought about by harm in the moving components, for example, orientation, brakes, gears, and so on, create stun beats in the ultrasonic recurrence band<sup>1</sup>. Notwithstanding, it doesn't give a lot of demonstrative data. Wear trash examination is the investigation of segment wear particles in the oil to decide the state of the machine parts<sup>2</sup>. Over the top centralization of the wear particles in the oil means irregular wear. It is

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moderately less exorbitant; in any case, it is a disconnected procedure and does not give much symptomatic data. The sound period in materials under nervousness is named as Acoustic Emission (AE). Exactly when a structure is subjected to an external jar, confined sources trigger the entry of essentialness as stress waves which multiply to the surface. Plastic miss-incident of breaks is the central wellsprings of AE in metals. AE can distinguish the improvement of subsurface cracks<sup>3</sup>. AE requires propelled signal taking care of systems. The whole system for accuse assurance is all the more over the top appeared differently in relation to structures in perspective of vibration. The condition of moving portions of a machine is assessed from the whole and nature of vibration, they make. Rot in brake condition conveys a development in vibration level. Thus, a development in the general level of the vibration shows a mechanical deterioration of no less than one parts of the brake. Since the vibration waveform will contain a scope of frequencies associated with the diverse brake parts, data of the frequencies inside the range at which an important augmentation in vibration level has happened can investigate the purposes behind the deterioration<sup>4</sup>. A close audit proposes vibration movement as a fitting instrument for the accuse assurance issue appeared differently in relation to AE Signals<sup>5</sup>.

## 2. Vibration Analysis

Vibration examination is one of the essential techniques in fault finding. A review of the works in the scope of vibration examination for condition checking of brake portions outlines the point of this region. The audit of the writing made under the subsections of ordinary strategies, time space investigation and recurrence area examination and example acknowledgment are portrayed underneath.

### 2.1 Time Domain Analysis

Time domain analysis is the physical signals with respect to time. There are many techniques available for the analysis. Some of the frequently used techniques have been discussed in this section.

#### 2.1.1 Overall Vibration Level

Determining over-all vibration level over an extensive band of frequencies is among the most key vibration measures. The case of general vibration level is plotted

against time and it goes about as a pointer of breaking down. The general level is every now and again implied as the banner RMS regard. As pinnacle is altogether influenced by commotion, RMS level is for the most part favored in machine condition observing applications. The general RMS level shows the machine condition in straightforward machines. Notwithstanding, it doesn't give quite a bit of indicative data. The same is not suited for complex apparatus. Truth be told, restricted blames here may go undetected until a huge auxiliary harm or cataclysmic disappointment occurs<sup>6</sup>.

#### 2.1.2 Wave-Shape Metrics

Faults which make short lived main impetuses, for instance, bearing insufficiencies may not through and through alter the general vibration level; however may achieve a quantifiably immense change in the condition of the banner. With different accuse sorts, the condition of the banner is a prevalent pointer of damage than the general vibration level. Peak element or kurtosis is regularly utilized as a non-dimensional measure of the state of the flag. Both of these flag measurements increments as the "spikiness" of the flag increments. Kurtosis typically ideal for condition observing applications; for similar reasons RMS is desirable over pinnacle. In any case, the peak figure is more across the board utilize on the grounds that meters which record peak element are more regular and moderate than kurtosis meters. The wave shape measurements won't identify deficiencies unless the plentifullness of the vibration from the flawed segment is sufficiently extensive to bring about a noteworthy change in the aggregate vibration level of the flag. This constrains their utilization.

#### 2.1.3 Time Synchronous Averaging

Time synchronous averaging is utilized to dispose of not synchronous flag parts from the turning parcels. Shed parts combine electrical unsettling influence, bearing vibrations and vibrations identified with different shafts or close-by mechanical get together. The probability of TSA is to take outfit run of the mill of the grungy standard over various headways endeavoring to expel or reduce whine from different sources, to update the pennant parts of intrigue. This constitutes a pre-treatment of the vibration standard and along these lines, can add to the steadfast quality or legitimacy of different procedures<sup>7-9</sup>.

### 2.1.4 Descriptive Statistics

Clear insights are the train of quantitatively depicting the principle elements of an accumulation of data. Distinct measurements condense a specimen to find out about the populace that the example of information is thought to speak to. A few measures that are normally used to depict an information set are measures of focal inclination and measures of changeability or dispersion. Measures of focal propensity incorporate the mean, middle, and mode while measures of fluctuation incorporate the standard deviation (or difference), the base and greatest estimations of the factors, kurtosis, and skewness<sup>10</sup>.

### 2.1.5 Time Series Modeling

A period plan is a social occasion of information concentrates; generally including dynamic estimations set aside several moments' interim. The basic considered time approach displaying is to fit the waveform information to a parametric time game-plan demonstrates and store up highlights in light of this parametric model. There are two sensible models, particularly, Auto-Regressive (AR) show up and the Auto-Regressive Moving Average (ARMA) appear. Auto-Regressive (AR) model is set up by time refinement and vibration plentifulness. As the AR demonstrate used the numerical methodology for fitting the variable, the AR coefficients address the standard highlights and can be utilized to pick the denounce types<sup>11</sup>. Dron et al<sup>12</sup> built up a technique for charge region in metal balls in light of the estimation of an auto in turn around model for the vibration pennants and mulled over the first and second request honest properties of the estimation botch<sup>13</sup> applied AR model to vibration signals collected from an affirmation engine and utilized the AR exhibit coefficients as evacuated parts. After a short time, notwithstanding, usage of the AR model or ARMA model is troublesome because of the flexible quality in outlining, particularly the need to pick the request of the model<sup>14</sup>. Among these approaches, specific estimations are enough used to center data as segments from the vibration development in many charge conclusion examine<sup>15-17</sup>.

## 2.2 Frequency Domain Analysis

The vibration movement from a machine can be looked upon as its stamp. Every portion with its own specific spring-mass properties has its own specific trademark repeat/frequencies; excitation of these adds to the over-

all stamp. In that capacity the vibration level is just an aggregate marker of machine condition. The focal favored viewpoint of the repeat space examination is that the repetitive method for the vibration banner is unmistakably appeared as tops in the repeat run at the frequencies where the emphasis happens. This considers weaknesses, which normally make specific trademark repeat responses, to be recognized early, dissected unequivocally and floated after some time as the condition separate. Regardless, the disservice of the repeat space examination is that a ton of information may be lost in the midst of the change method. This data is non-retrievable unless a persisting record of the grungy vibration flag has been made. The trademark blemish rehash of vibration of various parts can be enrolled for the machines working at unfaltering rate. The conformity in the level of repeat of a particular band (of frequencies) can be associated with a portion of a machine. By virtue of section level condition checking study, the modification in the level of repeat of a particular band can be associated with a particular condition of the portion. The change in the level of repeat of a particular band gives an indication of the kind of fault, thusly giving required scientific information. Recurrence area investigation (phantom examination) is usually utilized for blame finding of rotating machines<sup>18,19</sup>. A portion of the recurrence space examination procedures have been talked about in this area.

### 2.2.1 Fast Fourier Transform

By and by, the vibration flag is obtained and changed over to advanced frame by an information procurement framework. The Discrete Fourier Transform is utilized to change this flag into an advanced frame in the recurrence space. Cooley and Tukey<sup>20</sup> acquainted an effective calculation with perform Fast Fourier Transform (FFT). It is utilized as a part of a large number of the present day range analyzers, which changes over the time area motion into the recurrence space. There are many frequency domain analysis, namely band pass analysis<sup>21</sup>, shock-pulse method<sup>22</sup>, spike-energy<sup>23,24</sup>, enveloped-spectrum<sup>25</sup>.

### 2.2.2 Cepstral Analysis

Harmonics Music and sideband arranges in the power range can be perceived utilizing Cepstrum examination. There are a few translations of the noteworthiness of cepstrum<sup>26</sup>. Among them, the most normally utilized shape is power

cepstrum. The power cepstrum is portrayed as the switch Fourier change of the logarithmic power spectrum<sup>27</sup>. In the power cepstrum, cepstral examination is done in the quefrency zone and gives a measure of sporadic structures in the range. This strategy of charmingly related structures is diminished to fabulously one “quefrency” at what might as well be called the symphonious disconnecting. Cepstral examination has ended up being a productive instrument in the affirmation of bearing faults<sup>27</sup>, affirmation of voice contribute talk analysis<sup>28,29</sup> etc., The periodicity of the excitation is for the most part clear in the “quefrency” zone; notwithstanding, in the rehash space, it shows up as various low-level sidebands (segregated by the rehash of the motivations and focused about each of the resounding frequencies) which are from time to time hard to perceive.

### **2.2.3 Fault Detection**

A fault is a startling change or breakdown in a framework. Fault conclusion is a nearly related term. It is characterized as the way toward recognizing the state of the component under review and reason for the issue. Key fault identification systems are displayed in this sub-area. Fault finding methods are exhibited in consequent areas.

#### **2.2.3.1 Spectral Comparison**

A section like a brake can be thought to be in an OK work environment when without any other individual it is free of deficiencies and is accepting its allotted part in the mechanical assembly under consistently recognized working conditions. The standard power (estimate square) range is taken for the vibration movement under these conditions. This “example” range is used as a wellspring of point of view for evaluating resulting power spectra taken at standard breaks all through the machine life under practically identical working conditions<sup>29</sup>. The connection is for the most part done on a logarithmic plenitude scale. A development of 6 - 8 dB over the standard is seen as colossal while augment past 20 dB is considered as a troublesome problem<sup>30</sup>.

#### **2.2.3.2 Spectral Trending**

Spectral trending<sup>31,32</sup> gives a sign of the rate of blame movement. In its most straightforward shape, unearthly slanting includes drifting of the adjustments in the adequacy of all (or various chose) ghastly lines after some

time. For complex machines, this can regularly include an extensive number of information, bringing about data over-burden because of an expansive number of noteworthy otherworldly lines. To streamline the location procedure, a few parameters in view of the range have been proposed which give factual measures of phantom contrasts. Such unearthly parameters and their execution in recognition and analysis of bearing shortcomings are accounted for in literature<sup>33</sup>. It is accounted for that some of these parameters performed well in the recognition of the deficiencies. In any case, they are not of much criticalness versus analytic data.

### **2.2.4 Fault Diagnosis**

The procedure of diagnosis is performed with ghostly examination and drifting; commonly, just the frequencies distinguished as having critical changes are broke down in detail for indicative purposes. The vibration range of even generally basic machines can be very unpredictable because of the numerous symphonious structures of the vibration from different parts. The normal unearthly contrasts connected with different bearing shortcomings are examined by Su and Lin<sup>34</sup>. Blames, for example, expansive wear and unbalance, are appropriated deficiencies bringing on a noteworthy change in the mean adequacy of the vibration at discrete frequencies; these can be examined adequately. These defects show themselves as changes in a couple related frequencies in the range. Unexpectedness and mis-course of action cause low-repeat sinusoidal change achieving an extension of sidebands of particular frequencies (relies on upon the segment to be analyzed) and their sounds. Restricted deficiencies make short hasty vibration, which changes into countless adequacy frequencies in the range; they are hard to analyze or even distinguish.

## **3. Fault Diagnosis through Vibration Analysis**

Condition Monitoring (CM) is predictive maintenance process which monitors the condition of machinery. This can be achieved through an instrumentation technique such as machinery vibration analysis. The recurrence of the vibrations can likewise be mapped with a specific end goal to distinguish disappointments. Examination of the

defective vibration spectra versus great condition flag will give the data required to settle on a choice when upkeep ought to be done.

Vibrations can be measured utilizing seismic or piezo-electric transducers and whirlpool current transducers from the dominant part of basic machines. The measuring strategy for the vibration flag is an intricate procedure that requires specific preparing and experience. These frequencies relate to certain mechanical parts. FFT was utilized to change over the time space vibration flag to its identical recurrence area representation. Notwithstanding, recurrence examination (Vibration Signature Analysis) is just a single part of deciphering the data contained in a vibration flag.

In many industrial applications, vibration signal has been used for making fault related studies. In a study for detecting faults in a rotating machine, elements describe a device for detecting damage to rotators such as ball bearings<sup>35</sup>. In an another study, a roller bearing having a hairline fracture which will generate periodic vibrations each time the fracture contacts another machine element generating periodic vibrations were measured by using a vibration transducer attached to the machine<sup>36</sup>. In another study for finding faults in machines include a fault detection system for detecting mechanical faults of machines that have one or more rotating elements<sup>37</sup>. The system also includes a vibration sensor for sensing vibrations generated by at least targeted rotating machine elements during operation to produce a vibration signal.

Vibration signal was successfully used to monitor the tire pressure in an automobile<sup>38</sup>. In another study, vibration signal was successfully implemented to monitor the single point cutting tool<sup>39</sup>. The application of vibration analysis was implemented in various conditions monitoring system such as centrifugal pump fault diagnosis<sup>15</sup>, brake fault diagnosis<sup>17</sup> and bearing fault diagnosis<sup>40</sup>.

This vibration information can be dissected as recurrence area information or time space information utilizing previously mentioned strategies. Also, the nature of the vibration flag emerging from the stopping mechanism is occasional and irregular. Information demonstrating through machine learning methodology can take care of such issues to a more prominent degree<sup>41</sup>.

## 4. Machine Learning

In mid-1975, the goal of fault diagnosis was to store the

vibration extends and to give graphical instruments so that the master can quickly get to the data and choose the issue with the machine. Because of the progression in PC innovation, obtaining, stockpiling and preparing of a lot of information have turned out to be down to earth. The greater part of the information obtaining frameworks is equipped for logging constant information in advanced shape dependably. The inventive change that goes into the memory devices makes it possible to decrease the cost and size required to store tremendous data. Today's advancement gives the memory devices significantly more dependability. The processors with high handling speed permit specialists to take care of complex issues. A hefty portion of the machine learning methodologies is iterative in nature and they require such quick processors. The previously mentioned improvements quicken the use of machine learning techniques for taking care of issues continuously. Fault finding is one of the application regions, where machine learning techniques are generally utilized.

Include extraction, highlight determination, and highlight grouping are three critical strides in a machine learning approach. There are many elements accessible to be specific, measurable features<sup>16,17</sup>, histogram features<sup>42,43</sup> and wavelet features<sup>44</sup>. The required components were isolated from the vibration movements through segment extraction framework.

### 4.1 Feature Extraction

Statistical investigation of vibration signs gives the physical qualities of time space information. Research work reported by McFadden and Smith<sup>45</sup> described the statistical analysis of vibration signs with various parameter blends which was utilized to evoke data in regards to bearing deficiencies. A genuinely wide arrangement of factual parameters was chosen as a reason for the review. They are median, maximum, standard deviation, skewness, range, mean, standard error, sample variance, kurtosis, minimum and sum.

Viewing the hugeness of the time, it is found that the degree of vibration sufficiency shifts from class to class. A superior diagram than demonstrate the degree of collection is the histogram plot. To manufacture a histogram, the basic walk is to "canister" the degree of attributes that is, package the whole degree of qualities into a development of amongst times and a brief timeframe later tally what number of attributes fall into

every interim. The canisters are all around appeared as successive, non-covering breaks of a variable. The data got from a histogram plot can be utilized as fragments as a part of the blame finding. A delegate test from every brake condition (class) is taken and the histogram is plotted.

Wavelets are logical limits that cut up data into different repeat parts, and a short time later think each fragment with an assurance composed to its scale. Sets of wavelets are overall anticipated that would analyze data totally. A game plan of "fundamental" wavelets will separate data without openings or cover so that the disintegration method is numerically reversible. Thusly, sets of relating wavelets are useful in wavelet based weight/decompression estimations where it is alluring to recover the principal information with unimportant incident. ARMA models are generally utilized for expectation of financial and mechanical time arrangement<sup>46</sup>.

## 4.2 Feature Selection

The way toward selecting the best components from a pool of elements is called 'highlight choice'. The elements can be any measure of information focuses or the flag; however the importance of them will rely on upon how well they help during the time spent order. Numerous strategies are utilized for highlight determination. Some of them are PCA<sup>47</sup>, GA<sup>48</sup>, DT<sup>42,16,17</sup>. Among them, Principle Component Analysis (PCA) is broadly utilized.

PCA is one of the exhaustively utilized multi-dimensional segments change device. In PCA, the measure of data is measured regarding change. The objective of PCA is to decrease the dimensionality of the information while holding however much as could sensibly be foreseen from the collection in the foremost dataset. PCA is a system that can be utilized to patch up a dataset. A choice tree is a tree based learning procedure used to speak to arrangement rules<sup>16</sup>. A standard choice tree comprises of various branches. One branch is a chain of hubs from the root to a leaf, and every hub includes one trait. The rate of a quality in a tree gives the data about the significance of the related. The c4.5 calculation is a broadly utilized one to build choice trees.

## 4.3 Feature Classification

The classifier is a limit which maps a plan of commitments from highlight space to its contrasting classes. In the present audit, the classifier maps the game plan of isolated components to the condition of the machine parts, for

example, course, pump impellers, riggings, and brakes. Practically speaking, design grouping can be completed utilizing numerous classifiers. The accompanying segments depict quickly about the ordinarily utilized classifiers.

The condition of the braking system (incredible or inadequate) is on a very basic level soft in nature. Each one of the issues don't occur immediately. Taking all things into account, there is no restriction regard (crisp data) displayed utilizing fluffy rationale more closely<sup>49-51</sup>. For brake blame determination, fluffy rationale with measurable features<sup>17</sup> gives better order precision as 96.5 %.

If the planning components are secluded without goofs by a perfect hyperplane, the ordinary oversight rate on a test is compelled by the degree of the yearning of the bolster vectors to the measure of prepare vectors. The more small the level of the strengthen vector set, all the more wide the above outcome will be. Propel, the hypothesis is free of the estimation of the issue. In such case a hyperplane is inconceivable; the going with best is to minimize the measure of misclassifications while expanding the edge as for the reasonably asked for sections. A bit point of confinement is a principal part of the SVM and contributes in acquiring an overhauled and right classifier<sup>52</sup>. There is no formal approach to manage pick, which separate breaking point is suited to a class of classifier problem<sup>53</sup>. Most normally utilized bits are Radial Basis Function (RBF), polynomial, straight, multilayer perceptrons and sigmoid. SVM with both factual and histogram highlights gives 100% order precision for the roller bearing deficiency finding. For outward pump blame analysis, SVM produces 100 % accuracy<sup>54</sup>. The same is connected for brake blame conclusion and the arrangement precision was gotten as 98.91%<sup>55</sup>.

One usage of fake invulnerable frameworks called Clonal determination calculation. The Clonal Selection Classification Algorithm (CSCA) has been composed in view of the clonal determination hypothesis. The clonal determination hypothesis is a hypothesis to depict the assorted qualities of antibodies utilized guards the life form from invasion<sup>56</sup>. A manufactured resistant framework system that is propelled by the working of the Clonal choice hypothesis of gained invulnerability is CDCA. CSCA performs better with Statistical a component which gives 98.36% characterization precision for brake blame diagnosis<sup>57</sup>.

Gathering systems are as often as possible prepared to create more exact classifiers than the individual multiclass classifiers. It is major practice to change multiclass issues into various two-class ones. The dataset is broken down into a few two-class issues, the estimation is keep running on every one, and the yields of the ensuing classifiers are joined together. The Nested Dichotomy (ND) is one such basic technique which can be used as a learning computation to oversee multiclass issues direct. Lin Dong et al., developed a technique to upgrade runtime for the multi-class issue using END<sup>58</sup>. Another review reported a strategy to enhance the characterization exactness additionally utilizing woods of settled dichotomies<sup>59</sup>. The settled polarity calculation was effectively executed for the brake blame conclusion problem<sup>60</sup>.

The standard target of roughest is to mix a figure of thoughts from acquired data. Disagreeable set speculation gives the best approach to perceive and portray challenges in data sets of this sort when it is illogical to parcel the articles into described arrangements. The objective is to make a unimportant number of maybe most constrained standards or basic immaterial covering rules for each one of the cases. For mono-piece radiating pump, bearing shortcoming determination, the roughest hypothesis was effectively studied<sup>61</sup>.

The undertaking of grouping items in computerized reasoning is hard on the grounds that frequently the information might be uproarious or having superfluous properties. Various methodologies have been attempted with shifting achievement. Some outstanding plans and their representations incorporate ID 3, which utilizes choice trees<sup>62</sup> and the occasion based learners IB1 - IB5<sup>63</sup>. These plans have exhibited incredible grouping exactness over a substantial scope of areas. Be that as it may, these occasion based calculations need to handle genuine esteemed characteristics and properties with missing qualities. Many plans which handle genuine element qualities are stretched out to adapt to typical characteristics in a specially appointed way. Along these lines, a brought together approach is particularly expected to handle both genuine qualities and typical traits. Consequently, a case based K-Star learner was utilized to play out the brake blame analysis study<sup>64</sup>.

Best first learning tree makes incredible execution models. Right when building models, choice tree figurings restrict cases from the root focus to the terminal focus focuses. The best-first choice tree learning builds up the

"best" focus point first. It makes a completely extended tree for a given arrangement of information. Part criteria are relied upon to gage focus guide corruption toward locate the best focus point. The lessening of debasement is figured by subtracting the contamination estimations of successor focuses from the dirtying effect of the inside. Data and Gini summary are the two comprehensively utilized criteria as a bit of best-first choice tree learning<sup>62</sup>. In data hypothesis, the reduction in dirtying effect is measured by the data get. Essentially, the diminishing in sullying effect is measured by the Gini get in Gini record. The best first tree and choice tree estimations have been utilized for the brake charge assurance study to get a predominant demand accuracy<sup>65</sup>. There are many machine learning calculations which have been contemplated for the different segment blame conclusion issues. Among them, Naïve Bayes<sup>44</sup>, Bayes net<sup>44</sup>, rotation forest<sup>66</sup>, privately weighted learning<sup>67</sup> have been striven for the different part blame finding issues.

## 5. Future Scope

There are some more machine learning approaches which have not been even striven for the blame analysis contemplates. Counterfeit Immune Recognition framework (AIRS), Variational Mode Decomposition, insect minor. Manufactured resistant acknowledgment framework (AIRS) is a zone of study concentrated on the change of computational models in perspective of the benchmarks of the natural invulnerable framework (BIS). It is a developing region that examines and uses assorted immunological parts to deal with computational issues

Variational Mode Decomposition (VMD) decays the flag into different modes or inborn mode capacities utilizing the math of variety. Every method of the flag may have reduced recurrence bolster around a focal recurrence. VMD tries to discover these focal frequencies and natural mode capacities focused on those frequencies simultaneously utilizing an advancement approach called "Alternating Direction Multiplier Method (ADMM)"<sup>68</sup>. ADMM is utilized as an enhancement device to discover such focal frequencies simultaneously. The fundamental motivation behind disintegrating a flag is to distinguish different parts (distinct factual elements) of the flag. This work may concentrate on another calculation - VMD, which separates distinctive modes show in the flag. The

extricated factual component modes can be ordered utilizing different machine learning calculations.

## 6. Conclusion

Based on the above review, there are many scopes for the machine learning approaches in the fault diagnosis field. The literature shows that the suitably extracted statistical and histogram information can be used for diagnosing the problems. Based on this information, the decision about the action to be carried out will be scheduled. The machine learning approaches have been successfully studied for monitoring the machine components such as gears, tool condition, bearing faults, pump impeller faults, wind turbine blade faults, brake faults etc., the application of machine learning can be extended some other machine components.

## 7. References

1. Butler DE. The Shock-Pulse Method for the Detection of Damaged Rolling Bearings, Non-Destructive Testing. 1973; 6(2):92–95.
2. Trevor MH. Handbook of Wear Debris Analysis and Particle Detection in Liquids: Springer Science and Business Media, 1993.
3. Roberts T, Talebzadeh M. Acoustic Emission Monitoring of Fatigue Crack Propagation, Journal of Constructional Steel Research. 2003; 59(6):695–712.
4. Luo GY, Osypiw D, Irle M. Real-Time Condition Monitoring by Significant and Natural Frequencies Analysis of Vibration Signal with Wavelet Filter and Autocorrelation Enhancement, Journal of Sound Vibration. 2000; 236(1):413–30.
5. Abdullah MA, Mba D. A Comparative Experimental Study on the use of Acoustic Emission and Vibration Analysis for Bearing Defect Identification and Estimation of Defect Size, Mechanical Systems and Signal Processing. 2006; 20(7):1537–71.
6. Mercer C. Time Varying Overall Level Vibration (or Noise). Prosig Noise and Vibration Blog, 2001. <http://blog.prosig.com/2001/05/01/time-varying-overall-level/>.
7. Miller AJ. A New Wavelet Basis for the Decomposition of Gear Motion Error Signals and its Application to Gearbox Diagnostics, M.Sc. Thesis - Graduate Program in Acoustics, The Pennsylvania State University. 1999; 613:273–4366.
8. Dalpiaz G, Rivola A, Rubini R. Effectiveness and Sensitivity of Vibration Processing Techniques for Local Fault Detection in Gears, Mechanical Systems and Signal Processing. 2000; 14(3):387–412.
9. Badaoui E, Cohouet V, Guillet F, Daniere J, Velex P. Modeling and Detection of Localized Tooth Defects in Geared Systems, Transactions of the ASME. 2001; 123(3):422–30.
10. Prem S, Mann M. Introductory Statistics, 2nd edition: Wiley. 1995, p. 1–464.
11. Baillie DC, Mathew JA, Comparison of Autoregressive Modeling Techniques for Fault Diagnosis of Roller Element Bearings, Mechanical Systems and Signal Processing. 1996; 10(1):1–17.
12. Dron J, Rasolofondraibe L, Couet C, Pavan A. Fault Detection and Monitoring of a Ball Bearing Bench Test and a Production Machine via Autoregressive Spectrum Analysis, Journal of Sound and Vibration. 1998; 218(3):5011–525.
13. Poyhonen S, Jover P, Hyotyniemi H, Signal Processing of Vibrations for Condition Monitoring of an Induction Motor. First International Symposium on Control, Communications, and Signal Processing. New York, 2004, p. 499–502.
14. Andrew KS. Jardine J, Daming L, Dragon B, A Review of Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance, Mechanical Systems and Signal Processing. 2006; 20(7):1483–510.
15. Sakthivel NR, Sugumaran V, Babudevasenapati S. Vibration Based Fault Diagnosis of Monoblock Centrifugal Pump Using Decision Tree, Expert Systems with Applications. 2010; 37(6):4040–49.
16. Sugumaran V, Ramachandran KI. Effect of Number of Features on Classification of Roller Bearing Faults Using SVM and PSVM, Expert Systems with Applications. 2011; 38(4):4088–96.
17. Jegadeeshwaran R, Sugumaran V. Fuzzy Classifier with Automatic Rule Generation for Fault Diagnosis of Hydraulic Brake System using Statistical Features, International Journal of Fuzzy Computation and Modelling. 2015; 1(3):333–50.
18. Randall RB, Frequency Analysis, Copenhagen: Brüel and Kjaer, 1987.
19. Fansen K, Ruheng C. A Combined Method for Triplex Pump Fault Diagnosis, based on Wavelet Transform, Fuzzy Logic and Neuro-Networks, Mechanical Systems and Signal Processing. 2004; 18(1):161–68.
20. Cooley JW, Tukey JW. An Algorithm for the Machine Calculation of Complex Fourier Series, Mathematics of Computing. 1965; 19(90):297–301.
21. Rades M. Dynamics of Machinery – III, Editura, PRINTECH, 2008.
22. Lundy J. Detecting Lubrication Problems using Shock Pulse, Lubrication and Fluid Power. 2006; 1(4):57–62.
23. Sheam JM, Taylor JK. Using Spike Energy for Fault Analysis and Machine Condition Monitoring, IRD Mech. Analysis Technical Report. 1990; 59(1):123–42.
24. Julien LBJ, Ming X. Vibration Monitoring of Seal Less Pumps Using Spike Energy, Sound and Vibration. 1995; 29(9):12–20.
25. Mignano F. Envelop Detection, Shock and Vibration Digest. 1997; 29(3):8–23.

26. Harris CM, Piersol AG. Shock and Vibration Handbook: McGraw-Hill, New York, 2002.
27. Boogert BP, Helay MJR, Tukey JW. The Quefrency Analysis of Time Series for Echoes: Cepstrum Pseudo-Auto Covariance, Cross-Cepstrum and Shape Cracking. Proceedings of the Symposium on Time Series analysis. Wiley; 1963. p. 209–43.
28. Luke JE. Automatic Speaker Verification using Cepstral Measurements, *The Journal of the Acoustical Society of America*. 1969; 46(4):1026–32.
29. Mathew J. Monitoring the Vibrations of Rotating Machine Elements - An Overview, *Machine Condition Monitoring Research Bulletin*. Monash University. 1989; 1(1):2.1–2.13.
30. Randall RB. Computer Aided Vibration Spectrum Trend Analysis for Condition Monitoring, *Maintenance Management International*. 1985; 5(1):161–67.
31. Mingsian B, Jiamin H, Fucheng S. Fault Diagnosis of Rotating Machinery Using an Intelligent Order Tracking System, *Journal of Sound and Vibration*. 2005; 280(3-5):699–718.
32. Xiamin Z, Tejas HP, Ming JZ. Multivariate EMD and Full Spectrum based Condition Monitoring for Rotating Machinery, *Mechanical Systems and Signal Processing*. 2012; 27(1):712–28.
33. Mechefske CK, Mathew J. A Comparison of Frequency Domain Trending and Classification Parameters when used to Detect and Diagnose Faults in low Speed Rolling Element Bearings, *Machine Condition Monitoring Research Bulletin*. Monash University. 1991; 3(1):4.1–4.7.
34. Su YT, Lin SJ. On Initial Fault Detection of a Tapered Roller Bearing: Frequency Domain Analysis, *Journal of Sound and Vibration*. 1992; 155(3):75–84.
35. Noda B. Device for Detecting Damage on Rotators. U.S. Patent US 4007630, 1977.
36. Hicho MD. Method and Apparatus for Analyzing Rotating Machines. U.S. Patent US5109700, 1992.
37. Robinson JC, Vanhooris B, Miller W. Machine Fault Detection using Vibration Signal Peak Detector, U.S. Patent US5895857, 1999.
38. Praveen H, Sugumaran V. Tyre Pressure Monitoring System - Machine Learning Approach, *Recent Patents on Signal Processing*. 2014; 4(2):81–97.
39. Sanidhya Painuli SP, Elangovan M, Sugumaran V. Tool Condition Monitoring using K-Star Algorithm, *Expert Systems with Applications*. 2014; 41(6):2638–43.
40. Kumar H, Kumar TAR, Amarnath M, Sugumaran V. Fault Diagnosis of Bearings Through Vibration Signal using Bayes Classifiers, *International Journal of Computer Aided Engineering and Technology*. 2014; 6(1):14–28.
41. Jin Y, Liu XX, Liu WP. Design of Hydraulic Fault Diagnosis System based on Lab VIEW, *Advanced Materials Research*. 2012; 457(1):257–60.
42. Sakthivel NR, Indira V, Nair BB, Sugumaran V. Use of Histogram Features for Decision Tree Based Fault Diagnosis of Monoblock Centrifugal Pump, *International Journal of Granular Computing, Rough Sets and Intelligent Systems*. 2011; 2(1):23–36.
43. Sugumaran V, Ramachandran KI. Fault Diagnosis of Roller Bearing Using Fuzzy Classifier and Histogram Features with Focus on Automatic Rule Learning, *Expert Systems with Applications*. 2011; 38(5):4901–07.
44. Muralidharan V, Sugumaran V. A Comparative Study of Naïve Bayes Classifier and Bayes Net Classifier for Fault Diagnosis of Monoblock Centrifugal Pump Using Wavelet Analysis, *Journal of Applied Soft Computing*. 2012; 12(8):2023–29.
45. Fadden PDM, Smith JDS. Vibration Monitoring of Rolling Element Bearings by High Frequency Resonance Technique - A Review, *Tribology International*. 1984; 17(1):3–10.
46. Kashyap K, Rangasami L. Optimal Choice of AR and MA Parts in Autoregressive Moving Average Models, Pattern Analysis and Machine Intelligence, *IEEE Transactions*. 1982; 4(2):99–104.
47. Suykens JAK, Gestel TV, Vandewalle J, Moor BD. A Support Vector Machine Formulation to PCA Analysis and its Kernel Version, *ESAT-SCD-SISTA Technical Report*. 2003; 14(2):447–56.
48. Samanta B.-Al-Balushi KR, Al-Araim SA. Artificial Neural Networks and Support Vector Machines with Genetic Algorithm for Bearing Fault Detection, *Engineering Applications of Artificial Intelligence*. 2003; 16(4):657–65.
49. Zeng L, Wang Z. Machine-Fault Classification: A Fuzzy Approach, *The International Journal of Advanced Manufacturing Technology*. 1991; 6(1):83–94.
50. Huang YC, Yang HT, Huang CL. Developing a New Transformer Fault Diagnosis System through Evolutionary Fuzzy Logic, *IEEE Transactions on Power Delivery*. 1997; 12(2):761–67.
51. Wang H, Chen P. Sequential Condition Diagnosis for Centrifugal Pump System using Fuzzy Neural Network, *Neural Information Processing - Letters and Reviews*. 2007; 2(1):41–50.
52. Yang JY, Zhang YY. Application Research of Support Vector Machines in Condition Trend Prediction of Mechanical Equipment, *Lecture Notes in Computer Science*. 2005; 3498:857–64.
53. Qingbo H, Ruqiang Y, Fanrang K, Ruxu D. Machine Condition Monitoring using Principal Component Representations, *Mechanical Systems and Signal Processing*. 2009; 23(2):446–66.
54. Sakthivel NR, Sugumaran V, Nair BB. Application of Support Vector Machine (SVM) and Proximal Support Vector Machine (PSVM) for Fault Classification of Monoblock Centrifugal Pump, *International Journal of Data Analysis Techniques and Strategies*. 2009; 2(1):38–61.
55. Jegadeeshwaran R, Sugumaran V. Fault Diagnosis of Automobile Hydraulic Brake System using Statistical Features and Support Vector Machines, *Mechanical Systems and Signal Processing*. 2015; 52–53:436–46.
56. William E, Paul P. Immunology - Recognition and Response, *Scientific American Inc., W.H. Freeman and Company*, 1991; 2(1):39–81.
57. Jegadeeshwaran R, Sugumaran V. Brake Fault Diagnosis

- using Clonal Selection Classification Algorithm (CSCA) - A Statistical Learning Approach, *Engineering Science and Technology - An International Journal*. 2015; 18(1):14–23.
58. Dong L, Frank E, Kramer S. Ensembles of Balanced Nested Dichotomies for Multi-Class Problems, *Knowledge Discovery in Databases*. 2005; 3721:84–95.
  59. Rodríguez JJ, García-Osorio C, Jesús Maudes J. Forests of Nested Dichotomies, *Pattern Recognition Letters*. 2010; 31(2):125–32.
  60. Jegadeeshwaran R, Sugumaran V. Health Monitoring of a Hydraulic Brake System Using Nested Dichotomy Classifier-A Machine Learning Approach, *International Journal of Prognostics and Health Management*. 2015; 10(1):1–10.
  61. Sakthivel NR, Sugumaran V, Nair BB, Comparison of Decision Tree - Fuzzy and Roughset - Fuzzy Methods for Fault Categorization of Mono-Block Centrifugal Pump, *Mechanical Systems and Signal Processing*. 2010; 24(6):1887–906.
  62. Quinlan JR. Induction of Decision Trees, *Machine Learning*. 1986; 1(1):81–106.
  63. Aha DW, Noisy T. Irrelevant Novel Attributes in Instance-based Learning Algorithms, *International Journal of Man Machine Studies*. 1992; 36(2):267–87.
  64. Jegadeeshwaran R, Sugumaran V, Vibration Based Fault Diagnosis Study of an Automobile Brake System Using K STAR (K\*) Algorithm – A Statistical Approach, *Recent Patents on Signal Processing*. 2014; 4(1):44–56.
  65. Jegadeeshwaran R, Sugumaran V, Comparative Study of Decision Tree Classifier and Best First Tree Classifier for Fault Diagnosis of Automobile Hydraulic Brake System using Statistical Features, *Measurement*. 2013; 46(9):3247–60.
  66. Liaw A, Wiener M. Classification and Regression by Random Forest, *R News*. 2002; 2(3):18–22.
  67. Atkeson CG, Moore AW, Schaal S. Locally Weighted Learning for Control. In: *Lazy Learning*, Springer Netherlands; 1997. p. 75–113.
  68. Dragomiretskiy K, Zosso D. Variational Mode Decomposition, *IEEE Transactions on Signal Processing*. 2014; 62(3):531–44.